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Production Planning and Energy Contract Optimization

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Abstract

This thesis addresses the optimization of the production planning problem under energy availability constraints. This problem is a real challenge for manufacturers, who are today faced with several energy constraints to satisfy. The goal of the thesis is to develop appropriate mathematical models and optimization methods that can solve the handled problem.

In the first part of the thesis, a Single-Item Capacitated Lot-Sizing Problem with Flow-Shop System is studied by taking into account several energy sources (renewable and non-renewable). The aim is to minimize production, stock and energy costs by considering both the consumption and the mix of energy sources in the energy contract that the company subscribes to the energy supplier. To the best of our knowledge, this problem has not yet been addressed in the literature. In this part of the thesis, several Mixed Integer Linear Programming (MIP) models which serve different purposes are proposed.

In the second part of the thesis, the same problem is handled with the consideration of the stochastic aspect of renewable energy sources. The motivation behind this attempt is to provide manufacturers a decision making tool that can help them to increase the use of renewable energy sources while considering their uncertainty. Moreover, this tool helps choosing the proper contract capacity. As a result, the production plan is obtained in a different way compared to the previous problem in which the availability of energy is considered as known in advance. To model the uncertainty of the renewable energy sources, several probabilistic constraints are proposed. This study is the first attempt that applies the probabilistic constraints to model the uncertain availability of the renewable energy sources.

In the last part of the thesis, the developed models are solved by approximate resolution methods and the results are analyzed in detail.

Keywords: Operations Research, Optimization, Lot-Sizing, Energy, Renewable Energy, Probabilistic Constraints, Uncertainty, Heuristic.

Résumé

Cette thèse aborde l'optimisation du problème de la planification de production sous contraintes de disponibilité d'énergie. Ce problème constitue un véritable défi pour les industriels, qui doivent aujourd'hui faire face à plusieurs contraintes et réglementations énergétiques. L'objectif de la thèse est de proposer des modèles mathématiques appropriés et de développer des méthodes d'optimisation pour résoudre le problème traité.

Dans la première partie de la thèse, nous étudions le problème de dimensionnement de lots avec un système de production de type Flow-Shop en prenant en compte plusieurs sources d'énergie (renouvelables et non renouvelables). L'objectif est de minimiser les coûts de production, de stock et d'énergie en tenant compte à la fois de la consommation et de la combinaison des sources d'énergie dans le contrat énergétique que l'entreprise a souscrit auprès du fournisseur d'énergie. À notre connaissance, ce problème n'a jusqu'à présent jamais été abordé dans la littérature. Dans cette partie, plusieurs modèles de programmation linéaire en nombres entiers (PLNE) sont proposés.

Dans la deuxième partie de la thèse, le même problème est traité avec la prise en compte de l'aspect stochastique des sources d'énergie renouvelables. La motivation derrière cette approache est de fournir aux fabricants un outil d'aide à la décision pouvant les aider à accroître l'utilisation des sources d'énergie renouvelables tout en tenant compte de leur incertitude. De plus, cet outil les aide à choisir le contract le plus approrié à souscrire appropriée. En conséquence, la planification de la production est obtenue de manière différente du problème précédent dans lequel la disponibilité de l'énergie était considérée certaine. Pour modéliser l'incertitude des sources d'énergie renouvelables, plusieurs contraintes probabilistes sont proposées. Cette étude est la première tentative qui applique les contraintes probabilistes pour modéliser la disponibilité incertaine des sources d'énergie renouvelables.

Dans la dernière partie de la thèse, les modèles développés pour les problémes NP-difficile sont résolues par des méthodes de résolution approximative et les résultats sont analysés en détail.

Mots-clés: Recherche Opérationnelle, Optimisation, Dimensionnement de Lots, Energie, Energies Renouvelables, Contraintes Probabilistes, Incertitude, Heuristique

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Chapter 1

Introduction

Contents

In this chapter, an introductory brief is given about the context of the study. In the following, the handled problems in this thesis are summarized shortly. In the third part of this chapter, the contribution of this thesis is emphasized and the chapter is concluded by describing the general structure of this thesis.

1.1 Context

According to the report of U.S. Energy Information Administration, it is expected that energy consumption in non-OECD countries increases by 41% between 2015 and 2040 in contrast to a 9% increase in OECD countries (EIA [2017]). Another noteworthy fact presented in the report is that the industrial sector, which includes mining, manufacturing, agriculture, and construction, accounts for the largest share of energy consumption of any end-use sector, accounting for more than 50% over the entire projection period (Figure 1.1).

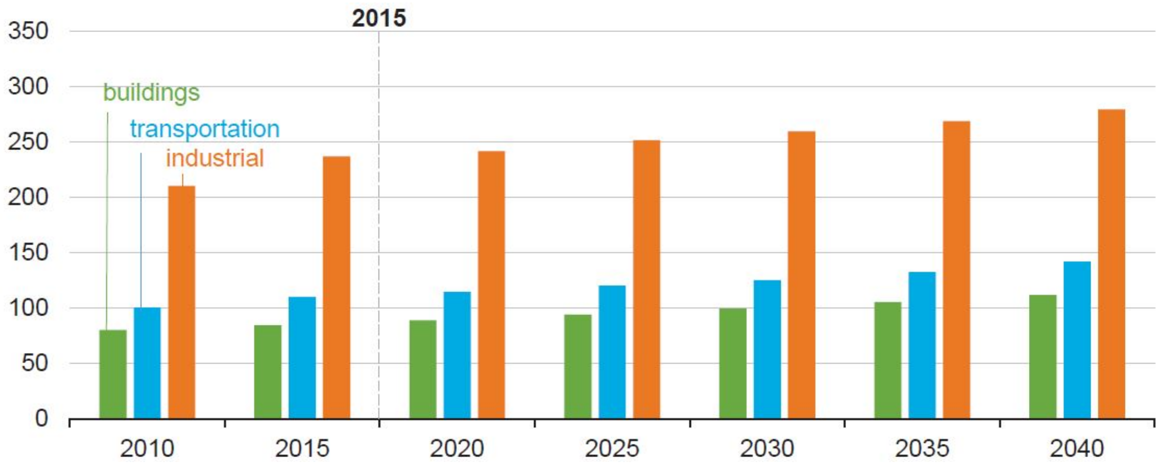

Figure 1.1: World energy consumption by end-use sector (quadrillon btu) EIA [2017]

When the balance between the energy sources is examined in Figure 1.2, it is seen that the world's energy need mainly relies on the fossil fuels which are responsible for the increased carbon emission. In addition to this side effect, the limited nature of the fossil fuels rises the concerns about the meeting the energy starvation of the world. The projected increase in energy consumption and changing climate conditions lead the governments to seek more sustainable and clean ways for energy generation.

There is no doubt that using renewable energy sources is the best option with their pollution-free and limitless nature to cope with the current environmental and sustainability issues. In recent years, the governments invested considerable amount of money in renewable energy generation technologies, announced the target levels to promote the integration of renewable energy sources, provided certain incentives to encourage individual or commercial consumers to use greater amount of renewable energy sources. In accordance with this worldwide trend, it can be said that the renewable energy sources

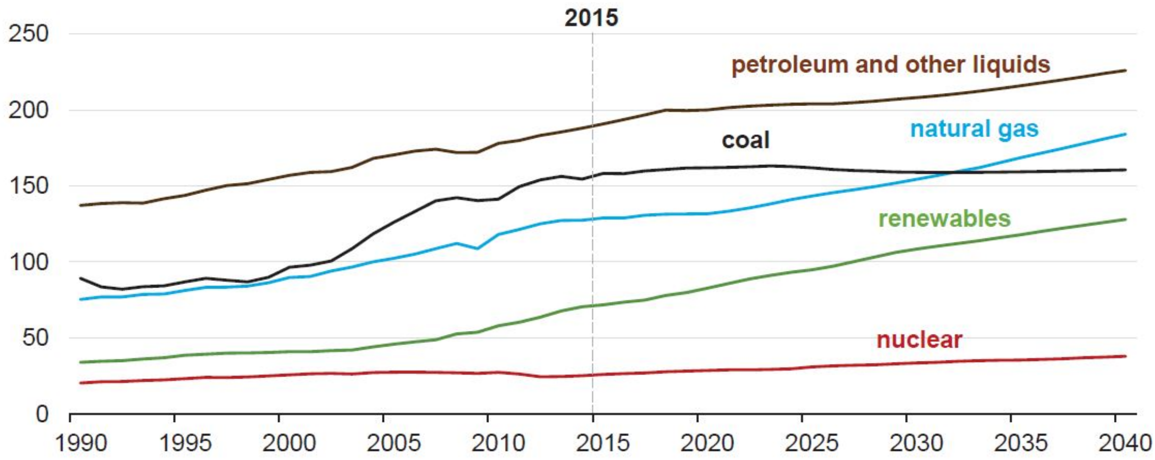

Figure 1.2: World energy consumption by energy source (quadrillon btu) (EIA [2017])

will get the fastest-growing share in the energy consumption of the world in the following years (Figure 1.2).

The European Union defines energy targets for 2020, 2030 and 2050 to monitor energy consumption of EU countries systematically. These targets provide a consistent policy framework for greenhouse gas emissions to the EU, renewable energy sources and energy efficiency. The 2020 energy targets known “20-20-20 Targets”define the priorities as follows:

a) Increase the share of renewable energies in the EU’s energy consumption by at least 20%

b) Reduce greenhouse gases by at least 20%,

c) Increase energy efficiency by at least 20%,

To achieve defined targets, the manufacturing sector has an important role since it has one of the largest share in the total energy consumption. Increasing the renewable energy consumption in the industrial area not only contributes to the declining the overall carbon emission levels significantly, but also facilitates to achieve the sustainability targets. In other words, if the conventional energy sources supplied to the industrial customers are diversified with the renewable ones; while the energy reserves of the world can be used more efficiently, environmental targets can be achieved by significantly declining carbon emission levels.

When it comes to the efficiency issue, one of the key acts which can raise the efficiency is to use the resources by reducing the waste as much as possible. This approach can be adapted to all the resources of the system such as energy, raw material, labour force etc. The efficient use of the resources is heavily dependent on the appropriate planning and scheduling strategies which are built in a consistency with the capacity of the system and the availability of the resources. When the constraints related to the resources are ignored, the generated production plans result in failure, failing plans cause the activities redone.

In a manufacturing system where the number of tasks redone increases, the efficiency can not be questioned.

The nature of energy is quite different from the other inputs of a production system, in terms of its storage and supply processes. Knowing the required energy load in advance is significantly important for the energy suppliers. It is not only necessary for planning the generation and transmission of the energy or managing the energy availability in a more efficient way but also to protect the energy generation facilities from the issues caused by huge demand fluctuations.

To cope with this issue, energy providers propose different energy tariffs and contract options to their customers and define certain limits for the amount of energy which can be supplied. The proposed tariffs, defined energy limits or pricing schemes by energy supplier reflect as constraints in the production planning process of the industrial customers. If the aforementioned consistency rule is recalled, considering the constraints and limitations defined by energy supplier is essential to build appropriate production plans, to satisfy the efficiency and minimize the energy costs of the production systems.

In the next section, the way of integrating the constraints sourced by the energy supply conditions into the production planning process with the purpose of increasing energy efficiency is explained.

1.2 The studied problems in this thesis

To create efficient production plans, there are two crucial questions that should be answered. The first one is, *“When and how much to be produced? ”* which can be formulated as “lot-sizing problems ”and the second question is *“how much, when and where the resources should be allocated? ”* which can be translated as “scheduling ”problem. While a manufacturer makes decisions for these questions, he/she should consider the objectives and the constraints of the manufacturing system. As these constraints source from the production environment itself, there might be some limitations which are defined by the suppliers of the manufacturing company. Since energy differs from the other inputs of a production system in terms of storage and supply conditions, to manage the energy need of a production system requires high compatibility between the industrial customer and the energy supplier. To satisfy the harmony between the two sides and to control the balance between the energy supply and demand; various tariffs are offered to the customers, which includes different pricing mechanisms and the power demand (capacity) options. The agreement between the two sides is guaranteed by signing the contract, also called "Energy Supply Agreement". In this point, one another decision problem emerges for the manufacturers *“Which of the offered capacity options can cover the needs of the production system? ”*

Another aspect we take into account is introducing renewable energy sources to the contract capacity selection procedure. Especially, in the last few decades, there is a rising awareness in societies to protect the planet, to produce or consume the goods/services in a more ecological friendly way. Replacing the traditional energy sources which have huge greenhouse effect on the planet with the limitless, clean and natural energy sources has become one of the major concerns of all countries. Due to the fact that the industrial customers have the largest share in the energy consumption and the great proportion of this consumption is heavily based on fossil resources, the industrial sector is scrutinized more than ever in terms of reducing carbon emissions. That's why, the manufacturing companies look for the ways of sustaining their production activities in more environmental-friendly ways. Obviously, increasing the use of renewable energy sources can overcome this issue.

Today, the share of renewable energy sources in the total purchased power is decided by the energy suppliers. As it is explained before, to reach the EU targets, the usage of the renewable energy sources is encouraged by the governments and industrial customers face new regulations for reducing their carbon emissions to the acceptable levels. Hence, deciding the best capacity option for the renewable energy sources will have vital importance, too. However, the stochastic nature of the weather dependent sources discourage the industrial customers who need the steady supply of the energy to realize the production plans without any interruption. The last question *"How can renewable energy sources be integrated into energy purchasing procedure by considering their uncertain nature? "*

In our study we combine three optimization problems and find the answers of the following questions to contribute increasing the energy and production efficiency:

1. Capacitated Lot Sizing Problem in Flow Shop System
   When and how much product should be manufactured?
   How should the production be organized?
2. Contract Capacity Selection Problem
   Which of the capacity option can optimally realize the planned production ?
   How can the best energy mix be generated from the proposed options?
3. Generating Best Energy Mix Under Renewable Energy Uncertainty
   How can the best energy mix be generated when the stochastic nature of the renewable energy sources is considered?

The primary objective is to develop an optimization model which can define the optimum production quantities, the allocation of the jobs to the machines and the optimum capacity options which can cover the need of the planned production. Therefore, the first two problems can be solved simultaneously by the developed model. The second objective is to integrate the stochastic nature of the renewable energy sources into the capacity selection problem and to build a bridge between the capacity selection procedure and lot sizing decisions under uncertainty. The last objective is to propose an appropriate solution approach which can deal with the complexity of the developed model and provide an optimal/near-optimal solution in a reasonable computational time.

1.3 The contribution of the thesis

The objective of this thesis is to address the single item capacitated lot sizing problem with the contract capacity selection problem in deterministic and non-deterministic way. The contributions of this study are given as follows.

Firstly, the models developed in this study can support decision makers to cope with several optimization problems that they face in real life such as defining optimum production plan and selecting the optimum capacity option which can cover the need of the system simultaneously. The problem is firstly handled in deterministic level, where all the parameters known in advance. A mixed integer linear programming model is developed. To evaluate and analyze the proposed model, a numerical study is conducted and the results are illustrated for giving better insight about the impact of the presented model. From scientific view, specific constraints are developed to compute exact power demand in a flow shop environment. Therefore, the studies of Fang et al. [2011] and Masmoudi et al. [2017a] which are built on the peak power calculation of two machine flow shop environment is improved and calculating the peak demand of flow shop environment including more than two machines becomes possible with the method proposed in this thesis.

Secondly, a single item capacitated lot sizing problem under uncertain renewable energy availability is addressed. Three types of probabilistic constraints and two types of objective functions which can compute the expected cost of the considered probabilistic events are developed. In the first type of probabilistic constraints, the risk in the supply of the renewable energy sources is translated as service level of the industrial customer. Therefore, it is aimed to determine the optimal production plan and energy contract option which minimizes the total production and energy costs by satisfying the external demand with a given service level. The chance constraint programming approach is used for the development of the first constraint. To best of our knowledge, our approach is the first attempt which deals with the uncertain nature of the renewable energy sources through the chance constraint programming. The rest of the constraints which are developed based on the expected availability and expected failure in the supply of the renewable sources are newly proposed constraints which can open new paths and give some inspirations to other researchers in the field. To highlight the effect of the proposed non-deterministic models, they are solved by taking into account different energy mixes such as mixing traditional and one type renewable sources or mixing the traditional source with the two types of renewable sources. The outcomes and their affect on the production plan are illustrated to present better sense. In practical point of view, the proposed models can be used as helpful decision making tools by the industrial customers to deal with the continuity risks in the supply of the renewable energy sources.

Thirdly, since the handled problem is NP-hard, a Fix-and-Relax heuristic is introduced to solve the problem. Two different relaxation procedures are applied and the performance of the solution approach is tested on randomly generated instances. It is seen that the obtained results are quite promising. The applied heuristic approach produces solutions with a small optimality gap for small problem sizes, for the larger instances, it allows to reach better results than the results obtained by commercial solvers within shorter times. The same heuristic approach is implemented for the solution of the developed non-deterministic models and it is seen that the proposed solution method can solve some of the small size instances which can not be solved by the commercial solver.

Overall, the developed models can contribute to increase the use of renewable energy sources, to create environmental-friendly production systems and to boost the energy efficiency.

The research conducted in this thesis has been presented in several conferences and the author is the main contributor of the following publications:

Journal Articles

1. Rodoplu, M., Arbaoui T., Yalaoui A., "A Fix-and-Relax Heuristic for the Single-Item Lot-Sizing Problem with a Flow-Shop System and Energy Constraints", International Journal of Production Research, 2019, p. 1-21.

International Conferences with Proceedings

1. Rodoplu, M., Arbaoui, T., Yalaoui, A. (2018). Energy Contract Optimization for the Single Item Lot Sizing Problem in a Flow-Shop Configuration and Multiple Energy Sources. IFAC-PapersOnLine, 51(11), 1089-1094.
2. Rodoplu, M., Arbaoui T., Yalaoui A., Single Item Lot Sizing Problem Under Renewable Energy Uncertainty. IFAC-PapersOnLine, 52(13), 18-23.

International Conferences without Proceedings

1. Rodoplu, M., Arbaoui T., Yalaoui A.,"Single-Item Lot-Sizing Problem for Flow Shop Environment with Multiple Energy Sources", EURO, 2019, 30th European Conference on Operational Research, 23-26 June, Dublin, Ireland
2. Rodoplu, M., Arbaoui T., Yalaoui A.,"Iterated Local Search for the Integrated Single Item Lot Sizing Problem for a Flow Shop Configuration With Energy Constraints", META, 2018, 7th International Conference on Metaheuristics and Nature Inspired Computing, 27-31 October, Marrakech, Morocco
3. Rodoplu, M., Arbaoui T., Yalaoui A., "Solving The Single Item Lot Sizing Problem "Under a Flow Shop Configuration With Multiple Energy Sources", OLA, 2018, International Workshop on Optimization and Learning: Challenges and Applications, 26-28 February 2018, Alicante, Spain

1.4 Structure of the thesis

The rest of this thesis is organized as follows: Chapter 2 presents a brief explanation about the key concepts related to the energy and its pricing schemes which will be frequently used in the remaining parts of the thesis. Moreover, a general literature review about the energy-aware production planing studies is provided and the conducted study in this thesis is positioned in the literature.

Chapter 3 introduces the developed deterministic optimization model for the addressed capacitated single item lot sizing problem with contract capacity selection. The considered production configuration, assumptions related to the production environment and the energy supply are described and the developed model is explained in detail and enriched with the illustrations. A numerical example is given to evaluate and analyze the proposed model.

In Chapter 4, the stochastic aspect of the renewable energy is taken into account. Three types of probabilistic constraints and two types of objective functions calculating the expected costs of the probabilistic events are presented and the developed models are tested via a commercial solver.

Chapter 5 proposes the use of the Fix-and-Relax approach for the solution of the developed model. The proposed relaxation methods and the fixing strategies are explained and the variants of the heuristic are tested on small, medium and large size instances for proposed deterministic model. The results are compared with the results obtained by the commercial solver. The performance of the proposed heuristic is discussed. Similar steps are followed for the application of the proposed heuristic for the developed stochastic models. Instead of testing different relaxation strategies; the one, which produces the high quality solutions when the deterministic model is tested, is selected as relaxation approach and the proposed stochastic models are tested on different instances and the results are analyzed.

Finally, the last chapter summarizes and concludes the study carried out in this work. The results are underlined and some perspectives are given for the future work.

Chapter 2

State of Art

Contents

2.1 Introduction

In this chapter, we present a comprehensive review of the studies related to the optimization of the production planning by taking into account energy aspect. Firstly, deterministic production optimization models are classified based on the different decision levels. Since it constitutes the basis of this thesis, the lot sizing problem is examined under the spotlight. Secondly, the studies that deal with the stochastic nature of the renewable energy sources are reviewed in detail. After surveying the frequently used modelling and solution approaches for the solution of the addressed problems, this chapter is summarized shortly and closed.

2.2 Production Planning by Considering Energy Aspect

The production planning models have been one of the most attractive research topics in the optimization community for years. The main purpose of the previously conducted studies has been to create optimum production plans in terms of costs. It has been seen that although the studied models achieve to create optimum production plans in terms of costs, sometimes, they involve some other global inefficiencies. From this starting point, the production planning models have evolved by considering different elements in the production planning models. For example, minimizing the production related costs has been studied by considering minimizing makespan or tardiness, etc. to eliminate possible inefficiencies in the production plans.

As Bougain et al. [2015] pointed out in their study, the proportion of the cost of electrical energy in manufacturing companies is up to 15% of overall production costs. It is a fact that although energy related costs have a huge share in the total production costs, the researchers have not paid attention to this cost item for years. Recently, with the increasing awareness to the issues such as scarcity in the traditional energy sources, reducing the carbon emission levels, integration of the renewable energy sources into the current energy market, the efficient management of the energy has become one of the important concerns of governments, industrial or residential customers and energy producers.

In the following sections, the production planning optimization models considering energy aspect are classified according to decision levels and reviewed. Thus, it is aimed to emphasize the increase in the number of the production planning optimization studies which combine the energy aspect with the other classical sources like machine, manpower etc. Before going through that part, it would be useful to give some information about the today's energy market and pricing of the electricity and power.

2.2.1 An Important Cost Item in The Manufacturing Industry: Electrical Energy

Electricity is one of the commodities that we need indispensably in daily life. In a residence, the demand for electricity can occur at any point when an electrical appliance is switched on. During the day, the demand for electricity varies depending on various variables. In a summer afternoon, the demand for electricity reaches peak points due to the operation of air conditioners in all industrial or residential places. In order to cope with these kind of demand fluctuations and to continue to serve their customers, the producers of other commodities produce more and more products in low season and stock them in order to meet the peak demands in high seasons. However, electricity is hard to store at large scale. Therefore, the supply of and demand for electricity should match and must be maintained in balanced way for the stability and reliability of the grids. If we assume that the amount of energy which can be supplied can be controlled by the utilities, how can the continuously changing power demand of the customers be controlled and matched with the supply? As the answer of this question is crucial to sustain the supply and demand balance for social and technical reasons such as giving reliable service to the customers, or preventing the utilities any damages caused from sudden peak demands, it is important for the economical reasons, too.

With the deregulation in the electricity market, growing competition between the energy suppliers, social and economical developments in worldwide such as increasing awareness for the environment issues, increasing oil prices etc. pushed the electricity producers to search the ways of generating and supplying the energy more efficiently which can minimize their operation costs. Since each utility has a certain capacity, meeting an excessive demand means investing for new larger generation plants. However, as Qdr [2006] pointed out in his study, the electricity systems are highly capital-intensive, and generation and transmission system investments have long lead times and multi-decade economic lifetimes. Instead of investing for new infrastructure of the new generation units, encouraging the customers to reduce or shift their consumption could mean avoiding or delaying building additional generating capacities. Thus, this would avoid or defer energy price increases that would otherwise be imposed on customers to help finance new investments in system capacity (UNIDO [2006]). Therefore, increasing the efficiency in the electricity generation challenge could be transformed into a *win-win* type relationships for the producers and customers. To achieve this target, the *demand side management* term is introduced to the electricity industry. In the next section, the details of demand side management concept is explained.

Demand Side Management

Demand side management (DSM) refers to the “planning, implementing, and monitoring activities of electric utilities that are designed to encourage consumers to modify patterns of electricity usage, including the timing and level of electricity demand" (EIA [1999]). With the advancement of electricity market liberalization, DSM has further evolved into the following two groups:

1) *Energy efficiency (EE)*, corresponds to reducing the energy required for the provision of services or products (Behrangrad [2015]).

2) *Demand response (DR)*, refers to changes in electrical usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized (Behrangrad [2015]).

The energy tariffs are implemented based on demand response mechanisms. As Thakur and Chakraborty [2016] pointed out in their study, there are two types of demand response mechanisms, one is based on pricing of tariff and other one is based on incentives for the consumer, shown in Figure 2.1. In price-based programs, electricity price is changed based on the time interval of the day. Therefore, the consumers can schedule their consumption according to varying electricity prices over the daytime. *Time-Of-Use (TOU) Rates, Critical Peak Pricing (CPP), Real Time Pricing (RTP)* are the most common price-based demand response mechanisms (Goldman et al. [2010], see Figure 2.1). In incentive-based implementations, the customers are rewarded by the energy suppliers in case of reducing their electric load upon the request of energy suppliers. By leaving incentive based pricing mechanism out of the context, giving more detail about the price-based mechanism will be beneficial to understand the context of the studies which will be mentioned in the following parts of this state of art.

As it is indicated before, price-based mechanism gives opportunity to the customers to shift their consumption habits according to varying electricity prices. In TOU pricing strategy, as its name suggests, the price of the electricity changes according to the different time periods of the day. Typically, the day is broken into three successive periods: peak, mid-peak, off-peak. The price of the electricity is fixed within these periods and the customers are informed in advance. This division is based on the time of day and the amount of electricity demanded. As it can be observed in Figure 2.2, PEAK rates are applied in the time period of the day where energy demand is the highest. This period mostly corresponds the late afternoon or evening when the people return to their home from work and start to use their television, oven or other appliances. Similarly, the OFF-PEAK periods are the time slices where the cost of electricity is the lowest. In these periods, the energy demand mostly decreases, due to the lower energy demand. MID-PEAK periods can be referred as the part of the day where energy demand varies.

In Critical Peak Pricing (CPP), electricity prices are increased to punitive levels at peak hours on critical days announced beforehand. In response to that, people may change their patterns of electricity usage by turning off their air conditioners at home and/or leaving the home to minimize electricity consumption (Kii et al. [2014]).

In Real Time Pricing (RTP) mechanism, electricity rates vary continually (typically hourly) in response to wholesale market prices (Goldman et al. [2010]).

In this thesis, we will focus on Time-of-Use (TOU) pricing strategy (Figure 2.2). It is expected that with the cost reduction in the renewable energy generation technologies, increasing environmental concerns, the deployment of renewable sources increases very fast. As a result, the increasing inclusion of renewable energy sources in daily life will have many positive effects on pricing mechanisms.

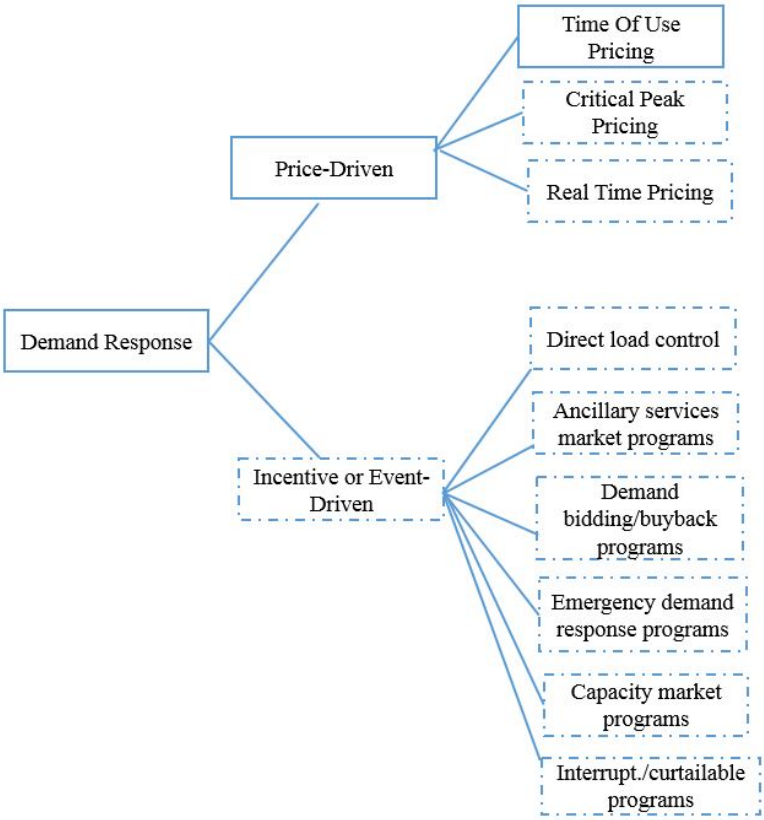

Figure 2.1: Demand response categories (Goldman et al. [2010])

Renewable Mix

The cleanest and most sustainable way of the energy generation is to use renewable energy sources which are limitless in the nature and pollution-free. However, the main drawback of the renewable energy sources is that they are overly dependent on the weather conditions. Due to this fact, since the power generation can not be sustained constantly, being dependent on the only renewable energy sources discourages, especially, the industrial customers who need a stable energy supply to sustain the production activities. A solar plant can generate a great amount of solar power during the central hours of a summer day. It is clear that it is not possible to operate the solar plant with the same performance during the night time or cold and cloudy winter days due to the lack of solar irradiation. In case of relying on the only solar power, the customers face the difficulties

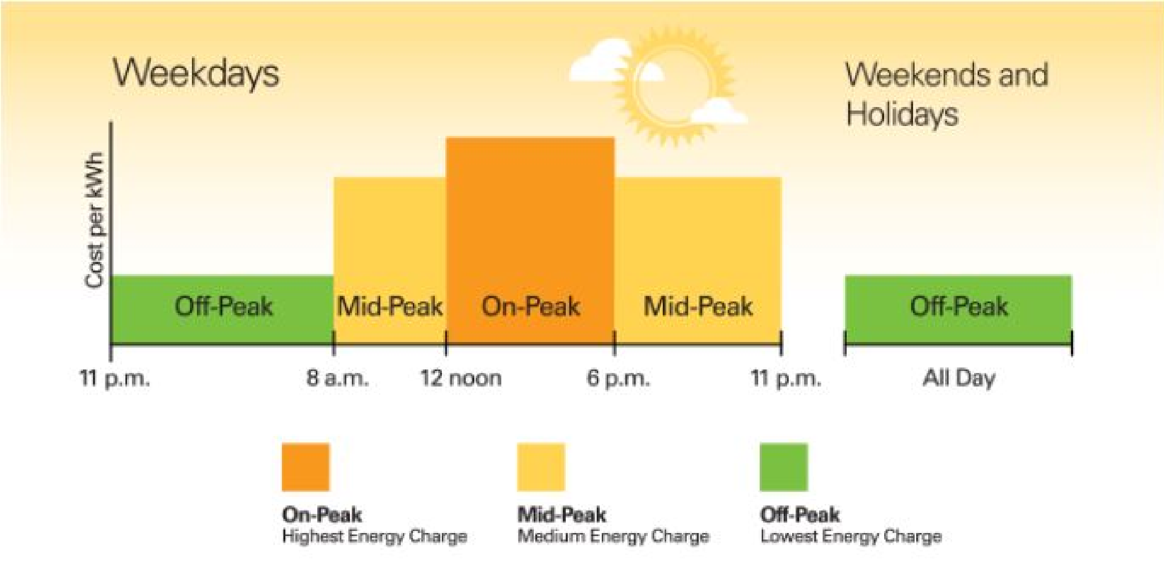

Figure 2.2: An example for TOU pricing scheme

to get the power they demand. Instead of leaning on only one type of renewable source, if they are combined with reliable conventional sources a backup can be provided for the renewable sources and the continuity of power supply can be guaranteed. From all these aspects, it can be interpreted that the conventional and renewable energy sources have certain advantages and disadvantages. So, at this point, the following question arises: *instead of dealing with the downfalls of the traditional and renewable energy sources separately, why not hybridize them to benefit from their different characteristics and to combine their advantages*?

Lazarov et al. [2005] defined a hybrid power system as a power system, that uses one renewable and one conventional energy source or more than one renewable with or without conventional energy sources, that works in "stand alone" or "grid connected" mode.

The idea of hybridizing the different energy sources originates from the power generation for remote areas (Nayar et al. [1989]). As Bizon et al. [2013] indicated in their study, conventional generation systems such as thermal and nuclear power system are not a proper solution to electrification of remote areas due to economical and technical issues. By combining different energy sources, it is aimed to compensate the deficit that might occur during the peak demand hours. Therefore, the cost of power generation facilities declines and since the possible losses in the power facilities are minimized as much as possible, the efficiency increases, too. Nonetheless, the starting point of hybridizing is to meet the power demand in the rural areas, the other benefits of this technology increased its deployment significantly.

Another motivation of hybridizing the energy sources is raising awareness for the environmental issues and the developed regulations by governments for increasing the cost of carbon emission. The power plants search for the ways of decreasing their carbon footprints and avoiding the additional costs.

Another important driver in the development of the hybrid power technologies is rapidly falling costs of the renewable technologies. Since 2009, the cost of solar has dropped by 75 percent, and wind by 66 percent (EREF [2018]). As a natural consequence of this case, the investments in the renewable energy technologies have dramatically increased as it can be clearly seen in Figure 2.3.

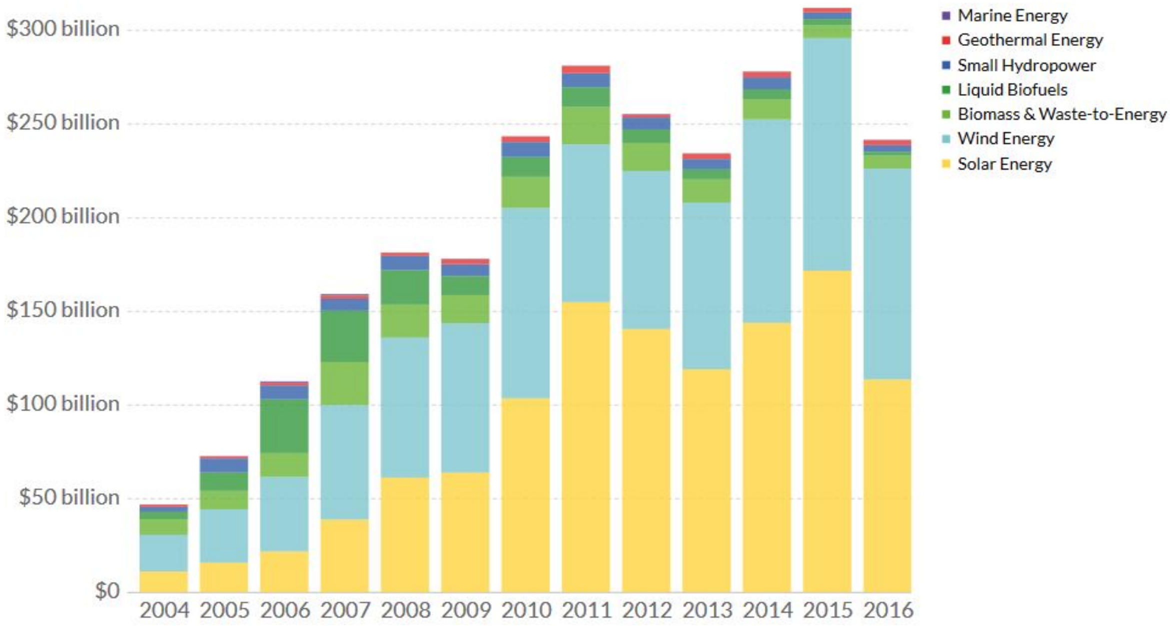

Figure 2.3: Investments in renewable energy by technology over the world (Ritchie and Roser [2019])

As the place of hybrid energy systems increases in daily life, various scientific studies are carried out in order to increase the efficiency and benefit from the established power facilities at the optimum level. As Khare et al. [2016] reviewed in their study, the hybrid energy technologies have been handled from the different angles and mainly the contexts such as pre-feasibility assessment (Hassan et al. [2016]; Khan and Iqbal [2005]; Lipu et al. [2013]), optimum sizing (Ahmadi and Abdi [2016]; Gupta et al. [2007]; Maleki et al. [2015]; Nadjemi et al. [2017]; Shi et al. [2017]; Yang et al. [2008]), modeling (Alam and Gao [2007]; Bansal et al. [2014]; Gupta et al. [2007]; Potamianakis and Vournas [2003], control aspects (Huang et al. [2011]; Jinhong et al. [2007]; Zhang et al. [2008]) and reliability issues (Kekezoglu et al. [2013]; Kishore and Fernandez [2011]; Nagarajan et al. [2013]). These studies form the core parts of the conducted hybrid energy related papers.

For further detail, it is recommended to revise the reviews of Guo et al. [2018]; Khan et al. [2018]; Khare et al. [2016]; Sawle et al. [2018]; Upadhyay and Sharma [2014].

As a result of increasing scientific and technological efforts, falling costs in the renewable generation technologies, the set goals to accelerate the transition from the conventional to renewable energy sources are far too modest. According to the latest report of EREF (European Renewable Energies Foundation) 100 % renewable energy system in Europe is now technically possible using existing storage and demand response technologies (EREF [2018]) . Particularly, for France, ADEME (Agence de l'Environnement et de la Maîtrise de l'Énergie) conducted a study that gives some perspectives about the 100 % renewable energy mix for electricity generation in 2050 by relying on some assumptions. The presented scenarios are quite impressive.

Figure 2.4 shows that even on a day in the middle of the winter, when the system relies on wind energy generation, the excessively generated wind power (demand is shown by black line) during the early hours of the day will be used in the late afternoon, during the hours the wind speed relatively decreases, by the developed storage technologies. Regardless the source of the generated energy, the projected overall demand management scheme is displayed in Figure 2.5.

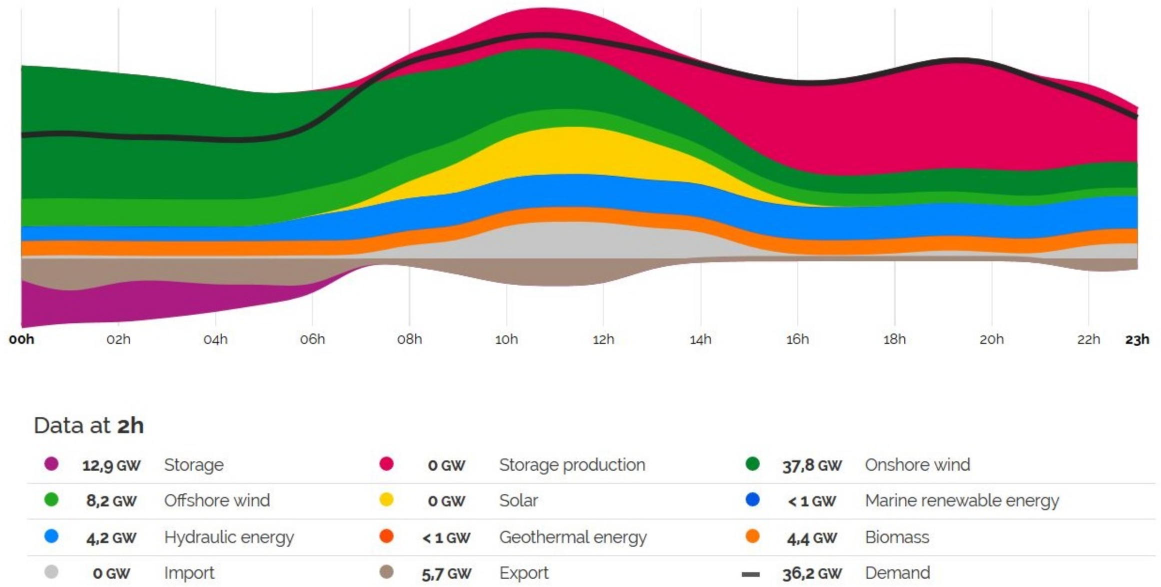

Figure 2.4: The projected electrcity mix on a day without sunshine, on 7th November,2050, in France, ADEME [2019]

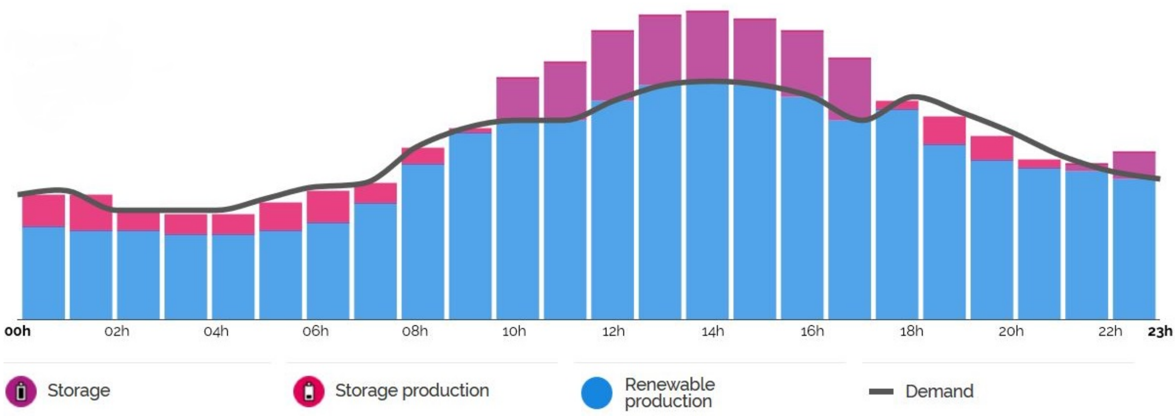

Figure 2.5: Demand management on 7th of June 2050, in France, ADEME [2019]

All these developments prove that renewable energy sources will be a part of our daily life and the end-users, especially industrial customers, will play an important role for efficient use of produced/stored energy sources. We had mentioned that the energy supply contracts signed between the energy retailers and the end users have a vital importance to control the generation and distribution of the energy. It will be even more important with the entrance of the high-technology and reliable storage systems.

Energy Contracting and Capacity Selection Problem

Before going through the contracts arranged for the electricity supply between the end-users and the energy retailers, we would like to present a general picture of the electricity market.

As it is simply illustrated in Figure 2.6, it is possible to divide the energy market into two parts: Wholesale and retailer market. In the wholesale market, trading is conducted between the generators and retailers. Two key mechanisms for purchasing and selling electrical energy are electricity pools and bilateral contracting (Sousa et al. [2015]).

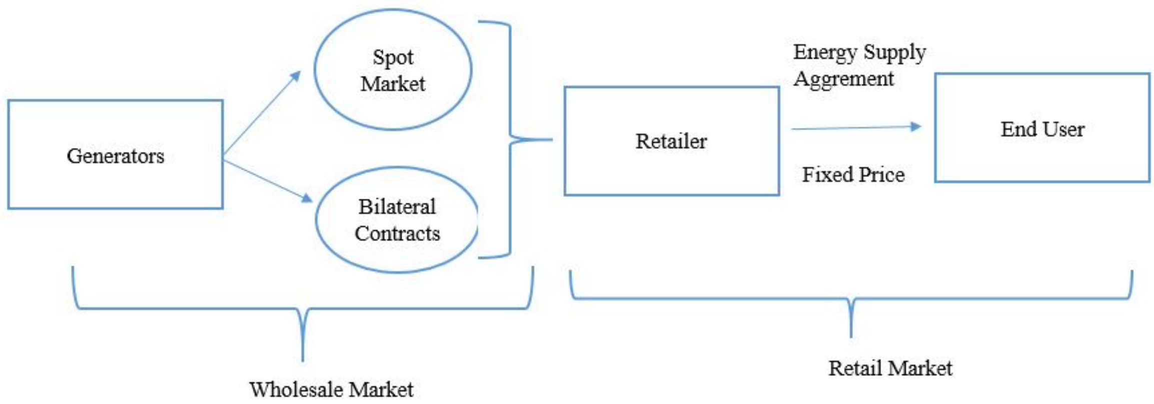

Figure 2.6: Simple market structure between end user, retailer, generator and the market

In spot market, for example in Australia, the price of the electricity is updated for each half-hour. The price is defined according to the energy supply and consumption balance. When the market needs more energy, more generators are operated and the price increases, in the other case the price of electricity falls down. This characteristic of the spot market facilitates to satisfy the balance between energy supply and market need.

To manage their financial case and demand of the customers in a more certain way, the retailers can prefer bilateral contract (BC) energy market in which, both buyers and sellers submit their bids and offers to the market operator. A contract is made if a buyer and a seller agree on the price-quantity-duration of the contract, simultaneously (Hajimiri et al. [2014]).

When it comes to the retailer market, the main actors are competitive retailers and the industrial or residential users. In this side of the electricity market, the energy is supplied according to regulated tariffs. In the next section, we will look at the proposed tariffs closely.

The Contract Capacity Selection Problem

As Lopes et al. [2010] and Lopes [2012] point out in their study, deregulation in electricity market led to the establishment of a wholesale market for electricity generation and a retail market for electricity retailing, where end-users can choose their supplier from competing electricity retailers.

In today's retail market, to be able to manage the possible risks and to boost the energy efficiency, the retailers need to define their customers' power need. Accordingly, they can purchase the required amount from the generators. As it is essential for the retailers, it enables the customers to know their power capacity in advance and to manage their consumption pattern aforementioned electricity pricing schemes. This approach reduces their energy costs, keeping the power demand in the agreed capacity contributes the energy efficiency.

An electricity supply agreement, we call it *capacity contract*, is arranged based on certain decisions. These decisions can be categorized as duration options (How long ahead do you need to be able to fix electricity prices?), portfolio management (How changeable is your property portfolio and your energy use?), defining volume tolerance, energy purchasing (the contract options) etc. Since volume tolerance is considered in the developed mathematical model in this thesis, giving more detail about it would be useful for the reader.

EDF (Electricité de France) defines *volume tolerance* as an agreed percentage variation to your forecasted consumption designed to cover you against unexpected variations of consumption and prevent you from being exposed to prices related to imbalance mechanisms within the wholesale market. There are three common options offered by EDF to the customers which are summarized in Table 2.1. In monthly option, 10% volume tolerance is offered as standard option but 20% tolerance option is also available. Accordingly, as long as the excessive power demand of the customers is lower than 10% of the contracted power, no penalty is charged. If the excessive amount is more than the 10% of the contracted power, the excessive amount is penalized and the penalty cost is added to the electricity bill. The monthly option requires a good understanding and visibility of the monthly power requirement. In the second option, since the volume tolerance is defined annually, it provides more flexibility to stay within the agreed tolerance interval if the customer is unable to predict the future power demand. Bespoke volume tolerance gives the customers the ability to choose a level that they can easily achieve.

In the proposed mathematical model which is detailed in Chapter 3, 10% tolerance option is considered, the integration of the bespoke volume tolerance in the energy efficient production models is regarded as a projected study.

When it comes to the tariffs, in France, the regulated tariffs are fixed by the state on recommendation of the commission of regularization of the energy (CRE, la commission de régularisation de l'énergie). Until 31 December 2015, there were three common tariffs

Table 2.1: Volume tolerance options offered by EDF

Volume tolerance	What you get
monthly	10% monthly as standard 20% option available
annually	options of 10% or 20%
bespoke	tailor your volume tolerance to your need

implemented in France: Tariff Bleu, Tariff Jaune et Tariff Vert. With the effect of the rapidly varying market conditions and the newly arranged governmental regulations, the "Tariff Jaune" et "Tariff Vert" are removed from the market as of December 31, 2015. Today, EDF presents two different options: Blue Tariff, Renewable Electricity Offer

Table 2.2: Basic pricing based Blue Tariff offered by EDF

Basic Tariff		
Subscribed power (kVA)	Subscription fee monthly (€/month)	Price of kWh (€/kWh)
3	7,66	15,31
6	9,21	15,31
9	10,86	15,62
12	12,58	15,62
15	14,24	15,62
18	15,96	15,62
24	19,81	15,62
30	23,65	15,62
36	26,69	15,62

Since EDF is the major energy supplier in key European markets: Belgium, France, Italy and the United Kingdom, etc. instead of exemplifying different tariffs presented by different retailers over the world, detailing the tariffs offered by EDF snaps the picture of the retailer and end user agreements in Europe. Based on this motivation, different options of the Blue Tariff offered by EDF are given as examples in Table 2.2 and Table 2.3. Before examining them in detail, providing some information about the shown prices in the tables will be useful.

A typical electricity bill is composed of two principal charges: The *Energy charge* is based on kilowatt hours, with the unit price varying by peak, medium and off-peak and the *capacity charge* which is determined by kilowatts per month based on maximum demand (in 15 minutes average) during the Time-Of-Use (TOU) period (Chen and Liao [2011]). The proposed tariffs involve the power demand (capacity) (KW) options, which can be supplied by the energy supplier to the customer, and their subscription prices and

Table 2.3: ON-OFF pricing based Blue Tariff proposed by EDF

Tariff ON-OFF			
Power Subscribed (kVA)	Subscription monthly (€/month)	Price of kWh (€/kWh)	
		ON	OFF
6	10,3	17,03	13,19
9	12,61	17,03	13,19
12	14,77	17,03	13,19
15	16,78	17,03	13,19
18	18,64	17,03	13,19
24	22,89	17,03	13,19
30	24,96	17,03	13,19
36	28,13	17,03	13,19

the electricity pricing options. As it can be observed in Table 2.2, a fixed rate is implemented for all day long in the basic option of the Blue Tariff. In Table 2.3, TOU pricing scheme is applied. Accordingly, the day is split into peak and off peak hours and the price of the electricity varies depending on the hours of the day. As it is pointed out before, the customers are informed about which pricing mechanism is used for calculating their energy charge in advance. Therefore, based on this information, they can shift their energy consumption patterns to the lower priced hours, if possible, to reduce the cost in the electricity bill.

Another act which can inflate the energy efficiency is to choose the correct power (capacity) option. When the power demand of the production system exceeds beyond the tolerance interval, since it might cause changes in the planning of generation or transmission procedures of the energy, the energy suppliers can penalize the customers. The calculated penalty costs are also added on the electricity bill. When a capacity option which is extremely higher than the needs of the production system is selected, the industrial client burdens an energy cost for unused amount of energy. To evade the penalty costs or unnecessary payment, the customers must be sure that the maximum demand calculated during the 15-minute interval in production facility will not exceed the contracted power value over a given month and cover the energy need of the manufacturing system. When the other needs and constraints of a production system are considered, matching the system's need with the proposed options in the market bears an optimization problem. The industrial customers must select such an optimum capacity option which can realize the production plan and reduce the energy cost and increase the energy efficiency by considering all the objectives and constraints of the production system. The effort of matching needs of a production system with the capacity options presented by energy market rises the *optimum energy contract selection problem* for industrial customers.

The conventional way to choose the contract capacity option is to check the historical data and to forecast the power demand of the next contractual period. In this case, since the contract capacity selection decision is made without matching the power demand of the precisely planned production, this case causes inefficiencies in the use of purchased power amount. Mostly, the additional costs sourced from these inefficiencies are underestimated and even not realized by the customers. Especially in the future, with the increase in the use of renewable energy sources, to manage the energy generation and storage operations and satisfy the balance between the power demand and power supply, getting the more precise data about their power demand from the customers will be much more important.

Despite the importance of the contract capacity selection procedure, there are few studies that handle this problem with different solution approaches. Tsay et al. [2001] applied evolutionary programming to solve optimal contract selection problem and Lee and Chen [2007] implemented iterative particle swarm optimization for the capacity selection problem including Time-Of-Use (TOU) rates. Yang and Peng [2012] improved Taguchi method that integrates the traditional Taguchi method and the PSO algorithm. Hwang et al. [2009] solved it by implementing Cat Swarm Optimization (CSO) and Particle Swarm Optimization (PSO) algorithms for the capacity selection problem. Chen and Liao [2011] proposed to solve the problem with linear programming. The common point of all these studies is that, optimum contract capacity is selected based on the historical data of energy consumption by applying various heuristic algorithms or linear programming techniques. However, there is no study which builds a direct connection between energy contract selection decisions and production planning decisions. Our study promises to bridge the two sides.

2.2.2 Classification of the Studies with Energy Aspect

Energy aspect can be considered in the different hierarchical levels of decision making process. This hierarchy is composed of three fold: Strategical, tactical and operational decisions levels. In this section, it is aimed to classify the previous studies which take into account energy aspect according to decision levels.

The Strategic Level

Strategic decisions,

a) are usually big, risky, and hard-to-reverse, with significant long-term effects,

b) they are the bridge between deliberate and emergent strategies,

c) they can be a major source of organizational learning,

d) they play an important role in the development of individual managers,

e) they cut across functions and academic disciplines (Papadakis and Barwise [2012]).

The decisions related to supply chain network design, definition of facility location, capacity allocation can be referred as strategic decisions.

With the increasing concerns about the efficient use of energy sources and environmental friendly products and production systems, decision makers have started to take into account energy aspect in the strategic decision process by considering economic, environmental and social goals. In parallel, the researchers have conducted several studies to help the decision makers. We would like to give some examples for the studies handling the energy aspect in the strategic level.

Li et al. [2008] presented a bi-objective mathematical model to describe the distribution center location and transportation mode option for green supply chain. The developed first objective function aims to maximize the profits while second one minimizes the carbon emission.

Ramudhin et al. [2010] integrated carbon emission and total logistics costs in the design of the supply chain using a multi-objective mixed-integer linear programming model that provides decision makers ability to evaluate the trade-offs between total logistics costs and carbon offsetting under different supply chain operating strategies, environmental regulatory constraints and carbon market evolution.

Wang et al. [2011] developed a multi-objective optimization model that defines the number of the distribution centers, and the quantity of the products which will be supplied between the centers and the environmental impact levels of each distribution centers. The purpose of the first objective function is to reduce total cost and the second one aims to decline CO_2 emission in all the supply chain.

Pishvaee and Razmi [2012] proposed a multi objective fuzzy mathematical programming model for designing an environmental supply chain under inherent uncertainty of input data in such problem and integrates the design of both forward and reverse supply chains besides considering the environmental impacts in the whole supply chain.

Chaabane et al. [2012] extended the model presented in Ramudhin et al. [2010] by consideration of the Life Cycle Assessment methodology to establish successful sustainable supply chains over time.

Mallidis et al. [2012] provided a model for supply chain network design including the decisions on using dedicated versus shared warehouses and transportation with the carbon emission consideration and proved that the shared use of transportation operations minimizes the amount of CO_2 and particulate matters emissions generated, while dedicated use minimizes cost.

Harris et al. [2014] proposed an evolutionary multi objective optimization approach to the capacitated facility location allocation problem for solving large instances that considers flexibility at the allocation level, where financial costs and CO_2 emissions are considered simultaneously.

It is possible to expand the content of this section by adding more works. However, since the studies carried out for strategic level decisions do not constitute the basis of the work produced in this thesis, it is kept short. In the next section, the ways of integrating energy aspect into the tactical decisions are explained and enriched with more examples.

The Tactical Level

Tactical decisions are the mid-term decisions guided by the strategical decisions. While the strategic decisions refer to the questions "what" and "why", tactical decisions answer the question of "how". The decisions related to inventory management, lot sizing are examples for tactical decisions.

Hua et al. [2011] introduced an environmental inventory model by extending the Economic Order Quantity (EOQ) model with the carbon trading constraints, accordingly, the optimal order quantity is defined under a carbon emission limit. They examined the impacts of carbon emission trading, carbon price, and carbon cap on order decisions, carbon emissions, and total cost. Bouchery et al. [2012] reformulated the classical Economic Order Quantity model as a multi objective problem by considering sustainable development criteria. Chen et al. [2013] developed EOQ models with carbon emission constraints and analyzed the different optimal solutions of cost and emission functions and provided some conditions to the decision makers under which the relative reduction in emissions is greater than the relative increase in cost. He et al. [2015] extended the study of Chen et al. [2013] by implementing different prices for carbon trading scheme. Toptal et al. [2014] developed a model to analyze a retailer's joint decisions on inventory replenishment and carbon emission reduction investment under three carbon emission regulation policies. Konur [2014] considered different truck characteristics (cost and emission characteristics) in an integrated inventory control and transportation problem with carbon emissions constraint. They developed carbon sensitive inventory models by modeling the EOQ model with truckload transportation costs and emissions in the presence of heterogeneous trucks. Bozorgi et al. [2014] proposed a new inventory model by improving the EOQ model with holding and transportation unit capacities for the items that should be stored in low temperature and aimed to minimize both costs and emissions. Konur et al. [2017] studied an integrated stochastic inventory control, supplier selection, and order splitting problem under two different delivery scheduling policies with environmental considerations. Two bi-objective mixed integer models for each supplier is developed to minimize the expected costs and carbon emissions per unit time. Ghosh et al. [2017] considered strict carbon cap policy to determine the optimal order quantity, reorder point and number of shipments in a two echelon supply chain under stochastic demand considering partial backorders. Xu et al. [2018] developed two distributionally robust news vendor models with the constraints of carbon cap and cap-and-trade regulations and the effects of emission reduction and partial demand information on operational decisions of the newsvendor problem are analyzed.

Absi et al. [2013] studied lot sizing problem with carbon emission constraints. They proposed four types of carbon emission constraints named as periodic carbon emission constraint, cumulative carbon emission constraint, global carbon emission constraint and rolling carbon emission constraint. They proved that when the uncapacited lot sizing problem is combined with the constraints except periodic carbon emission constraints, the problem becomes NP-hard problem. It is proved that the variant created by combining periodic carbon emission constraint is solved optimally using a dynamic programming algorithm. By inspiring from this study, the version built with periodic carbon emission constraint is studied comprehensively in Absi et al. [2016]. In this paper, they analyzed the impact of fixed carbon emissions and the selected mode (combination of a production facility and transportation mode for supplying products) at each period. Yu et al. [2013] solved the lot-sizing problem by limiting the production with the carbon cap and taking into account multiple production modes which imply multiple setup cost structures in the model. Benjaafar et al. [2013] studied lot sizing problem with different emission regulations, including strict emission caps, taxes on emissions, cap-and-offset, and cap-and-trade. They proposed to integrate the developed carbon emission sensitive lot sizing problems for the cases in which a single firm and multiple firms operate. They proved that the firms can significantly reduce their carbon emissions without increasing their costs by making only operational adjustments and by collaborating with other members of their supply chain. Akbalik and Rapine [2014] studied single item ULSP with carbon-and-trade policy by considering the impact of two different budget limitations on the carbon trade of the firms. Velázquez-Martínez et al. [2014] integrated the global carbon emission constraint into the lot sizing problem and analyzed the impact of the carbon emission level on the transportation decision-making. Helmrich et al. [2015] studied a lot-sizing problem with an emission constraint under concave cost and emission functions. Even though the study of Helmrich et al. [2015] is similar to the study of Absi et al. [2013] in terms of the concept, the main difference between the two is that while Absi et al. [2013] consider a bound on the average emission per unit produced, Helmrich et al. [2015] limit the total emission, thus, a capacity constraint is generated for the model indirectly. Kantas et al. [2015] developed a mixed-integer linear programming (MILP) capacitated lot-sizing model for analyzing the economic and environmental feasibility of ethanol production. In the proposed model the carbon emission and water consumption are limited and excessive amount of water consumption and carbon emission is penalized. Overall, the developed model aims to minimize production, setup, inventory, biomass purchasing costs and the tax penalty for the excessive amount of CO_2 emissions and excessive water usage during production. Zouadi et al. [2015, 2018, 2016] studied hybrid manufacturing/remanufacturing lot sizing and supplier selection with returns, under carbon emission constraint. Accordingly, the sum of the unit carbon emission, which occurs as the result of set-up and transportation activities at each period, is not allowed to exceed the predefined maximum environmental impact level. Purohit et al. [2016] developed the non-stationary stochastic lot-sizing model by integrating carbon emission and cycle service level constraint based on the study of Tarim and Kingsman [2004]. Liu [2016a] studied two variants of the discrete lot-sizing and scheduling problem. In the first version, they proposed the bi-objective model in which renewable energy is considered and earliness, tardiness and CO_2 emissions are minimized simultaneously. In the second version, the model is subjected to the carbon emission constraint.

Unlike the studies of Absi et al. [2013]; Akbalik and Rapine [2014]; Helmrich et al. [2015]; Velázquez-Martínez et al. [2014], which consider single item and single machine production environment, Wu et al. [2018a] applied periodic carbon emission constraint for capacitated multi-item lot sizing problem with multi-machine. Chowdhury [2018] proposed models for lot sizing problem for a multi-item multi-level capacitated batch production system with setup carryover, emission control and backlogging. Qiao et al. [2019] studied optimal lot sizing for two-stage production planning under different carbon policies by establishing a make-to-order model for the manufacturer and its internal supplier.

The main characteristic of the above summarized studies is that energy aspect is integrated into the different variants of the lot sizing problems by targeting to limit the carbon emission levels in accordance with the different carbon regulations and to minimize the operational costs respecting the ecological ones. It can be said that the starting point of the previous studies is ecological concerns rather than economical ones.

Different from the previous studies, Yildirim and Nezami [2014] proposed a joint preventive maintenance-production planning model for a multi-item capacitated lot-sizing problem to hedge against demand loss, unscheduled machine downtime, and replanning of activities in an energy-efficient manufacturing company. Masmoudi et al. [2015] took into account the power and electricity consumption costs and proposed a model for capacitated single item lot sizing problem. In their study, instead of given production cost as in the classical lot sizing problem, electricity cost dependent production cost which varies from one period to another is considered. Moreover, the total power demand is calculated for each period and limited by the maximum amount of power which can be supplied by the energy supplier. The developed model aims to identify the optimum production quantities by minimizing the production and energy costs. To best of our knowledge, the study of Masmoudi et al. [2015] is the first attempt which combines lot sizing problem with the energy aspect in this manner. Later, Masmoudi et al. [2016] extended their study for multi-item capacitated lot sizing problem. In their following studies Masmoudi et al. [2017a,b] proposed various approaches for the solution of the proposed mathematical models. After their pioneering study, a few more studies have been published, which take into account energy aspect for the lot sizing problems. Giglio et al. [2017] proposed a model for the integrated lot sizing and job shop scheduling problem in manufacturing/remanufacturing systems. In their study, to compute the total energy cost, they took into account the energy consumption of the machines when they produce, when they are on stand-by mode and the required energy for compressing the processing times. They aimed to find the optimum quantities to be manufactured and remanufactured or backlogged in each period and to identify the actual processing time of each lot on each machine by minimizing the total production and energy related costs. Johannes et al. [2019]; Wichmann et al. [2018] investigated the cost saving potentials that are missing and developed a formulation for the consideration of time-dependent energy prices in simultaneous lot-sizing and scheduling. They inspired from the study of Masmoudi et al. [2015], however, they considered the energy consumption costs of different machine states such as "preserve" and "stand-by". Rapine et al. [2018b] handled single-item multi-resource continuous setup lot sizing problem (CSLP) with energy related constraints and limited the energy consumption of set-up and production activities by the available energy at each period by referring the study of Masmoudi et al. [2017a]. They contributed to the literature by proposing a new combinatorial algorithm to solve the lot sizing problems with energy constraints and proved that energy oriented single item lot sizing problem can be seen as the extension of the integrated capacity acquisition and lot sizing problem by departing from the study of Atamtürk and Hochbaum [2001] and extended this study in Rapine et al. [2018a].

As it can be seen from our modest review, there is a growing body of literature for the studies that consider the energy and environmental aspects in tactical decision making. The question of how the tactical decisions can be implemented under energy constraints is also fruitful research area for the researchers. In the next section, the ways of integrating energy aspect in the operational decision making are exemplified.

The Operational Level

The operational level decisions give the directions about how the tactical level decisions are implemented. As Schmidt and Wilhelm [2000] point out in their study, the question at the operational level is when to perform a manufacturing task and at which facility so that due dates are met to the fullest extent possible. Scheduling decisions can be referred as the operational level decisions.

Since 1960s scheduling problems have received a significant attention from the researchers; different variants of them have been modeled, analyzed and various appropriate approaches have been developed for the solution of the developed models. Over the years, the traditional scheduling problems have evolved and enriched with different components. Energy efficient scheduling studies have been one of the growing trends in recent years. For better understanding of the evolution of the energy efficient scheduling studies, several review studies have been conducted. When the conducted studies are evaluated according to their objective functions, two main research outlines of the application of scheduling methods in increasing energy efficiency of manufacturing systems can be defined: Energy Saver Objectives and Budget Saver Objectives (Figure 2.7). For the purpose of energy saving, the strategies such as Turn on/Turn off, machine speed scaling, optimizing flexible systems where energy consumption and processing times are controllable can be given as examples. When reducing the energy bill is targeted, considering the time vary energy price mechanism in the scheduling decisions is the most widely applied way.

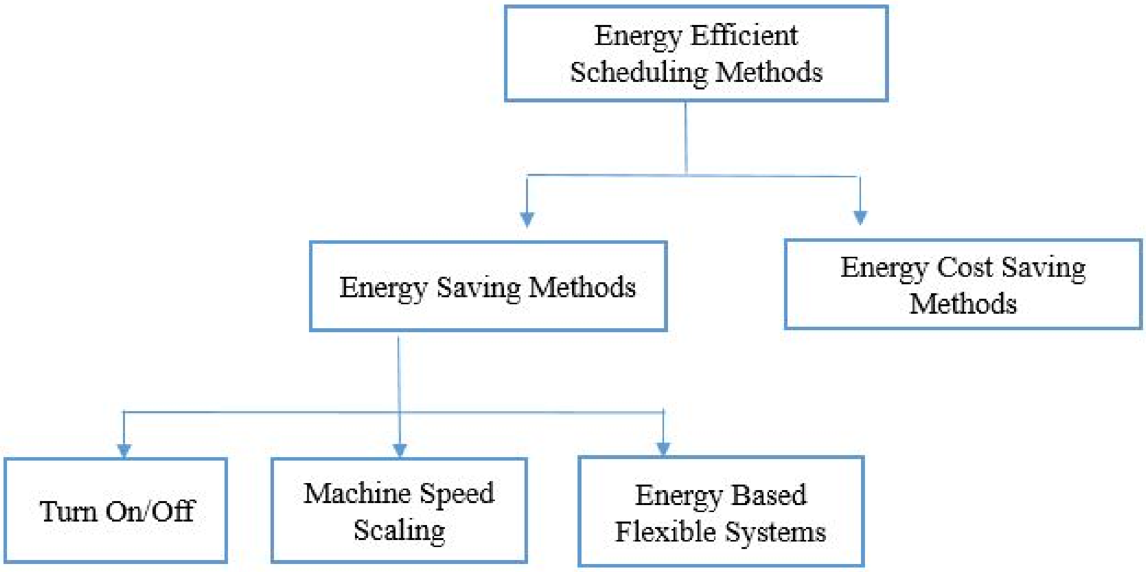

Figure 2.7: Classification of the application of energy efficient scheduling methods

The study of Mouzon et al. [2007] can be regarded as one of the earliest attempts for reducing the energy consumption while scheduling the machines. They, firstly, investigated the energy saving potential of the machines by looking for the non-bottleneck machine environment and showed that if scheduling is conducted by turning of non-bottleneck (underutilized) machines when they are idle, a significant amount of energy can be saved in a certain amount of time. Later, they extended this study by proposing a multi-objective model which aims to minimize the energy consumption by following the same turn off/on strategy and total tardiness on a single machine (Mouzon and Yildirim [2008]). Dai et al. [2013] proposed a multi-objective optimization model which aims to minimize total energy consumption and makespan for the flexible flow shop environment and to reduce the occurring energy waste by determining whether machine tools should be on or off. Liu et al. [2014] followed the turn on and off strategy to minimize the energy consumption and carbon emission of a single machine system. Che et al. [2017] conducted a similar study to the study of Mouzon and Yildirim [2008] and addressed the single-machine scheduling problem with turn on/off mechanism to minimize total energy consumption and maximum tardiness simultaneously. Meng et al. [2019] implemented turning off and on strategy for an energy-conscious hybrid flow shop scheduling problem with unrelated parallel machines and proposed an improved genetic algorithm for the solution of the problem. They compared its performance with the simulated annealing and migrating birds optimization approach.

As Zhang and Chiong [2016] specified in their study, for some production systems, it is not possible to turnoff machines completely during each of the idle periods, either because restarting the machines requires a considerable amount of additional energy or due to the fact that frequent on and off switches may cause damage to the machine tools. For these type of systems, the alternative way for energy efficient scheduling is to scale the speed of the machines. In the speed scaling approach, the speed of the machines can be tuned, thus, the processing times and energy consumption can be controlled according to the purposes. The studies of Angel et al. [2012]; Pruhs et al. [2008]; Yao et al. [1995] can be given as examples for the application of speed scaling approach in scheduling problems. Fang et al. [2011] developed a multi-objective mixed integer linear programming formulation for optimizing the operating schedule of a two-machine flow shop that considers both productivity (makespan) and energy (peak load and carbon footprint) related criteria. The operation speed is allowed to vary in order to affect the peak load and energy consumption and the peak power demand is limited. Similar to their former study, Fang et al. [2013] focused on the objective of minimizing the makespan and power consumption under peak power restrictions for permutation flow shop problem by considering the different speed sets for the machines. Mansouri et al. [2016] developed a multi-objective mathematical model in which the total energy consumption and makespan are minimized. They incorporated different machine running speed to consider energy saving by altering processing times. Lu et al. [2017] proposed a novel multi-objective mathematical model for permutation flow shop problem by considering both makespan and energy consumption minimization. In their study, as an alternative to the turn off/on strategy which can shorten the service life of the machines, in addition to processing stage and the idle stage, they take into account the energy consumption of setup stage, transportation phase (by considering speeds of the transportation) and public energy consumption (light, air conditioning, etc.).

Zhang and Chiong [2016] introduced the objective of minimizing energy consumption for job shop scheduling model based on a machine speed scaling framework. Kemmoe et al. [2017] addressed job shop scheduling problem and the developed model minimizes the total completion time (makespan) by taking into account the power consumption of operations and a variable power threshold.

The study of Bruzzone et al. [2012] can be referred as one of the novel studies under the cap of energy-saver oriented studies. They focused on the energy efficiency in flexible systems that contain several machines and resources which are able to process the available jobs by consuming different levels of energy and time (Giglio et al. [2017]). In their study, they started from a reference schedule of the machines in flexible flow shop systems which is schemed without considering energy saving objective. After, the reference schedule is modified to account for energy consumption without changing the jobs'assignment and sequencing by respecting the maximum peak power limitation. Liu et al. [2017] followed the similar research framework with Bruzzone et al. [2012] and they contributed to the energy-aware scheduling studies by considering the processing-time-dependent product quality. The energy consumption is related to operation speeds, facility states and product qualities. The objective function of the proposed model is to minimize the amount of the energy consumed by processing, non-processing and re-processing operations.

After reviewing some of studies whose objectives are reducing the energy consumption, some of the prominent studies focusing on the decreasing energy cost can be listed. The model developed by Shrouf et al. [2014] enable operations manager to implement least costly single machine production scheduling by considering variable energy prices during the day and determining processing, idle, turning on and off times. Aghelinejad et al. [2018] improved the study of Shrouf et al. [2014] by using just one decision variable for the jobs representation contrary to Shrouf et al. [2014] who used two variables for defining the job situation in each period. Reducing the number of variables enables to increase the performance of applied solution approaches and to obtain results for relatively larger instances in affordable time periods.

Castro et al. [2009] presented a mathematical model which can minimize the total electricity cost by considering time-dependent electricity prices and availability for parallel machine systems. Mitra et al. [2012] aimed to minimize electricity for continuous power-intensive processes under time-sensitive electricity price and maximum power availability restriction. Moon et al. [2013] proposed a mixed integer model which minimizes the makespan of production and the time-dependent electricity costs for unrelated parallel machine problem by considering hourly varying electricity prices according to the peak and off-peak time intervals. Ding et al. [2016] proposed a new time-interval-based MILP formulation which can minimize the electricity cost without knowing the exact starting (or stopping) time of job processing in unrelated parallel machine scheduling by considering TOU pricing scheme. Different from the previous studies, instead of keeping the electricity prices steady for relatively longer time periods like 3-8 hours, they considered more frequently fluctuated electricity prices, to make the problem tractable under such TOU policies. A column generation heuristic is proposed.

Wang and Li [2013] introduced load management scheme and proposed a MINLP model which minimizes the electricity related costs and power demand costs under TOU pricing. The other contribution of their study is that they integrated the machine reliability aspects into their model. Bego et al. [2014] presented a methodology for the application of Critical Peak Pricing (CPP) program, for manufacturing systems with multiple machines and buffers. They developed a MINLP formulation to establish the mathematical model with the objective to minimize the electricity bill cost as well as the potential penalty cost due to the non-fulfillment of the target production. The developed nonlinear model is solved by commercial solver LINGO. Luo et al. [2013] proposed a new multi-objective ant colony optimization meta-heuristic considering to minimize the production efficiency (makespan) and electric power cost with the presence of TOU electricity prices for hybrid flow shop scheduling problem. Fernandez et al. [2013] proposed a novel method to reduce power demand during peak periods for a flow shop system by utilizing “Just-for-Peak” buffer inventory that is built up during off-peak periods. Optimal building policy of the“Just-for-Peak”buffer inventory and load management actions are identified by minimizing the sum of the holding cost of “Just-for-Peak” buffer inventory and the energy consumption cost throughout the production horizon. Zhang et al. [2014] developed a time-indexed integer programming formulation to identify flow shop manufacturing schedules that minimize electricity cost and the carbon foot print under TOU electricity pricing scheme. They demonstrated that shifting electricity usage from peak hours to mid-peak or off-peak hours, while reducing the energy cost may increase CO_2 emission. The trade-off between the two objectives is shown via Pareto frontier. Wang et al. [2018] draw attention to the point that with time-indexed integer programming proposed by Zhang et al. [2014], only few instances with fairly small number of jobs can be solved within a reasonable computational time. Instead, they developed a mixed integer linear programming model for a two-machine permutation flow shop scheduling problem to minimize the total electricity cost of processing jobs under TOU electricity tariffs. They proposed iterated local search algorithm with problem-tailored procedures and move operators.

When the energy-conscious job shop scheduling studies are reviewed, the studies of Selmair et al. [2016] and Masmoudi et al. [2019] can be cited as recently published studies. Selmair et al. [2016] minimized the total energy cost for under hourly varying energy prices. They proposed to compute the power consumption of the states "ramp up","setup", and "ramp down" in addition to the power consumed during the processing or standby periods. Masmoudi et al. [2019] proposed a model to minimize production costs in terms of energy, while respecting a power peak limitation, along with traditional production constraints.

For further details about the energy aware scheduling studies, we refer the reader the reviews of Gahm et al. [2016] and Biel and Glock [2016]. In the following section, the lot sizing problem which form the core of our study is detailed.

2.3 Lot Sizing Problem

A production activity is triggered by the demands of the customers. While the companies can build their master plan according to the order sizes, planning the production in detail by sizing the production lots and inventory levels becomes one of the most challenging tasks in production planning. Roughly speaking, manufacturing the products in large-sized lots decreases the number of the machines set-up. Naturally, the manufacturer can save the set-up and set-up related costs (workforce, energy etc). However, this type of production increases the inventory costs since products are produced more than the actual demand. Based on this, defining the optimum sizes for production and inventory has a vital importance. The trade-off between inventory and set-up costs bears the lot sizing problem and over the decades researchers and manufactures look for the answer of the question: *How much and when should be produced*? for the optimum use of resources and increasing the profitability. It can be summarized that the main objective of the lot sizing problem is to determine the size of the production and inventory lots by minimizing production, set-up and holding related costs and satisfying the demand of the number of products over a defined time horizon.

In the literature, the lot sizing problem is classified according to certain characteristics. Before elaborating the variants of the lot sizing problem, the main characteristics of it will be explained briefly.

2.3.1 Characteristics of The Lot Sizing Problem

Recently, Brahimi et al. [2017] has updated and extended their previous survey Brahimi et al. [2006] and provided an comprehensive study about the characteristics of the lot sizing problems and applied solution methods. To keep it simple, we will summarize the main characteristics of lot sizing problem by inspiring from the review study of Karimi et al. [2003]. The main characteristics can be ordered as follows:

—Production Periods

In terms of production periods, lot sizing problems can be categorized into two groups: Big bucket problems and small bucket problems. Big bucket problems are those where the time period is long enough to produce multiple items (in multi-item problem cases), while for small bucket problems the time period is so short that only one item can be produced in each time period (Karimi et al. [2003]) . As the Continous Setup Lot Sizing Problem (CSLP) which is introduced by Karmarkar and Schrage [1985] can be referred as small bucket problem, Uncapacitated Lot Sizing Problem (ULSP) presented by Wagner and Whitin [1958] and Capacitated Lot Sizing Problem (CLSP) can be cited as big bucket problems.

—Number of level

Concerning the number of levels, there exists two types of production: Single level and multi-level. When the final product is produced directly after the processing of the raw material, this type of production is categorized as single-level. In multi-level production, raw materials undergo a course of operations until the the final product is obtained. There is producer-consumer relation among the sub-components of the end product. In other words, the output of one machine is the input of the other one. In Figure 2.8, three different production schemes representing respectively serial, assembly and general types of multi-level system are displayed.

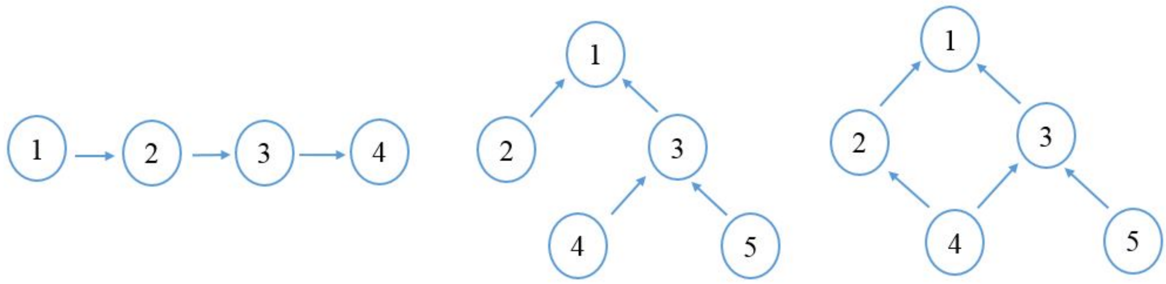

Figure 2.8: Serial, assembly and general types of multi-level production (respectively) (Brahimi et al. [2006])

—Number of product

As the number of products, the number of the end item (final product) that must be produced in a period is regarded. As there is only one final product in single-item problems, the planning of several end products is handled in multi-item problems.

—Capacity or resource constraints

The resources of a production system such as manpower, budget, equipment, energy etc. might be subject to some limitations and these limitations must be taken into account while production plans are built. When there is no restriction on the resources, the problem becomes *uncapacitated*; if there are clearly defined capacity limits, the problem is *capacitated*.

—Demand

In lot sizing problems, the most used terms of defining the characteristics of demand are: *static, dynamic; deterministic or probabilistic*. When the value of the demand does not change over the time, this type of demand structures is named as static. Dynamic demand means that the value of the demand changes over the time. If the value of demand is known in advance, it is called deterministic. If the value of demand is not known and depends on some uncertain cases, this type of demand is defined as probabilistic. The probabilistic type demand structure can also be categorized as static or dynamic. In the static probabilistic case, the probabilistic distribution does not change while it varies over the time in non-stationary probabilistic demand structure.

—Set-up structure

If the set-up time/cost in a period are independent of the sequence and the decisions in previous periods, it is termed a simple set-up structure, but when it is dependent on the sequence or previous periods, it is termed as complex set-up (Karimi et al. [2003]). The complex set-up type models can be classified into three groups: set-up carry over, family or major set-up and sequence-dependent set-up.

—Inventory shortage

In some cases, the inventory shortages are allowed and it is possible to satisfy the demand of the current period in the future periods. This case is called *backlogging*. In the opposite case, when the inventory shortages occur, it might not be possible to meet the demand in the future period. This case is handled as *lost sales* and considered in the modelling of the lot sizing problems accordingly.

After this small introduction about the lot sizing problems, the variants of the lot sizing problem are discussed in detail in the next section.

2.3.2 Variants of The Lot Sizing Problem

In the previous section, even if the characteristics of lot sizing problems are not detailed exhaustively, the variant tree which is built based on only the main characteristics proves that lot sizing problems have a wide range of varieties (Figure 2.9).

In Figure 2.9, the characteristics that are left out of the context of our study is shown with dashed-lined boxes. Since the the capacitated lot sizing problem is an expanded version built by adding a capacity constraint to the uncapacitated version, the general formulation of the studied problem in this thesis is introduced by starting from the uncapacitated single item lot sizing problem.

—Uncapacitated Single Item Single Level Lot Sizing Problem

The parameters of the problem:

T: Number of periods.
s_t: The set-up cost in period *t*.
p_t: The unit production cost in period *t*.
h_t: The unit inventory cost in period *t*.
d_t: The deterministic demand in period *t*.

The decision variables:

Y_t: The binary set-up variable, equals to 1 if the product is produced in period *t*, 0 otherwise.
X_t: The production quantity to be produced in period *t*.
I_t: The unit of inventory at the end of period *t*.

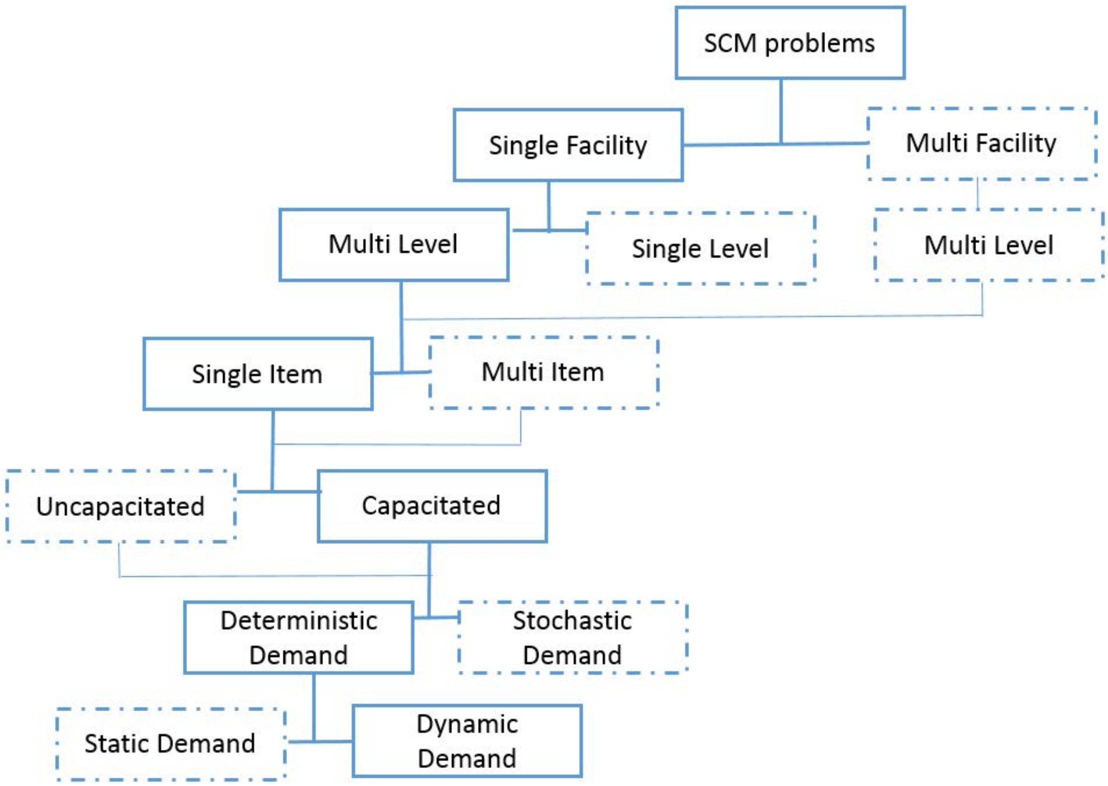

Figure 2.9: A classification of supply chain management problems (Rizk and Martel [2001])

$$Minz = \sum_{t=1}^{T}(s_t Y_t + p_t X_t + h_t I_t) \tag{2.1}$$

$$X_t + I_{t-1} = d_t + I_t \quad \forall t = 1, ..., T \tag{2.2}$$

$$X_t \leq Y_t \sum_{\tau=t}^{T} d_\tau \quad \forall t = 1, ..., T \tag{2.3}$$

$$Y_t \in \{0, 1\} \quad \forall t = 1, ..., T \tag{2.4}$$

$$X_t, I_t \geq 0 \quad \forall t = 1, ..., T \tag{2.5}$$

The objective function minimizes the sum of the set-up, production and inventory costs. The constraint (2.2) satisfies the production and inventory balance between the periods. The following constraint (2.3) ensures that the amount of production in the current period can not exceed the total demand that must be met in the following periods and guarantees that the production can be conducted only when the machine is set-up at period t. Finally, the constraints (2.4,2.5) are the general binary and non-negativity constraints. When the following constraint is added to the model presented above;

$$a.X_t \leq R_t \quad \forall t = 1,...,T \tag{2.6}$$

where;
a: The resource consumption per unit of production.
R_t: The available capacity of resource R in period t.
the presented model is transformed to the Capacitated Single Item Single-Level Lot Sizing Problem.

—Capacitated Multi-Level Lot Sizing Problem
Because of the parent-component relationship between items, production at one level leads to demand for components at a lower level (dependent demand) (Gicquel et al. [2008]).
The parameters of the problem:
T: Number of periods.
N: Number of levels.
R : Number of the resources.
$s_{i,t}$: The unit set-up cost of production i in period t.
$p_{i,t}$: The unit production cost of production i in period t.
$h_{i,t}$: The unit inventory cost of production i in period t.
$d_{i,t}$: The deterministic demand in period t.
$Sc(i)$: List of the successor products of product i.
$R(r)$: List of products requiring the resource r to be manufactured.
$k_{i,j}$: Number of the product i that is necessary to produce one unit of product j.
$ST_{i,t}$: Set-up time for product i in period t.
$w_{i,t}$: Processing time of one unit of i in period t.
$cap_{r,t}$: The available capacity of resource r in period t.

The decision variables:
$Y_{i,t}$: The binary set-up variable, equals to 1 if the product i is produced in period t, 0 otherwise.
$X_{i,t}$: The production quantity of product i to be produced in period t.
$I_{i,t}$: The unit of inventory of product i at the end of period t.

$$Minz = \sum_{t=1}^{T}\sum_{i=1}^{N}(s_{i,t}Y_{i,t} + p_{i,t}X_{i,t} + h_{i,t}I_{i,t}) \tag{2.7}$$

$$X_{i,t} + I_{i,t-1} = d_{i,t} + I_{i,t} + \sum_{j \in Sc(i)} (k_{i,j}.X_{j,t}) \quad \forall t = 1,...,T \quad \forall i = 1,...,N \tag{2.8}$$

$$\sum_{i \in R(r)} (ST_{i,t}.Y_{i,t} + w_{i,t}.X_{i,t}) \leq cap_{r,t} \quad \forall t = 1,...,T \quad \forall r = 1,...,R \tag{2.9}$$

$$X_{i,t} \leq (\sum_{t=1}^{T} \sum_{i=1}^{N} d_{i,t}).Y_{i,t} \quad \forall t = 1,...,T \quad \forall i = 1,...,N \tag{2.10}$$

$$Y_{i,t} \in \{0,1\} \quad \forall t = 1,...,T \tag{2.11}$$

$$X_{i,t}, I_{i,t} \geq 0 \quad \forall t = 1,...,T \tag{2.12}$$

Similar to the Single-Level Capacitated Lot Sizing Problem, the objective function (2.7) minimizes the sum of the production, set-up and inventory related costs. The constraint (2.8) translates the inventory flow by considering the number of the child products which are necessary to produce the parent ones. The constraint (2.9) is the capacity constraint of the model. The relation between the states of the machines and the production quantities is built by (2.10). The constraint (2.11) defines the binary variables and the constraint (2.12) guarantees the pozitivity of the decision variables.

2.3.3 Complexity Analysis and Solution Approaches

The single item uncapacitated problem is firstly discussed by Wagner and Whitin [1958]. In their paper, the optimal solution is obtained in $O(T^2)$ by using dynamic programming approach. Aggarwal and Park [1993] and Wagelmans et al. [1992] improved the dynamic programming approach recursion. Federgruen and Tzur [1991] proposed the simple forward algorithm which enables to solve the single item lot sizing problem in O (T log T).

Florian and Klein [1971], Florian et al. [1980] and Bitran and Yanasse [1982] proved the NP-hardness of single item capacitated lot sizing problem in their study. Chen and Thizy [1990] has shown that the multi-item CLSP problem is strongly NP-hard. Recently, Rapine et al. [2018b] studied on the energy-aware lot sizing problem where the amount of available energy in each period is limited and they showed that the handled problem is NP-hard even in very restricted cases with null production cost and null holding costs, also showed that the problem is polynomially solvable if all energy consumption parameters are stationary.

The literature based on complexity analysis of the variants of the lot sizing problems is quite volumed. In this section, for the sake of the simplicity, the complexity analysis of the variants which are not studied in this thesis is excluded from the context. For further detail about the complexity of the lot sizing problems, it is recommended the reader to refer to the study of Brahimi et al. [2017].

Since the most lot-sizing problems have an NP-hard characteristic, various solution approaches have been applied to cope with these difficult problems over the years. The solution approaches for the capacitated lot sizing problem are classified into three groups:

1) Problem-specific greedy heuristics

The heuristics under this cap is also known as single resource heuristics, common-sense or specialized heuristics. The main idea behind them the problem is solved by starting from scratch and working period-by-period or starting from a given initial solution and lot sizes are successively increased to achieve cost saving with some feasibility routines (feedback mechanisms, look-ahead mechanisms) and priority indexes, in other words, cost criterions (Silver Meal Silver and Meal [1969], Least Unit Cost (Dogramaci et al. [1981]), Groff Groff [1979]) are used for selecting the best candidate in the moves (Buschkühl et al. [2010]).

2) Mathematical-programming-based approach

The most common applied mathematical programming based approaches are Branch and Bound (Chen and Thizy [1990]; Stadtler [1997],) Branch-and-Cut and Valid Inequalities (Belvaux and Wolsey [2000]; Miller et al. [2000], Fix-and-Relax Heuristics (Akartunali and Miller [2009]; Dillenberger et al. [1994]; Federgruen et al. [2007]), Rounding Heuristics (Eppen and Martin [1987]; Maes et al. [1991]), Dantzig-Wolfe decomposition and Column Generation (Bitran and Matsuo [1986]; Huisman et al. [2005])

Lagrangian heuristics are implemented by applying the Lagrangian relaxations iteratively. Two types of them are widely used for the solution of lot sizing problems: Lagrangian Relaxation Heuristics (Chen and Chu [2003]; Hindi et al. [2003], Lagrangian Decomposition Heuristics (Millar and Yang [1994])

3) Meta-heuristics

Local Search Heuristics (Chen and Chu [2003]; Haase [1998]), Variable Neighborhood Search (Hindi et al. [2003]), Simulated Annealing Heuristics and Tabu Search Heuristics (Berretta et al. [2005]; Özdamar et al. [2002]), Genetic Algorithms (Duda [2017]; Özdamar et al. [2002]; Xie and Dong [2002], Memetic Algorithms (Berretta and Rodrigues [2004]), Ant Colony Optimization Heuristics (Pitakaso et al. [2006]).

2.3.4 Integrated Lot Sizing and Scheduling Studies

Two of the problems that a production manager usually copes with in the management of a manufacturing company at the planning level are 1) the determination of the quantity of products to be manufactured at a given period with the objective of minimizing the total cost including production, holding and setup costs, and 2) the definition of the best resource allocation and the best starting and completion times of jobs with the goal of optimizing some criteria such as minimizing the makespan, maximizing the throughput, etc. (Giglio et al. [2017]; Gómez Urrutia et al. [2014]). As the reader can realize, the first problem corresponds the lot sizing problem which has been detailed in the previous sections. The second problem defines the scope and the objective of the scheduling problem. The viability of the decisions made at a tactical level is heavily depend on the success of the implementation of them at the operational level. Similarly, the tactical level decisions made without respecting the capacity constraints of the operations result in infeasible solutions. To satisfy the consistency between the different levels, integrating the problems and dealing with them simultaneously has a vital importance.

Over the years, lot sizing and scheduling problems are studied individually by considering different characteristics and generating different variants of them. With the studies of Dauzère-Pérès and Lasserre [2002]; Drexl and Kimms [1997]; Ouenniche et al. [1999] which draw attention to the importance of incorporating the scheduling and lot sizing decisions for planning the production in a coherent and realistic way, studies which combine both problems have significantly increased.

—Single Machine Problems

Almada-Lobo et al. [2007] studied the single machine multi-item capacitated lot sizing problem (CLSP) with sequence-dependent set-ups and costs. Shim et al. [2011] considered the single machine CLSP with sequence-dependent setup costs while preserving the set-up state between two consecutive time periods. Although the problem they studied has already been studied by Haase [1996] before, they aimed to improve the solution approach by suggesting a two-stage heuristic including backward and forward improvement method between the initial and the solutions obtained in the following iterations. Stadtler [2011] extended the single-level single machine proportional lot sizing problem (PLSP) to a multi-level single machine PLSP with a zero lead time offset. Gicquel and Minoux [2015] studied the multi-product discrete lot sizing for single machine scheduling with sequence-dependent changeover costs and a new family of multi-product valid inequalities for the problem is presented.

—Parallel Machines Problems

Toledo and Armentano [2006] dealt with the single stage CLSP in the setting of unrelated parallel machines and they proposed a heuristic based on the Lagrangian relaxation of the capacity constraints. Beraldi et al. [2008] developed new rolling horizon and Fix-and-Relax heuristics for the identical parallel machines lot sizing and scheduling problem with sequence-dependent set-up costs. Dolgui et al. [2009] handled the multi-product lot sizing and scheduling on unrelated parallel machines with the purpose of minimizing the makespan. The studies of Fiorotto et al. [2015], Xiao et al. [2015] and Wu et al. [2018b] can be cited as the recently published studies which deal with the lot sizing problem by integrating the constraints of parallel machines scheduling.

—Job Shop Problems

Karimi-Nasab and Seyedhoseini [2013] proposed an integer linear programming formulation for a simultaneous multi-level multi-product lot sizing and scheduling problem in a job shop environment. They built their mathematical model on realistic assumptions such as considering flexible machines which enable the production manager to change their working speeds. Gómez Urrutia et al. [2014] addressed the solution of multi-item multi-period multi-resource single-level lot sizing and scheduling problem for job-shop configurations and they offer combining a Lagrangian heuristic with a sequence improvement method which iteratively feeds the heuristics. Giglio et al. [2017] studied the integrated lot sizing and energy-efficient job shop scheduling problem in manufacturing/remanufacturing systems. The developed mixed-integer programming model is solved by Relax-and-Fix heuristic approach.

—Flow Shop Problems

In particular, since the integrated lot sizing and flow shop problem is studied in this thesis, a comprehensive review will be presented about the previous studies which incorporate these two problems.

Mohammadi and Fatemi [2010] and Mohammadi et al. [2010a,b,c] studied the multi-level multi-product capacitated lot sizing problem for pure flow shop system with sequence-dependent set-up costs. The objective of the developed models is to minimize the set-up, inventory and production cost. Since the handled problem is NP-hard, they applied a MIP-based heuristic approaches such as rolling-horizon and Fix-and-Relax heuristics. The main principle of these solution methods is to decompose the global problem into smaller, tractable, manageable and easier sub-problems and to solve these sub-problems subsequently by using the information from previously solved ones. In the study of Mohammadi [2010] the same solution approach is applied for the solution of multi-level multi-product capacited lot sizing problem for flexible flow shop systems. One of the common points of these studies conducted by Mohammadi et al., they concluded that the use of metaheuristic approaches for the solution of the developed models will be better option to deal with the complexity of the problem especially for the larger instances. Mohammadi and Ghomi [2011] combined genetic algorithm with rolling horizon approach for the the capacitated lot sizing problem in pure flow shops with sequence-dependent setups. Mohammadi et al. [2011] proposed a genetic algorithm for the simultaneous lot sizing and sequencing problems in permutation flow shops involving sequence-dependent setups and capacity constraints.

Similar to the studies of Mohammadi et al., Babaei et al. [2011] handled multi-level and multi-period capacitated lot sizing and scheduling problem with sequence-dependent set-ups and set-up carry over in flow shop environment. The main contribution of their study is that lot sizing problem is integrated with the scheduling problem by considering the backlogging features. Accordingly, the objective of the developed model is modified as minimizing the sum of the sequence-dependent setup costs, the storage costs, the production costs and the shortage cost. In their latter study, they applied genetic algorithm approach for the solution of the same problem (Babaei et al. [2014]). The obtained solutions by genetic algorithm is compared with the developed lower bounds.

Filho et al. [2012] proposed to use the asynchronous team (A-Team) solution approach for the model presented by Mohammadi et al. [2010a]. The main philosophy behind the A-Team approach comprises distinct heuristic algorithms, called agents, that communicate through shared memories which store the solutions obtained by the agents. They showed that the proposed A-Team procedures outperform the literature heuristics, especially for large instances.

Ramezanian et al. [2013c] handled multi-product multi-period lot sizing and scheduling problem in capacitated permutation flow shop with sequence-dependent setups and developed a more efficient alternative of the mathematical model which is presented in Mohammadi et al. [2010c]. In comparison to the former model, the number of the binary and continuous decision variables is significantly decreased and the newly developed model which is easier to solve is solved with MIP-based heuristic approaches. Ramezanian et al. [2013b] considered the problem of lot sizing and scheduling of multiple product types in a capacitated flow shop with machine availability constraints for multi-period planning horizon and three MIP-based heuristics based on iterative procedures are used to solve problem instances. Ramezanian et al. [2013a] extended the previous model by considering a new practical condition such as overlapping operations and solved the extended model by MIP-based and simulated annealing approaches. They concluded that the simulated annealing can solve the large-sized instances in a reasonable time. Mortezaei and Zulkifli [2013] developed a mathematical model for the integration of lot sizing and flow shop scheduling with lot streaming. Ramezanian and Saidi-Mehrabad [2013] addressed lot sizing and scheduling problem for a flow shop system with capacity constraints, sequence-dependent setups, uncertain processing times and uncertain multi-product and multi-period demand. The uncertain parameters are modeled by means of probability distributions and chance-constrained programming theory.

Mahdieh [2013] studied on the integrated capacitated lot sizing and scheduling problems in a flexible flow line system where flow shop and parallel shop manufacturing systems are hybridized.

Villadiego et al. [2014] studied on integrated lot-sizing and sequencing problem in a permutation flow shop with machine sequence-dependent setups and proposed an iterated greedy heuristic to cope with the complexity of the problem.

Ramezanian et al. [2017] proposed to use particle swarm optimization approach for the solution of joint lot-sizing and scheduling problem in multi-product, multi-period flexible flow shop environments.

Masmoudi et al. [2015] developed a model for lot sizing problems in a flow shop system with energy consideration. Accordingly, they developed an mixed integer programming model subjecting to the classical capacitated lot sizing constraints and flow shop constraints including the machine overlapping considerations. The other novelty of their study is that the constraint setting a strict limit on the maximum instantaneous power demand in each period is added to the model. To the best of our knowledge, the study of Masmoudi et al. [2015] is the first attempt combining lot sizing problems in flow shop system with energy consideration.

It is a fact that, in real life, energy suppliers can provide the energy to their customers in a certain balance. To keep this balanced energy flow, they negotiate with the customers for different power options including different tariffs and reach an agreement. By inspiring from the real life practices, in this thesis, the model of Masmoudi et al. [2015] is extended to the optimum energy contract capacity selection problem. The proposed model in this thesis aims to identify optimum production quantity that satisfies the demand by considering system and energy constraints and to select the optimum energy contract capacity offered by the suppliers according to production configuration. Since the proposed model takes into account the capacity options offered by the energy suppliers, it aims to synchronize energy needs of the production system and the market options. Consequently, it satisfies more realistic production plans which are convenient with conditions of the energy supplier.

The other motivation behind the proposed model is that, today, the share of renewable energy sources in the total purchased power is decided by the energy suppliers. As it is explained before, to reach the EU targets, the usage of the renewable energy sources is encouraged by the governments and industrial customers face new regulations for reducing their carbon emissions to the acceptable levels. Hence, deciding the best capacity option for the renewable energy sources will have vital importance, too. From this point of view, the proposed model will be a very useful decision making tool for the industrial customers in coming years. To the best of our knowledge, the presented study in this thesis, is the first attempt which combines optimal energy contract selection problem with lot sizing problem for flow-shop configuration by integrating renewable energy sources.

In the following section, the studies integrating the renewable energy availability to the lot sizing and scheduling problems will be summarized to emphasize the place of the study conducted in this thesis in the literature precisely.

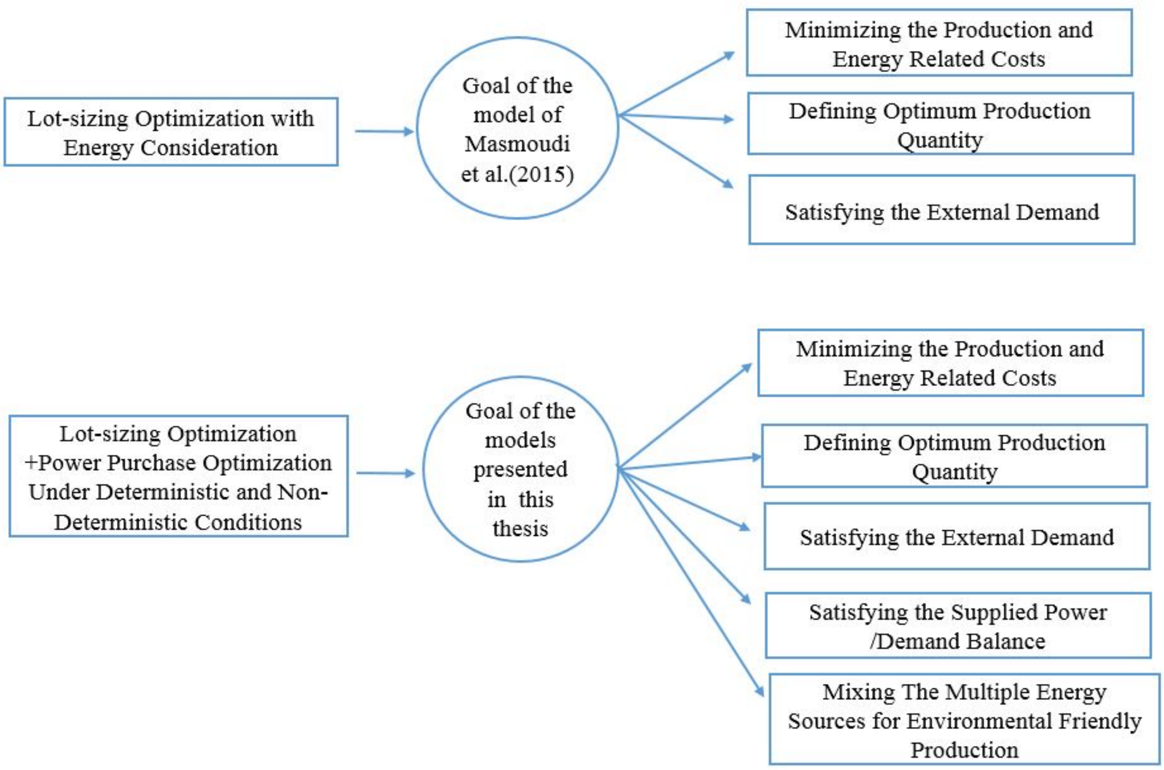

Figure 2.10: Comparison between the model developed by Masmoudi et al. [2015] and the models studied in this thesis

2.4 Renewable Energy Integration to The Lot Sizing and Scheduling Studies

2.4.1 Uncertain Parameters Consideration in Lot Sizing Problems

In a typical production system, there are numerous parameters which are considered in the production planning process. While some of these parameters are known deterministically, some of them have a uncertain nature and are hard to predict. In the most optimization problems studied in the field of Operations Research, the parameters, which have a stochastic nature in real life world, are assumed deterministic for simplicity. However, developing the models on more realistic assumptions such as unknown demand, stochastic resource availability or machine breakdown can produce more purposive results and analyses for the decision makers.

Aloulou et al. [2014] reviewed the non-deterministic lot sizing models in the literature. They classify the lot sizing studies conducted by considering non-deterministic parameters according to the *dem* (demand), *lead* (lead time),*yie* (yield, including cases of machine unavailability intervals, defective production, and uncertainty in supply in the case of procurement), *tim* (production times, setup times), *cap* (production capacity or inventory bounds), *cost* (unit production cost, setup cost, unit purchase price, profit), *res* (resources different from production capacity, including budget), *all* (all input parameters).

We recommend the reader to review the study of Aloulou et al. [2014] for further details. When it is examined, it is seen that the studies dealing with the uncertain demand or yield have the largest share in the non-deterministic lot sizing problems.

In the second part of this thesis, since the uncertain nature of the availability of the renewable energy sources is considered and integrated into the capacitated lot sizing problem, it is thought that filtering the studies considering uncertain capacity and resource parameters in lot sizing problems from the whole review of Aloulou et al. [2014] provides a bird's eye view for the reader (Table 2.4).

Table 2.4: Lot sizing studies including the capacity and resource uncertainty Aloulou et al. [2014]

Uncertain Parameter	Modelling Approach	Reference
cap.	fuzzy	Pai [2003]
cap.	prob	Erdem et al. [2006]
cap.	prob	Aghezzaf et al. [2007]
dem., cap.	fuzzy	Tang et al. [2000]
dem., cap.	sim	Xie et al. [2004]
cap.,res	fuzzy	Maity and Maiti [2007]
cap.,res,cost	fuzzy	Maiti and Maiti [2006]
dem,cost,cap	fuzzy	Torabi and Hassini [2008]
dem., yie., cap.	sce	Guan [2011]; Guan and Liu [2010]
all	sim	Mehra et al. [2006]
all	que	Vandaele and De Boeck [2003]
all	prob, game	Yao and Cassandras [2012]
all	sim	Olhager and Persson [2006]
all	fuzzy	Aliev et al. [2007],Petrovic et al. [2008]
all	sce	Sodhi and Tang [2009]

In Table 2.4, the main solution approaches are listed as *game* (game theory formulation), *prob* (probabilistic formulation including Markov chain and stochastic programming formulations), *que* (queue theory models), *fuzzy* (fuzzy logic formulation), *sce* (stochastic or deterministic scenarios formulation), *sim* (stochastic or discrete event simulation).

The common part of the studies summarized in Table 2.4, they do not involve the energy aspect.

For modelling approach, it is seen that fuzzy logic formulation is the most preferred way to model the uncertain features in the lot sizing models. In the studies of Maiti and Maiti [2006]; Maity and Maiti [2007], the chance constraint programming with fuzzy parameters is applied to model the problem. In this thesis, to model the stochastic renewable availability of the renewable energy sources, probabilistic chance constraint programming approach which is detailed in Chapter 4 is implemented.

To sum up, the non-deterministic lot sizing model studied in this thesis opens a new path in terms of considered uncertain parameter and the way of implementation of the modelling approach.

2.4.2 Integration of Renewable Energy Sources into Scheduling Problems

It is possible to see the reflections of the fast deployment of the use of renewable energy sources in the literature. Over a few decades, while the studies based on the energy-efficient production systems have been a magnet for the researchers, now, with the %100 renewable energy projections, the direction of the studies has started to change towards to generating green-efficient production systems. This perspective that motivates us to integrate renewable energy sources, gives inspiration to the other researchers, too.

Moon and Park [2014] dealt with minimizing the total production cost of the flexible job shop scheduling problem with time-dependent and machine-dependent electricity cost by considering energy storage and renewable energy resources such as solar energy and wind. Liu [2016a,b] used the interval number theory for renewable energy in uncertainty modelling and proposed two novel interval single-machine scheduling problems. They proposed multi-objective model which minimizes the total weighted flow time and carbon emission. Beier et al. [2017] presented a method for real-time control of manufacturing systems with several processes and intermediate buffers to increase utilization of (on-site) generated variable renewable energy sources without compromising system throughput. The main objective of their study is not to optimize a (future) production schedule, but being capable of adapting a manufacturing system electricity demand to volatile supply without requiring forecast data input. For this purpose, they developed a real time control and implemented it in a simulation prototype. Zhai et al. [2017] proposed a dynamic scheduling approach to minimize the electricity cost of a flow shop with a grid-integrated wind turbine. They employed a time-indexed mixed integer linear programming (MILP) model for flow shop scheduling under real time pricing. To update the speed of the wind and electricity prices time series models are used. Once the electricity price and wind energy forecasts were obtained on ARIMA, they are applied to the model solved by CPLEX solver. Thus, the machine scheduling and hourly energy costs are provided. Biel et al. [2018] developed a two-stage stochastic optimization procedure that computes a production schedule and energy supply decisions for a flow shop system. In the first stage, a bi-objective mixed integer linear program minimizes the total weighted flow time and the expected energy cost, based on the generated wind power scenarios. In the second stage, energy supply decisions are adjusted based on real-time wind power data. Wu et al. [2018b] proposed a multi-objective flexible flow shop scheduling problem that considers changing processing time due to uncertainty of the renewable energy sources. The developed model minimizes the makespan and the carbon emission. To calculate the solar power generation at any t hour of the day, Normal distribution is used and the probability density function is simplified by considering peak solar power generation on cloudy and sunny days. A hybrid non-dominated sorting genetic algorithm with variable local search is proposed to solve the developed model. Fazli Khalaf and Wang [2018] studied a two-stage stochastic flow shop scheduling problem to minimize the total electricity purchase cost. The energy need of the system is met by on-site generation as well as power grid. In the first stage, the optimum production schedule for flow shop system is built by considering the forecasted renewable energy generation and the energy cost is minimized. In the second stage, the errors of the forecasted renewable supply is compensated by real-time electricity price and the variability of renewable generation.

The scarce number of the studies on integrating renewable energy sources into the scheduling and lot sizing studies proves that this area has newly been explored and there are many rooms for further studies and improvements.

2.5 Summary and Conclusion

The efficient use of energy reserves and increasing the use of renewable energy resources are one of the most important targets of the nations. The industry sector plays a very important role in achieving these targets. Recently, growing body of literature about the energy aware production plans proves the importance of the industrial sector in the boosting the energy efficiency.

The study of Masmoudi et al. [2017a] has opened new paths for energy efficient lot-sizing problems by introducing the power limitations. The gap in their study is to synchronize the power need of the production system and the market options. This case causes lack of balance between the power demand and supply and results in unrealistic production plans. This gap is realized and it is aimed to show new directions to the researchers about merging the energy generation and distribution constraints with the production related constraints for managing the energy reserves of the world better.

In addition to this, when it is compared, the number of the publications based on the energy-aware planning, in conventional manner, with the number of the studies compromising the renewable energy availability, the field of the renewable energy oriented production planning has many rooms to improve. When, particularly, non-deterministic lot sizing problems are investigated, there is limited study in which the resource parameters are handled in stochastic manner.

All these gaps have been realized and motivated us to conduct the presented work in this thesis.

Chapter 3

The Single Item Lot Sizing Problem with Energy Aspect and Capacity Contract Selection Problem: Models and Exact Solution

Contents

3.1 Introduction

As it is pointed out in the state of art section, especially, in the last decades, there is a rising awareness for energy-efficient manufacturing models. As a result of this upward trend, the number of publications focusing on the energy efficiency in the production systems increases. While the great majority of the work done in this field aim the efficient use of energy for scheduling problems, to the best of our knowledge, the first study that considers energy constraint for lot sizing problems is the study of Masmoudi et al. [2015].

Just as the other producers, the primary target of energy producers is to satisfy the power demand of their customers. The energy consuming behaviour of the customers can change all day long and generate fluctuations in the power demand. To satisfy the power demand of their customers and protect energy generation facilities from the damages caused by these sudden fluctuations, energy producers need to schedule energy production accurately. To do so, they try to set the power need of their customers by offering them certain power contract options. Therefore, they can minimize the fluctuations in the power demand and sustain the energy supply in a safer and balanced way.

Masmoudi et al. [2015, 2016, 2017a] introduced the energy considerations in the capacitated single item lot sizing problem in a flow-shop system with the purpose of minimizing the energy costs. Although their model helps industrial customers to decrease the production and energy costs simultaneously, since the constraints on energy suppliers are left out of the context, the fluctuations in the power demand configurations are observed. While there is no production in some periods, then there is no power demand and there is excessive power demand in some periods. This case not only causes supply difficulties for the energy supplier, but also causes inefficient energy management on the consumer side since it brings on paying for unused energy or being penalized for excessive energy usage according to energy purchasing agreements.

This chapter presents a mixed-integer model which is developed for the resolution of capacitated single item lot sizing problem for flow-shop systems by considering energy contract options. To the best of our knowledge, the proposed model in this thesis is the first attempt which combines the capacitated single item lot sizing problem for a flow-shop system with the capacity contract selection problem. Additionally, the problem is solved by mixing renewable and traditional energy sources by considering the fact that traditional energy sources will be replaced/mixed with the renewable energy sources in the future.

This chapter is organized as follows: In Section 3.2, firstly, the mathematical model developed by Masmoudi et al. [2017a] is presented with an illustrative example. Based on the analysis of this model, we emphasize the fact that the required power is evaluated based on upper bound. In Section 3.3, since the computation of the exact value of the required power has a crucial importance to match the system power need with the energy contract options in our model, the model of Masmoudi et al. [2017a] is improved. In Section 3.4, capacity contract selection constraints are introduced and mathematical models are developed to address this aspect jointly to the lot sizing problem. Illustrative examples are given and computational experiments are conducted. Finally, Section 3.5 concludes this chapter with some remarks.

3.2 Single Item Lot Sizing Problem with Energy Constraint _ Model of Masmoudi et al. [2017a]

3.2.1 Problem Statement

In the study of Masmoudi et al. [2017a], the single item capacitated lot sizing problem for flow shop configuration is studied. For production configuration, a flow shop manufacturing system composed of N machines and N buffers is considered (Figure 3.1). The planning horizon is divided into T periods. Each period (t=$1,...,T$) is portrayed by its duration L_t (not necessary equal for all the periods), a price of electricity Co_t, a price of power θ_t and an external demand d_t.

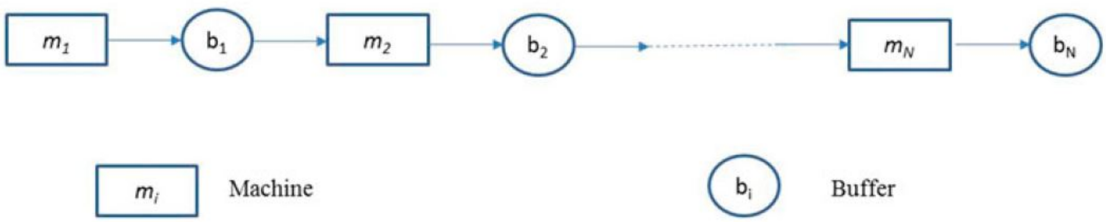

Figure 3.1: A typical manufacturing system with N machines and N buffers [Masmoudi et al., 2017a]

3.2.2 Objective

The objective of the study is to identify the production quantities ($x_{m,t}$) for each machine (m=$1,...,N$) at each period (t=$1,...,T$) by minimising the total cost including electricity, power, storage, set-up while satisfying the external demand (d_t, t=$1,...,T$) and production related constraints and power limitation at each period (α_t).

3.2.3 Assumptions

- The external demand is deterministic, known in advance and must be satisfied at the end of each period, that is, backlogging is not considered.
- A single product is considered.

— The production plan is elaborated for a horizon of T periods (t=1,...,T).

— The first machine is never starved and the last machine is never blocked at each period.

— The capacity of each machine is limited by the length of the period and maximum available power.

— A machine m can only start the production when all the quantity to be produced ($x_{m,t}$) is available at the output of the previous machine (*Vertical Interaction Constraint*).

— For each machine, a single set-up is allowed at each period.

— The power demand (E_t^{max}) at each period is computed by considering the power of machines running in parallel and it should not exceed a defined maximum power (α_t).

3.2.4 Mathematical Model of Masmoudi et al. [2017a]

Notations

The parameters and the decision variables of the problem are presented in Table 3.1. Each machine is characterized by its power (ϕ_m) and its processing time (p_m). In the study of Masmoudi et al. [2017a] the electrical consumption cost of machine m at period t per unit of product ($\psi_{m,t}$) is calculated by multiplying processing time of the machine (p_m), power of the machine (ϕ_m) and the price of electricity (Co_t) in period t. Thus, electricity consumption integrated to production cost is obtained.

Mathematical Model $\_P_0$

$$Min z = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) + \sum_{t=1}^{T}(\theta_t.E_t^{max}) \tag{3.1}$$

$$x_{N,t} + I_{N,t-1} = d_t + I_{N,t} \quad \forall t = 2,...,T \tag{3.2}$$

$$x_{m,t} + I_{m,t-1} = I_{m,t} + x_{m+1,t} \quad \forall m = 1,...,N-1, t = 2,...,T \tag{3.3}$$

$$x_{m,t} \leq y_{m,t}\sum_{\tau=t}^{T} d_\tau \quad \forall m = 1,...,N, t = 1,...,T \tag{3.4}$$

$$I_{m-1,t-1} \leq x_{m,t} + M.v_{m,t} - 1 \quad \forall m = 2,...,N, t = 2,...,T \tag{3.5}$$

Table 3.1: List of parameters and variables of the model of Masmoudi et al. [2017a]

Parameters	
N	Number of machines.
T	Number of periods.
ϕ_m	The power of the machine m.
p_m	Processing time for machine m.
Co_t	The price of electricity during period t.
$\psi_{m,t}$=$\phi_m.p_m.Co_t$	Electrical consumption cost of machine m at period t per unit of product.
h	The holding cost per unit.
$w_{m,t}$	The set-up cost of machine m in period t
d_t	External demand at period t.
L_t	Length of period t.
M	A large number.
θ_t	The price of power in period t.
α_t	Maximum power which can be supplied by the supplier at period t.
Decision variables	
$x_{m,t}$	Quantity produced by machine m in period t.
$I_{m,t}$	Inventory level of machine m at the end of period t.
$C_{m,t}$	Completion time of machine m in period t.
E_t^{max}	The maximum power demand during period t.
	Binary variables
$y_{m,t}$	A binary variable, equal to 1 if machine m runs in period t, 0 otherwise.
$v_{m,t}$	A binary variable, equal to 1 if the quantity $x_{m,t}$ is available in buffer *m-1* at the beginning of period t, 0 otherwise.
$f_{m,r,t}$	A binary variable, equal to 1 if $C_{r,t} > C_{m,t} - x_{m,t}.p_m$, 0 otherwise.
$g_{m,r,t}$	A binary variable, equal to 1 if $C_{m,t} \geq C_{r,t}$, 0 otherwise.

$$x_{m,t} \leq I_{m-1,t-1} + M.(1 - v_{m,t}) \quad \forall m = 2,...,N, t = 2,...,T \tag{3.6}$$

$$C_{m,t} - x_{m,t}.p_m \geq C_{m-1,t} - x_{m-1,t}.p_{m-1} + (x_{m,t} - I_{m-1,t-1}).p_{m-1} - M.v_{m,t} \quad \forall m = 2,...,N, t = 2,...,T \tag{3.7}$$

$$C_{m,1} - x_{m,1}.p_m \geq C_{m-1,1} - x_{m-1,1}.p_{m-1} + x_{m,1}.p_{m-1} \quad \forall m = 2,...,N \tag{3.8}$$

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.9}$$

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.10}$$

$$E_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (f_{m,r,t} + g_{m,r,t} - 1).\phi_r \quad \forall m = 1,...,N, t = 1,...,T \tag{3.11}$$

$$E_t^{max} \leq \alpha_t \quad \forall t = 1, ..., T \tag{3.12}$$

$$I_{m,1} = x_{m,1} - x_{m+1,1} \qquad \forall m = 1, ..., N-1 \tag{3.13}$$

$$I_{N,1} = x_{N,1} - d_1 \tag{3.14}$$

$$C_{1,1} - x_{1,1}.p_1 = 0 \tag{3.15}$$

$$I_{N,0} = I_{N,T} = 0 \tag{3.16}$$

$$C_{m,t} - x_{m,t}.p_m \geq 0 \quad \forall m = 1, ..., N, t = 1, ..., T \tag{3.17}$$

$$C_{m,t} - x_{m,t}.p_m \leq L_t.y_{m,t} \quad \forall m = 1, ..., N, t = 1, ..., T \tag{3.18}$$

$$C_{m,t} \leq L_t \quad \forall m = 1, ..., N, t = 1, ..., T \tag{3.19}$$

$$f_{m,m,t} = g_{m,m,t} = 0 \quad \forall m = 1, ..., N, t = 1, ..., T \tag{3.20}$$

$$x_{m,t}, I_{m,t}, C_{m,t} \quad int. \quad \forall m = 1, ., N, t = 1, ., T \tag{3.21}$$

$$\begin{gathered} y_{m,t}, v_{m,t}, f_{m,r,t}, g_{m,r,t}, \in \{0, 1\} \\ \forall m = 1, ..., N, t = 1, ..., T \end{gathered} \tag{3.22}$$

$$x_{m,t}, I_{m,t} \geq \ 0 \quad \forall t = 1, ..., T, m = 1, ..., N \tag{3.23}$$

The first part of the objective function (3.1) aims to minimize the production costs including electrical consumption, set-up and holding costs and the second part attempts to minimize the power cost. The equations (3.2) and (3.3) balance the demand and production quantity. The relation between the state of the machine *m=1,...,N* in period *t=1,...T* and the production quantity is built with constraint (3.4).

It is assumed that a machine *m* can only start the production when all the quantity to be produced ($x_{m,t}$) is available at the output of the previous machine. This relation between the machines is called *vertical interaction constraint* (Masmoudi et al. [2017a]; Mohammadi et al. [2010c]; Ramezanian et al. [2013b]). As it can be observed in Figure 3.2, the constraints (3.5) and (3.6) compare the production quantity to be produced on machine m in period t (e.g. $x_{2,2}$) with the buffer stock level of machine *m-1* from the previous period (e.g; $I_{1,1}$). Therefore, the availability (at the beginning of the period) of production quantity produced by machine m in period t is checked and the value of the variable $v_{m,t}$ is identified. If the buffer level is not sufficient at the beginning of period t_2, which is translated as $v_{m,t}$=0, the second machine can only start the production when the production quantity ($x_{2,2}$) to be produced is available. In other words, the second machine waits for the first machine to complete the production quantity to be produced on second machine. Constraints (3.7) and (3.8) assure this vertical interaction between the machines.

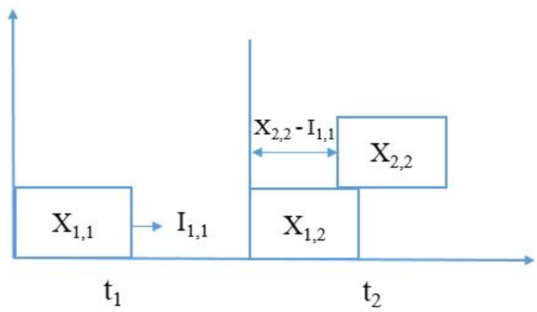

Figure 3.2: An example for vertical interaction between the machines

Since each period is limited with a certain length of time, to satisfy the external demand, the machines can overlap by assuring the vertical interaction. The constraints (3.9) and (3.10) are introduced to define the existence of an overlap between two machines in period t. In Figure 3.3, some possible positions of the machines are displayed. While the constraint (3.9) compares the completion time of machine r and starting time of machine m, the constraint (3.10) compares the completion times of the machines m and r. The variables $f_{m,r,t}$ and $g_{m,r,t}$ play a role to define if the machine overlapping exists. As it can be observed in Figure 3.3, the case of $f_{m,r,t} = g_{m,r,t} = 1$ or $f_{r,m,t} = g_{r,m,t} = 1$, guarantees the overlap between the machines m and r. When any of the pairs of $f_{m,r,t}$ and $g_{m,r,t}$ variables is equal to 0, it means that there is no overlap between the machines m and r as it can be seen in the first and last configurations in Figure 3.3.

We would like to draw reader's attention to a specific point in the configurations where there is no overlap. In the first configuration on the left hand side in Figure 3.3, the completion time of machine r (C_r) is earlier than the starting time of the machine m. When the constraint (3.9) is called:

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.24}$$

it is seen that, in such a case, the value of $f_{m,r,t}$ can be 0 or 1. Similarly, when the constraint (3.10) is called:

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.25}$$

It is possible to comment in the same way for the $g_{r,m,t}$ variable of the same configuration, as it can take 0 or 1 values.
In the study of Masmoudi et al. [2017a], since the objective function tries to minimize the sum of the power cost, in such cases where it is possible that $f_{m,r,t}$ and $g_{m,r,t}$ can be equal to 0 or 1, the objective function restrains increase in the E_t^{max} and imposes the variables $f_{m,r,t}$ and $g_{m,r,t}$ to be 0. That's why Masmoudi et al. [2017a] did not need to fix the values of the variables $f_{m,r,t}$ and $g_{m,r,t}$ in such cases by relying on the objective function in (3.26).

$$Minz = ... + \sum_{t=1}^{T} (\theta_t.E_t^{max}) \tag{3.26}$$

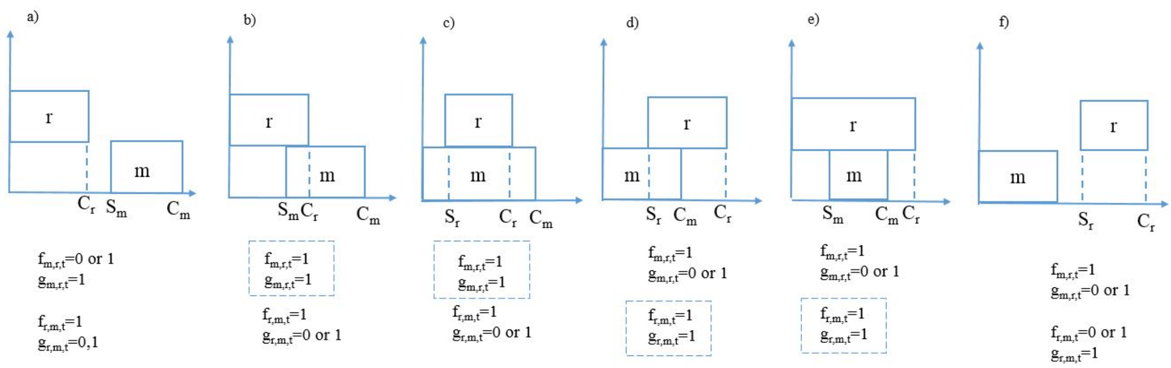

Figure 3.3: Possible interactions between the machines

E_t^{max} is an upper bound of the power demand required by the system in period t and is determined by constraint (3.11), depending on the overlap between the operating machines. Let's consider the production configuration in Figure 3.4 where two machines operate by overlapping. The constraint (3.11) is as follows:

$$E_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (f_{m,r,t} + g_{m,r,t} - 1).\phi_r \quad \forall m = 1,...,N, t = 1,...,T \tag{3.27}$$

When the peak power is calculated by referencing machine *r*, the constraint is transformed as follows:

$$E_t^{max} \geq \phi_r . y_{r,t} + \sum_{m=1,r\neq m}^{N} (f_{r,m,t} + g_{r,m,t} - 1).\phi_m \quad \forall r = 1,...,N, t = 1,...,T \tag{3.28}$$

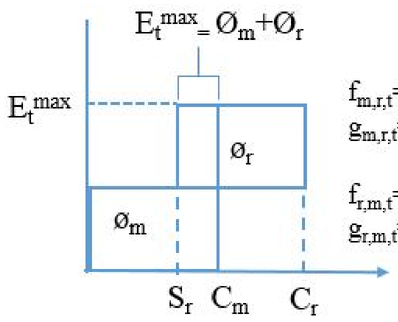

Figure 3.4: Computation of the upper bound of the required power of overlapping machines

where $y_{r,t}$, $f_{r,m,t}$ and $g_{r,m,t} = 1$ as in Figure 3.4, the upper bound (E_t^{max}) of the power demand is found:

$$E_t^{max} \geq \phi_r + \phi_m \tag{3.29}$$

Constraint (3.12) limits the peak power demand with the maximum power quantity (α_t) that can be supplied by the energy supplier. Note that α_t is, in this model, a data corresponding to the energy contract option between the industrial customer and the energy supplier. The initial conditions are defined by constraints (3.13)-(3.16). Constraints (3.13) and (3.14) define respectively the quantities of buffer stock in the first period and stock level in the last machine at the first period. Constraint (3.15) fix the starting point in the first period. The equality (3.16) guarantees no inventory in the beginning and at the end of the production horizon. The constraints (3.17)-(3.19) keep the starting and completion times of each machine in the same period. Each machine has to start and finish the production in the same period. The general state about the machine overlaps are defined by constraints (3.20). Constraints (3.21)-(3.23) describe the binary, integer and continuous variables of the model.

3.2.5 Illustrative Example

We present in this subsection the solution obtained with the model developed by Masmoudi et al. [2017a], for an illustrative example. The planning period is composed of five periods (T=5) and a system with three machines (N=3) is considered. The handled example is coded as (N3_T5). The period and machine related data are given respectively in Table 3.2, Table 3.3.

Table 3.2: Time related data of Instance N3_T5

Period (t)	1	2	3	4	5
d_t *(piece)*	45	52	49	50	52
L_t *(min)*	1080	360	1080	360	1080
Co_t *($/KWh)*	0.16	0.08	0.16	0.08	0,16
α_t *(KW)*	30	30	30	30	30
θ_t *(KW)*	19.8	1	19.8	1	19.8
w_1, t *($)*	68	67	67	98	56
w_2, t *($)*	98	93	53	65	74
w_3, t *($)*	86	83	85	59	60

Table 3.3: Machine related data of Instance N3_T5

machine(m)	1	2	3
ϕ_m(KW)	9	6	8
p_m (min)	6	7	5

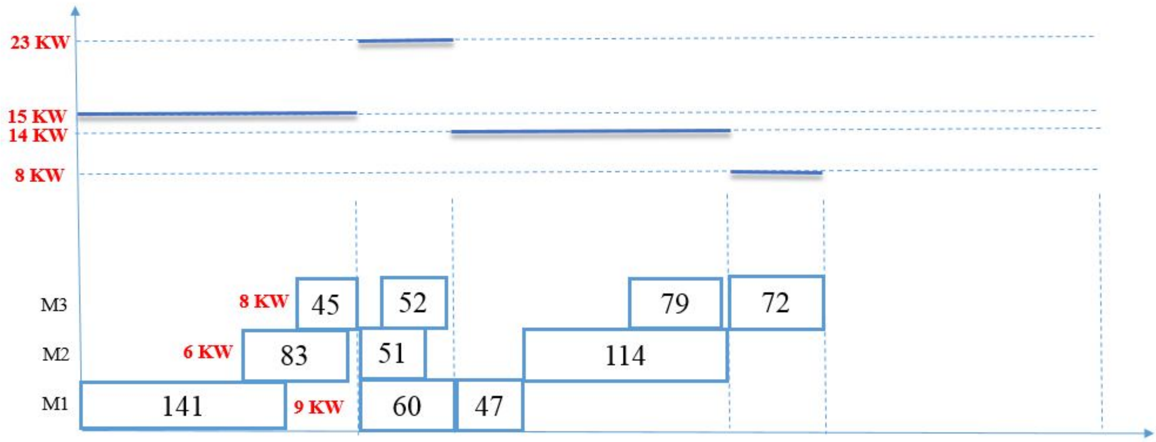

Figure 3.5: The manufacturing configuration obtained by the model of Masmoudi et al. [2017a]

The production configuration in Figure 3.5 represents the optimal solution for the example N3_T5. The squares represent the machines and the numbers in the squares signify optimum production quantity. The power demand of each machine is displayed next to the squares and the maximum power demand for each period is shown top of the time intervals with lines. The values of the variables of $f_{m,r,t}$ and $g_{m,r,t}$ are defined by the constraints (3.9) and (3.10) and the upper bound of the power demand is calculated with the help of the constraint (3.11). The results are displayed in Table 3.4. Since there is only one machine running in the fourth period, the values are given in Table 3.4 until third period.

For better sense, the relation between the second and third machine in the first period can be exemplified. In this specific case, where *m=2* and *r=3*, the constraints which define the overlap can be translated as follows:

Table 3.4: The values of the variables which define the existence of the overlap between the machines for the example in Figure 3.5

		r=1		r=2		r=3		Over.Mac.	$\phi_m + \phi_m$
		$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$		
t=1	m=1	0	0	1	0	1	0		
	m=2	1	1	0	0	1	0	2,1	15
	m=3	0	1	1	1	0	0	2,3	14
								E_t^{max}	15
t=2	m=1	0	0	1	1	1	1	1,2,3	23
	m=2	1	0	0	0	1	0		
	m=3	1	0	1	1	0	0	3,2	14
								E_t^{max}	23
t=3	m=1	0	0	1	0	1	0		
	m=2	0	1	0	0	1	1	2,3	14
	m=3	0	1	1	0	0	0		
								E_t^{max}	14

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1, ..., N, r = 1, ..., N \neq m, t = 1, ..., T \tag{3.30}$$

$$C_{3,1} - C_{2,1} + x_{2,1}.p_2 \leq M.f_{2,3,1} \tag{3.31}$$

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1, ..., N, r = 1, ..., N \neq m, t = 1, ..., T \tag{3.32}$$

$$C_{2,1} - C_{3,1} \leq M.g_{2,3,1} - 1 \tag{3.33}$$

Accordingly, $f_{2,3,1}$ is equal to 1 and $g_{2,3,1}$ is equal to 0. All the values of $f_{m,r,t}$ and $g_{m,r,t}$ are found in the same fashion and shown in Table 3.4. In the table, under the column named "*Over.Mac*", the overlapping machines are shown according to the reference machine. For example, in the second period when the reference machine is m=1 , it is seen that the machine m=1 overlaps with the second (*r=2*) and third machines (*r=3*) where the overlap is defined by the variables $f_{1,2,2}$, $g_{1,2,2}$ and $f_{1,3,2}$, $g_{1,3,2}$ are equal to 1. We would like to draw attention of the reader to the point that, in the second period when the reference machine m=2, the overlapping machines which are r=1 and r=3 can not be found according to the current formulations since $g_{2,1,2} = 0$ and $g_{2,3,2} = 0$. This problem is addressed in the following sections as "symmetry problem" and detailed. Based on the values of the decision variables, peak power is computed with the following constraint:

$$E_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1, r\neq m}^{N} (f_{m,r,t} + g_{m,r,t} - 1).\phi_r \quad \forall m = 1,...,N, t = 1,...,T \tag{3.34}$$

$$E_t^{max} \geq \phi_1.y_{1,2} + ((f_{1,2,2} + g_{1,2,2} - 1).\phi_2 + (f_{1,3,2} + g_{1,3,2} - 1).\phi_3) \tag{3.35}$$

$$E_t^{max} \geq 9 + (6 + 8) \tag{3.36}$$

Therefore, the peak power demand in the second period is calculated as 23 KW. The required power is calculated in the same way for all the other periods. As it can be seen from Figure 3.5, the peak power demand varies during the planning horizon. While manufacturer demands 15 KW for the first period, this value changes to 23 KW, 14 KW and 8KW for the following periods. Since there is no production, as the natural result of this case, any power is demanded for the last period.

It is necessary to emphasize that the model of Masmoudi et al. [2017a] has important contribution since it considers energy aspect for the lot sizing problem for flow shop systems. As they promise in their study, the developed mathematical model defines the sizes of the production lots and appropriate machine scheduling which can satisfy the external demand by minimizing the production and energy related costs.

However, when the peak power demand configuration is examined, a fluctuating power trend is observed. There is no load balance between the periods and occurring energy demand scheme is not realistic and convenient to supply for energy supplier. Since the energy producers have difficulties to forecast these type of swinging power demand configurations, planning the energy generation and distribution becomes hard, too. To give better service to their customers, they offer power options to their customers. This real life practice can be evaluated as a sort of *win-win* type relationship. While energy producers keep the customers' power demand in certain intervals and plan their production accordingly, the industrial customers can negotiate for the power option that can cover the energy need of their production system. At this point, a question of which capacity option is the best to conduct the production activities in a safer and less costly way rises.

Our mathematical model combines single item lot sizing problem for flow shop systems with the capacity selection problem. Before giving the details about the developed model in this thesis, it is necessary to focus on the shortcomings of the model developed by Masmoudi et al. [2017a] to underlie the base for our model.

3.3 Improvement of Peak Power Computation

In the studies of Mohammadi et al. [2010c]; Ramezanian et al. [2013b] and Masmoudi et al. [2017a] the production configuration is built on the assumption of vertical interaction. According to this assumption, a machine m can only start the production when all the quantity to be produced at period t ($x_{m,t}$) is available at the output of the previous machine. This relation between the machines is built by the constraints (3.5) and (3.6) and illustrated in Figure 3.2. Moreover, the machines can run in parallel with only one set-up per period. In this case, peak power demand is computed by taking into account the power of the overlapping machines. To identify the existence of the overlapping between the machines, variables of $f_{m,r,t}$ and $g_{m,r,t}$ are introduced to the model by Masmoudi et al. [2017a] and the constraints (3.9) and (3.10) are built with this purpose. The peak power demand is calculated by considering this overlap between the machines in the following constraint as it is detailed before:

$$E_t^{max} \geq \phi_m . y_{m,t} + \sum_{r=1, r\neq m}^{N} (f_{m,r,t} + g_{m,r,t} - 1).\phi_r \quad \forall m = 1,...,N, t = 1,...,T \tag{3.37}$$

After testing the model developed by Masmoudi et al. [2017a] on the different size of instances, it is realized that the proposed method, in their study, for computing the required power for each period computes the upper limit of the peak power demand instead of computing exact peak power value for some of the instances.

Let's consider the production configurations presented in Figure 3.6 and Figure 3.7. To identify the values of the variables $f_{m,r,t}$ and $g_{m,r,t}$, let's recall the related constraints:

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.38}$$

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.39}$$

According to the constraints (3.38) and (3.39), the values of the variables $f_{m,r,t}$ and

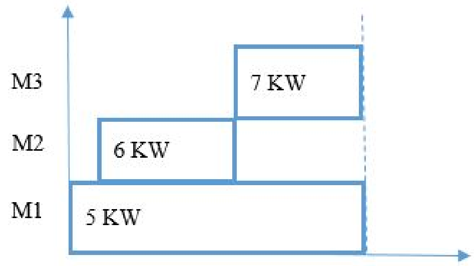

Figure 3.6: Example (1) in which upper bound of peak power is computed

Table 3.5: The resolution of the configuration in Figure 3.6

	r=1		r=2		r=3		Over.Mac	$\phi_m+\phi_r$
	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$		
m=1	0	0	1	1	1	1	1,2,3	18
m=2	1	0	0	0	1	0		
m=3	1	1	0	1	0	0	3,1	12
							E_t^{max}	18

$g_{m,r,t}$ are given in Table 3.5. Since the values of the variables $f_{1,2,t}$= $g_{1,2,t}$=1 and $f_{1,3,t}$=$g_{1,3,t}$=1, the peak power demand is computed as 18 KW. Whereas, in this configuration, the overlap only exists between the first and second machines and first and third machines. The correct peak power demand must be computed by comparing the peak power demands of overlapping machine groups.

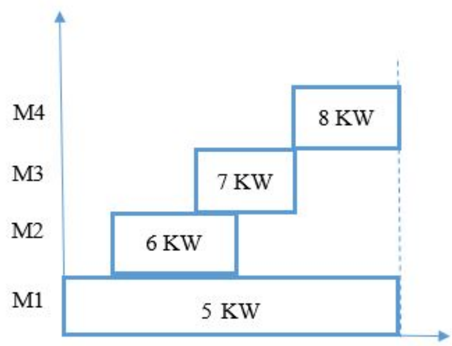

Figure 3.7: Example (2) in which upper bound of peak power is computed

When the configuration in Figure 3.7 is analysed, similar to the instance in Figure 3.6, it is seen that the upper bound of the peak power demand is computed. Since the values of the variables $f_{1,2,t}$= $g_{1,2,t}$=1 and $f_{1,3,t}$=$g_{1,3,t}$=1 and $f_{1,4,t}$=$g_{1,4,t}$=1, the peak power demand is computed as 26 KW. Whereas, there are two groups of overlapping machines. The first group includes first, second and third machines and the second overlapping group is composed of first and fourth machines. Accordingly, the peak power demand must be

Table 3.6: The resolution of the configuration in Figure 3.7

	r=1		r=2		r=3		r=4		Over.Mac.	ϕ_m+ϕ_r
	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$		
m=1	0	0	1	1	1	1	1	1	1,2,3,4	26
m=2	1	0	0	0	1	0	1	0		
m=3	1	0	1	1	0	0	1	0	3,2	13
m=4	1	1	0	1	0	1	0	0	4,1	13
									E_t^{max}	26

the maximum value of the peak power demands of overlapping machine groups which is 18 KW= max (5 KW+6 KW+7KW, 5KW+8KW).

When the values in Table 3.5 and Table 3.6 are carefully examined, a significant deficiency can be immediately recognized.

In Table 3.5, when the reference machine *m=1*, it is seen that the machine m overlaps with the second and third machine, which is correct. Similarly, it can be seen that third machine (*m=3*) has an overlap with the first machine (*r=1*) since $f_{3,1,t} = g_{3,1,t} = 1$. However, when it comes to the second machine (*m=2*), since any of the variables such as $f_{2,r,t}$ and $g_{2,r,t}$ is not equal to 1, it seems that second machine does not overlap with any of the machines in the production configuration. Whereas there is an overlap between the first and second machine. Even though these overlap is satisfied when the reference machine *m=1* (when the overlap is checked according to the direction $m \to r$) to *r=2*, since machine *m=1* has an overlap with the machine *r=3* at the same time, in such cases, the developed model computes the upper bound of the power demand.

The same shortcoming can be observed in Table 3.6. The found values of the variables show us that the first machine *m=1* overlaps with the second, third and fourth machines (*r=2, r=3, r=4*). The overlaps between the machines 3-2 or machines 4-1 are also proved. However, when the reference machine *m=2*, the overlap between second and first; second and third machines are missing. As in the previous example, this overlap relation can only be built when the reference machine *m=1* and the overlapping case is checked according to the reference machine *m=1*. We call for it *symmetry issue* for $f_{m,r,t}$ and $g_{m,r,t}$ variables, since the overlap can be satisfied from only one direction.

This drawback in the model of Masmoudi et al. [2017a] is abolished by developing new power constraints. The newly proposed constraints are constructed in two folds:

Firstly, the *symmetry issue* is defined and solved. Secondly, to be able to identify the overlapping machine groups, new variables $ws_{m,r,t}$ are introduced. In the following section, development of new power constraints is detailed.

3.3.1 Satisfying the Symmetry for $f_{m,r,t}$ and $g_{m,r,t}$

As it is explained before, it is intended to identify the existence of overlapping machines by defining the values of variables $f_{m,r,t}$ and $g_{m,r,t}$. According to this attempt, as long as the values of $f_{m,r,t}$ and $g_{m,r,t}$ are equal to 1, it is concluded that the machines m and r run in parallel.

In this subsection, we will look closer the symmetry issue in the variables $f_{m,r,t}$ and $g_{m,r,t}$ which may cause the computation of the upper bound of power demand at each period. Let's consider the configuration in Figure 3.8 and recall the constraints to identify the values of the variables of $f_{m,r,t}$ and $g_{m,r,t}$:

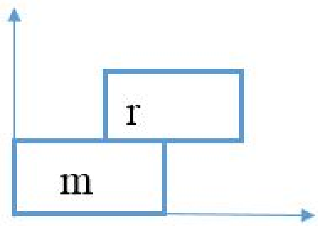

Figure 3.8: An illustrative example

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.40}$$

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.41}$$

Accordingly the values of $f_{m,r,t}$=1 and $g_{m,r,t}$=0; $f_{r,m,t}$=1 and $g_{r,m,t}$=1.

When the overlap between the machines m and r is evaluated by referencing the machine m, since $f_{m,r,t}$=1 and $g_{m,r,t} = 0$, it seems there is no overlap between the machines m and r. Obviously, this is not a correct deduction since there is an overlap between the machines. When reference machine is changed to r and the existence of overlap is checked, this time the values are found as $f_{r,m,t}$=1 and $g_{r,m,t}$=1. Therefore, the overlap is satisfied between the two machines. Satisfying the overlap between the machines only from one direction causes missing the interaction of that machine with the others.

To cope with this problem, firstly, the values of the variables $f_{m,r,t}$ and $g_{m,r,t}$ are fixed either 1 or 0 and with this purpose the following constraints are introduced to the model:

$$\mathrm{C}_{m,t} - x_{m,t}.p_m - \mathrm{C}_{r,t} \leq \mathrm{M}.(1 - f_{m,r,t}) - 1 \quad \forall m = 1,...,\mathrm{N}, r = 1,...,\mathrm{N}, r \neq m, \forall t = 1,...,\mathrm{T} \tag{3.42}$$

$$\mathrm{C}_{r,t} - \mathrm{C}_{m,t} \leq (\mathrm{M}.(1 - g_{m,r,t})) + 1 \quad \forall m = 1,...,\mathrm{N}, r = 1,...,\mathrm{N}, r \neq m, t = 1,...,\mathrm{T} \tag{3.43}$$

Therefore, the constraint couples (3.40-3.42) and (3.41-3.43) fix the values of the variables of $f_{m,r,t}$ and $g_{m,r,t}$.

In the second step, a new variable $\mathrm{A}_{m,r,t}$ is introduced which identifies the existence of overlap between the machines and following constraints are developed by taking into account the symmetric versions of the variables of $f_{m,r,t}$, $g_{m,r,t}$.

$$\mathrm{A}_{m,r,t} = \begin{cases} 1, & \text{if there is an overlap between the machines } m \text{ and } r. \\ 0, & \text{otherwise} \end{cases} \tag{3.44}$$

Thus, as long as the overlapping condition ($f_{m,r,t} = g_{m,r,t} = 1$) is satisfied in at least one direction, $m \rightarrow r$ or $r \rightarrow m$, the existence of overlap between the machines m and r is guaranteed.

$$f_{m,r,t}.g_{m,r,t} + f_{r,m,t}.g_{r,m,t} \leq \mathrm{M}.\mathrm{A}_{m,r,t} \quad \forall m = 1,...,\mathrm{N}, r = 1,...,\mathrm{N}, r \neq m, t = 1,...,\mathrm{T} \tag{3.45}$$

$$f_{m,r,t}.g_{m,r,t} + f_{r,m,t}.g_{r,m,t} - 1 \geq \mathrm{A}_{m,r,t} - 1 \quad \forall m = 1,...,\mathrm{N}, r = 1,...,\mathrm{N}, r \neq m, t = 1,...,\mathrm{T} \tag{3.46}$$

Let's have a look at the identification of the overlap between the machines in the configurations shown in Figure 3.6 and Figure 3.7. In Table 3.5, we had drawn attention to the fact that when the reference machine *m=2*, the machines which overlap with the second machine are not identified. Let's take necessary values from the Table 3.5 and apply the newly developed constraints (3.45) and (3.46). The overlap defining variables for the first and second machines for the configuration in Figure 3.6 are as follows;
$f_{2,1,t}$=1, $g_{2,1,t}$=0 and $f_{1,2,t}$=1, $g_{1,2,t}$=1 by applying the constraints 3.45 and 3.46 where *m=2* and *r=1*.

$$f_{2,1,t}.g_{2,1,t} + f_{1,2,t}.g_{1,2,t} \leq \mathrm{M}.\mathrm{A}_{2,1,t} \tag{3.47}$$

$$1.0 + 1.1 \leq \mathrm{M.A}_{2,1,t} \tag{3.48}$$

then, $\mathrm{A}_{2,1,t}$ is obtained as 1. Therefore, the overlap between the first and second machines is identified. All the other values of $\mathrm{A}_{m,r,t}$ are found in the same fashion and displayed in Table 3.7 and Table 3.8. When the results in Table 3.8 are examined in detail, it is seen that the overlap between the machines 2-1-3 is satisfied on the contrary of Table 3.6.

Table 3.7: New resolution of the configuration in Figure 3.6

	r=1	r=2	r=3	Over.Mac.
	$\mathrm{A}_{m,r,t}$	$\mathrm{A}_{m,r,t}$	$\mathrm{A}_{m,r,t}$	
m=1	0	1	1	1,2,3
m=2	1	0	0	2,1
m=3	1	0	0	3,1

Table 3.8: New resolution of the configuration in Figure 3.7

	r=1	r=2	r=3	r=4	Over.Mac
	$\mathrm{A}_{m,r,t}$	$\mathrm{A}_{m,r,t}$	$\mathrm{A}_{m,r,t}$	$\mathrm{A}_{m,r,t}$	
m=1	0	1	1	1	1,2,3,4
m=2	1	0	1	0	2,1,3
m=3	1	1	0	0	3,1,2
m=4	1	0	0	0	4,1

Thus, symmetry issue in the variables $f_{m,r,t}$ and $g_{m,r,t}$ is solved. In the following section, the overlapping machine groups are identified based on the newly developed variable $\mathrm{A}_{m,r,t}$.

3.3.2 Identifying Overlapping Machine Groups

After assuring the existence of overlap by the variable $\mathrm{A}_{m,r,t}$, the peak power computation is improved by identifying the overlapping machine groups. In order to do that, the variable $ws_{m,r,t}$ is introduced to the mathematical model which is defined as follows:

$$ws_{m,r,t} = \begin{cases} 0, & \text{if there is at least one machine } r' \ (1 \leq r' < r) \text{ which overlaps with machine } m \\ & \text{but does not overlap with machine } r \text{ in period } t \\ 1, & \text{otherwise} \end{cases} \tag{3.49}$$

The key point of $ws_{m,r,t}$ is that it allows not only identify the overlap between the machines m and r but also checks their state with the following machines, thus, it helps to define the overlapping machine groups. To achieve that in a correct way, it checks the machine overlap in an order. With the help of the definition of $ws_{m,r,t}$, firstly, the existence of an overlap between *r'* and *m* is defined, if there is no overlap between *r'* and *m*, the value of $ws_{m,r,t}$ is equal to 0 already regardless what are the states of the other machines, and the states of the following machines until the machine *r* are checked.

To make it clearer, let's consider the configuration Figure 3.7 and handle machine *m=1* as reference machine and define the values of the variables $ws_{1,3,t}$ and $ws_{1,4,t}$. When *m=1* and *r=3*, the machine *r'=2*; when *m=1* and *r=4*, the machines *r'=2,3*. (see, Table 3.9). To define the value of $ws_{1,3,t}$, the procedure of overlapping check works as follows:

— Does the machine r=2 overlap with machine *m=1*? *Yes.*

— Does the machine *r=2* overlap with machine *m=3*? *Yes.*

Then the value of $ws_{1,3,t}$ is equal to 1.
When it comes to the variable $ws_{1,4,t}$, the machines between them *r'=2* and *r'=3* must be checked according to the machines *m=1* and *r=4*.

— Does the machine *r=2* overlap with machine *m=1*? *Yes.*

— Does the machine *r=2* overlap with machine *m=4*? *No.*

As it is identified in the definition of $ws_{m,r,t}$, if there is *at least one* machine *r'* overlaps with machine *m* but does not overlap with machine *r*, then the value of $ws_{m,r,t}$ becomes equal to 0. Therefore the value of $ws_{1,4,t}$ becomes 0. All the values are found in the same way in Table 3.9. As a result of this recursive procedure, the overlapping machine groups are defined and separated from each other when it is necessary.

Finally peak power demand is computed by comparing the peak power required for these machine groups which run in parallel as it is purposed in the beginning. To translate the given definition and purpose of the variable $ws_{m,r,t}$ to its mathematical correspondence, the following constraints are developed:

$$\sum_{r'=1, r'\neq m}^{r-1} (\mathrm{A}_{r',r,t}.\mathrm{A}_{m,r',t}) \geq (\sum_{r'=1, r'\neq m}^{r-1} \mathrm{A}_{m,r',t}).ws_{m,r,t} \quad \forall m = 1,...,\mathrm{N}, t = 1,...,\mathrm{T}, r = 2,...,\mathrm{N} \tag{3.50}$$

$$\sum_{r'=1, r\neq m}^{r-1} (\mathrm{A}_{m,r',t}) - \sum_{r'=1, r\neq m}^{r-1} (\mathrm{A}_{r',r,t}.\mathrm{A}_{m,r',t}) \geq (1 - ws_{m,r,t}) \quad \forall m = 1,...,\mathrm{N}, t = 1,...,\mathrm{T}, r = 2,...,\mathrm{N} \tag{3.51}$$

For better understanding, let us see the example in Figure 3.7 and compute the power demand step by step by considering newly developed constraints. By referencing first machine (*m=1*), we can compute the value of variable $ws_{1,4,t}$ where *r=4*. In this case, second and third machines can be regarded as the machine *r'* (*r'=2,3*). Accordingly, constraint (3.45) becomes:

$$f_{1,2,t}.g_{1,2,t} + f_{2,1,t}.g_{2,1,t} \leq \mathrm{M}.\mathrm{A}_{1,2,t} \tag{3.52}$$

and constraint (3.46) becomes:

$$f_{1,2,t}.g_{1,2,t} + f_{2,1,t}.g_{2,1,t} - 1 \geq \mathrm{A}_{1,2,t} - 1 \tag{3.53}$$

then, $\mathrm{A}_{1,2,t}$ is equal to 1. By following the constraints (3.45) and (3.46), the values of the other necessary variables like $\mathrm{A}_{r,r',t}$ for *r'=2* and *r'=3* and $\mathrm{A}_{m,r',t}$ for *r'=3* can be found. After defining the overlap relations between the machines via the variable $\mathrm{A}_{m,r,t}$, to define the value of the variable $ws_{1,4,t}$, the constraints (3.50) and (3.51) are considered. Accordingly, constraint (3.50) becomes:

$$(\mathrm{A}_{2,4,t}.\mathrm{A}_{1,2,t}) + (\mathrm{A}_{3,4,t}.\mathrm{A}_{1,3,t}) \geq (\mathrm{A}_{1,2,t} + \mathrm{A}_{1,3,t}).ws_{1,4,t} \qquad \text{(m=1 and r=4)} \tag{3.54}$$

Then $ws_{1,4,t}$ becomes equal to 0. In case of necessity, the constraint (3.51) can be checked and the value of the variable $ws_{m,r,t}$ is fixed. In the same fashion, other variables can be found. For the reference configuration in Figure 3.7, the values of the variables are found and summarized in the Table 3.9.

In Table 3.9, in the last column including the multiplication of the variables $\mathrm{A}_{m,r,t}$ and $ws_{m,r,t}$ is introduced to identify the overlapping machine groups. As it can be noticed in the Table 3.9, when the overlapping machines are examined for each reference machine (*m*), it is seen that the machines *m=1,2,3* and *m=1,4* overlap. Therefore, just like it is illustrated in Figure 3.7, two independent overlapping machine groups are identified.

The following challenge is to compute the power demand of the machines by considering the overlapping machine groups. To do this, the following constraint is developed and replaced with the constraint (3.11) in the model of Masmoudi et al. [2017a]:

$$\mathrm{E}_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{\mathrm{N}} (\mathrm{A}_{m,r,t}.ws_{m,r,t}.\phi_r) \quad \forall m = 1,...,\mathrm{N}, t = 1,...,\mathrm{T} \tag{3.55}$$

Accordingly, the power requirement of the first group of overlapping machines is computed as 18KW while the power need of the second group is 13 KW. Thus, by the newly developed constraints the power demand of the configuration in Figure 3.7 is computed as 18 KW. The shortcoming of the model of Masmoudi et al. [2017a] is handled, instead of computing the upper bound of the power demand (26KW), the exact power need of the

Table 3.9: The resolution of the configuration Figure 3.7 according to the overlapping machine groups

Reference Mac.	r	r'	$A_{m,r',t}$	$A_{r',r,t}$	$ws_{m,r,t}$	$A_{m,r,t}$	$A_{m,r,t}.ws_{m,r,t}$
	–	–	–	–	–	–	–
	2	–	–	–	1	1	1
m=1	3	2	1	1	1	1	1
	4	2	1	0	0	1	0
		3	1	0			
						Over.Mac	1,2,3
						E_t^{max}	18 KW
	–	–	–	–	1	1	1
	2	–	–	–	–	–	–
m=2	3	1	1	1	1	1	1
	4	1	1	1	0	0	0
		3	1	0			
						Over.Mac	1,2,3
						E_t^{max}	18 KW
	–	–	–	–	1	1	1
	2	1	1	1	1	1	1
m=3	3	–	–	–	–	–	–
	4	1	1	1	0	0	0
		2	1	0			
						Over.Mac	1,2,3
						E_t^{max}	18 KW
	–	–	–	–	1	1	1
	2	1	1	1	1	0	0
m=4	3	1	1	1	1	0	0
		2	0	1			
	4	–	–	–	–	–	–
						Over.Mac	1,4
						E_t^{max}	13 KW

machines is calculated. After all these developments, we would like to present the entire version of the improved model.

3.3.3 Mathematical Model _P_1

$$P_1: \quad Min z = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) + \sum_{t=1}^{T}(\theta_t.E_t^{max}) \tag{3.56}$$

$$x_{N,t} + I_{N,t-1} = d_t + I_{N,t} \quad \forall t = 2,...,T \tag{3.57}$$

$$x_{m,t} + I_{m,t-1} = I_{m,t} + x_{m+1,t} \quad \forall m = 1,...,N-1, t = 2,...,T \tag{3.58}$$

$$x_{m,t} \leq y_{m,t} \sum_{\tau=t}^{T} d_\tau \quad \forall m = 1,...,N, t = 1,...,T \tag{3.59}$$

$$I_{m-1,t-1} \leq x_{m,t} + M.v_{m,t} - 1 \quad \forall m = 2,...,N, t = 2,...,T \tag{3.60}$$

$$x_{m,t} \leq I_{m-1,t-1} + M.(1 - v_{m,t}) \quad \forall m = 2,...,N, t = 2,...,T \tag{3.61}$$

$$\begin{aligned} C_{m,t} - x_{m,t}.p_m \geq C_{m-1,t} - x_{m-1,t}.p_{m-1} + (x_{m,t} - I_{m-1,t-1}).p_{m-1} - M.v_{m,t} \\ \forall m = 2,...,N, t = 2,...,T \end{aligned} \tag{3.62}$$

$$C_{m,1} - x_{m,1}.p_m \geq C_{m-1,1} - x_{m-1,1}.p_{m-1} + x_{m,1}.p_{m-1} \quad \forall m = 2,...,N \tag{3.63}$$

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.64}$$

$$C_{m,t} - x_{m,t}.p_m - C_{r,t} \leq M.(1 - f_{m,r,t}) - 1 \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, \forall t = 1,...,T \tag{3.65}$$

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{3.66}$$

$$C_{r,t} - C_{m,t} \leq (M.(1 - g_{m,r,t})) + 1 \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \tag{3.67}$$

$$f_{m,r,t}.g_{m,r,t} + f_{r,m,t}.g_{r,m,t} \leq M.A_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \tag{3.68}$$

$$f_{m,r,t}.g_{m,r,t} + f_{r,m,t}.g_{r,m,t} - 1 \geq A_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \tag{3.69}$$

$$\sum_{r'=1, r'\neq m}^{r-1} (A_{r',r,t}.A_{m,r',t}) \geq (\sum_{r'=1, r'\neq m}^{r-1} A_{m,r',t}).ws_{m,r,t} \quad \forall m = 1,...,N,\ t = 1,...,T,\ r = 2,...,N \tag{3.70}$$

$$\sum_{r'=1, r\neq m}^{r-1} (A_{m,r',t}) - \sum_{r'=1, r\neq m}^{r-1} (A_{r',r,t}.A_{m,r',t}) \geq (1 - ws_{m,r,t}) \quad \forall m = 1,...,N,\ t = 1,...,T,\ r = 2,...,N \tag{3.71}$$

$$E_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1, r\neq m}^{N} (A_{m,r,t}.ws_{m,r,t}.\phi_r) \quad \forall m = 1,...,N,\ t = 1,...,T \tag{3.72}$$

$$E_t^{max} \leq \alpha_t \quad \forall t = 1,...,T \tag{3.73}$$

$$I_{m,1} = x_{m,1} - x_{m+1,1} \qquad \forall m = 1,...,N-1 \tag{3.74}$$

$$I_{N,1} = x_{N,1} - d_1 \tag{3.75}$$

$$C_{1,1} - x_{1,1}.p_1 = 0 \tag{3.76}$$

$$I_{N,0} = I_{N,T} = 0 \tag{3.77}$$

$$C_{m,t} - x_{m,t}.p_m \geq 0 \quad \forall m = 1,...,N,\ t = 1,...,T \tag{3.78}$$

$$C_{m,t} - x_{m,t}.p_m \leq L_t.y_{m,t} \quad \forall m = 1,...,N,\ t = 1,...,T \tag{3.79}$$

$$C_{m,t} \leq L_t \quad \forall m = 1,...,N,\ t = 1,...,T \tag{3.80}$$

$$A_{m,1,t} = ws_{m,1,t} \quad \forall t = 1,...,T, \forall m = 1,...,N \tag{3.81}$$

$$A_{m,m,t} = 1 \quad \forall t = 1,...,T, \forall m = 1,...,N \tag{3.82}$$

$$f_{m,m,t} = g_{m,m,t} = 0 \quad \forall m = 1,...,N, t = 1,...,T \tag{3.83}$$

$$x_{m,t}, I_{m,t}, C_{m,t} \quad int. \quad \forall m = 1,.,N, t = 1,.,T \tag{3.84}$$

$$\begin{gathered} y_{m,t}, v_{m,t}, f_{m,r,t}, g_{m,r,t}, \in \{0,1\} \\ \forall m = 1,...,N, t = 1,...,T \end{gathered} \tag{3.85}$$

$$x_{m,t}, I_{m,t} \geq 0 \quad \forall t = 1,...,T, m = 1,...,N \tag{3.86}$$

As the reader can realize, the presented model P_1 includes non-linear constraints. To be able to use the commercial linear solvers to solve the proposed model, it must be linearized. In the next subsection, the required linearization steps are followed.

3.3.4 Linearization of The Non-Linear Constraints

The newly proposed constraints for identifying the exact power demand at each period are built by multiplying the decision variables in a straightforward way. To benefit from the linear solvers and make the studied model the easiest possible, a linearization procedure is performed on the developed non-linear constraints. The linearization steps which are applied for the proposed model can be classified into two groups:

The linearization of the product of two binary variables which is performed for the constraints (3.68),(3.69),(3.70),(3.71) and (3.72) and the linearization of the product of one positive integer variable and binary variable which is applied for the constraint (3.70).

The constraints (3.68) and (3.69) can be linearized as follows:

$$\begin{gathered} (f_{m,r,t} + g_{m,r,t} - 1) + (f_{r,m,t} + g_{r,m,t} - 1) \leq M.A_{m,r,t} \\ \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \end{gathered} \tag{3.87}$$

$$\begin{gathered} (f_{m,r,t} + g_{m,r,t} - 1) + (f_{r,m,t} + g_{r,m,t} - 1) - 1 \geq A_{m,r,t} - 1 \\ \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \end{gathered} \tag{3.88}$$

The left hand side of the constraints (3.70) and (3.71) and the right hand side of the inequality (3.72) include the same product which is obtained from the multiplication of two binary variables. Suppose that $X = Y.Z$ where X,Y,Z are binary variables. To be able to linearize this equation, three inequalities can be added to the existing model as following:

$$X \leq Y \tag{3.89}$$

$$X \leq Z \tag{3.90}$$

$$X \geq Y + Z - 1 \tag{3.91}$$

To simplify constraint (3.72), a new variable $KK_{m,r,t}$ is introduced and it is supposed that $KK_{m,r,t} = A_{m,r,t} * ws_{m,r,t}$, accordingly the constraint (3.72) is reformulated as follows:

$$E_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (KK_{m,r,t}.\phi_r) \quad \forall m = 1,...,N, t = 1,...,T \tag{3.92}$$

To define the value of the variable $KK_{m,r,t}$, three inequalities are added to the original model in the same fashion in constraint (3.89-3.91).

$$KK_{m,r,t} \leq A_{m,r,t} \tag{3.93}$$

$$KK_{m,r,t} \leq ws_{m,r,t} \tag{3.94}$$

$$KK_{m,r,t} \geq A_{m,r,t} + ws_{m,r,t} - 1 \quad \forall m \neq \forall r = 1,...,N, t = 1,...,T \tag{3.95}$$

When it comes to the constraint (3.70), different from the constraints (3.72), both sides of the constraint involve non-linear expressions. Before starting the linearization approach, let us recall the constraints (3.70) and (3.71).

$$\sum_{r'=1,r'\neq m}^{r-1} (A_{r',r,t}.A_{m,r',t}) \geq (\sum_{r'=1,r'\neq m}^{r-1} A_{m,r',t}).ws_{m,r,t} \quad \forall m = 1,...,N, t = 1,...,T, r = 2,...,N \tag{3.96}$$

$$\sum_{r'=1,r\neq m}^{r-1} (A_{m,r',t}) - \sum_{r'=1,r\neq m}^{r-1} (A_{r',r,t}.A_{m,r',t}) \geq (1 - ws_{m,r,t}) \quad \forall m = 1,...,N, t = 1,...,T, r = 2,...,N \tag{3.97}$$

Since the left hand side of the constraint is the product of the two binary variables, this side can be linearized with the same way which is applied for constraint (3.68). However, right hand side involves the product of one integer and binary variables. To make the linearisation approach easier, the non-linear components are redefined with new variables. Suppose that $\mathrm{KP}_{m,r',t} = \mathrm{A}_{r',r,t}.\mathrm{A}_{m,r',t}$ and $\mathrm{F}_{m,r,t} = (\sum_{r'=1,r'\neq m}^{r-1} \mathrm{A}_{m,r',t}).ws_{m,r,t}$. The constraints (3.70) and (3.71) are reformulated as follows:

$$\sum_{r'=1,r'\neq m}^{r-1} (\mathrm{KP}_{m,r',t}) \geq (\mathrm{F}_{m,r,t}) \quad \forall m = 1,...,\mathrm{N}, t = 1,...,\mathrm{T}, r = 2,...,\mathrm{N} \tag{3.98}$$

$$\sum_{r'=1,r\neq m}^{r-1} (\mathrm{A}_{m,r',t}) - \sum_{r'=1,r\neq m}^{r-1} (\mathrm{KP}_{m,r',t}) \geq (1 - ws_{m,r,t}) \quad \forall m = 1,...,\mathrm{N}, t = 1,...,\mathrm{T}, r = 2,...,\mathrm{N} \tag{3.99}$$

In constraint (3.98), $(\mathrm{KP}_{m,r',t})$ is linearized as the constraint (3.72) is linearized since it has the same structure with the variable $(\mathrm{KK}_{m,r,t})$. Accordingly, three inequalities are added to the original model as in the following:

$$\mathrm{KP}_{m,r',t} \leq \mathrm{A}_{r',r,t} \tag{3.100}$$

$$\mathrm{KP}_{m,r',t} \leq \mathrm{A}_{m,r',t} \tag{3.101}$$

$$\mathrm{KP}_{m,r',t} \geq \mathrm{A}_{r',r,t} + \mathrm{A}_{m,r',t} - 1 \forall m = 1...\mathrm{N}, \forall r = 2,...,\mathrm{N}, m \neq r, t = 1,...,\mathrm{T}, m \neq r' = 1...r-1 \tag{3.102}$$

It is supposed that D=A*B where D and A are the integer variables and B is the binary variable as in the right hand side of the constraint (3.70). In this case, the equality is linearized by adding four constraints as follows:

$$\mathrm{D} \geq 0 \tag{3.103}$$

$$\mathrm{D} \leq \mathrm{A} \tag{3.104}$$

$$\mathrm{D} \leq \overline{\mathrm{A}}.\mathrm{B} \tag{3.105}$$

$$\mathrm{D} \geq \mathrm{A} - (1 - \mathrm{B}).\overline{\mathrm{A}} \tag{3.106}$$

where $\overline{\mathrm{A}}$ represents the upper bound of the integer variable of A. From this scheme, to linearize the variable $F_{m,r,t}$, the following four constraints are added to the original model.

$$F_{m,r,t} \geq 0 \tag{3.107}$$

$$F_{m,r,t} \leq \Big(\sum_{r'=1,r'\neq m}^{r-1} A_{m,r',t}\Big) \tag{3.108}$$

$$F_{m,r,t} \leq (r-1)(ws_{m,r,t}) \tag{3.109}$$

$$F_{m,r,t} \geq \Big(\sum_{r'=1,r'\neq m}^{r-1} A_{m,r',t}\Big) - (r-1).(1-ws_{m,r,t}) \forall m = 1...N, \forall r = 2,...,N, m \neq r, t = 1,...,T, \tag{3.110}$$

Therefore, the developed non-linear constraints are transformed to the linear constraints and can be solved by the linear solvers easily. We consider the formulation with constraints (3.56-3.67),(3.73-3.88), (3.92-3.95),(3.98-3.102) and (3.107-3.110) as the formulation of our problem. This formulation is solved using a commercial solver and tested on a set of instances. In the following section, numerical study is conducted to assess the proposed model.

3.3.5 Computational Experiments

In this section, to validate and evaluate the improved model, computational experiments are implemented. The developed model is solved by CPLEX 12.6 on an Intel Core i7 with 2.7 GHz and 8 GB RAM on different sizes of instances. Before discussing the results of the numerical study, the data generation procedure for the different sizes of instances is also described in detail for the sake of convenience.

Data Generation Procedure

For computational experiments, a part of the required data have been obtained from literature (Table 3.10). We consider the Time-Of-Use (TOU) rate structure. In order to define the lengths of the periods, some TOU tariffs from real life are examined and the lengths of ON and OFF periods are set as 1080-360 minutes correspondingly. In our study, ON periods are matched with longer time periods since it is more common in real life examples, but it is also possible that the energy suppliers offer some tariffs which they provide cheaper energy (OFF-ON) for a longer time period. The price of the energy is assumed as 1$ for OFF periods while it is taken as 19,8 $ for ON periods. The maximum power (α_t) that can be supplied by the energy supplier is presumed as 40 KW for each

Table 3.10: Literature inspired randomly generated data

Parameter	Interval	Reference
Co_t	{0.16$, 0.08$}	[Wang and Li, 2013]
$w_{m,t}$	$U[50,100]$	[Masmoudi et al., 2017a; Mohammadi et al., 2010c]
ϕ_m	$U[5,10]$	[Masmoudi et al., 2017a; Mohammadi et al., 2010c]
p_m	$U[5,10]$	[Masmoudi et al., 2017a; Mohammadi et al., 2010c]

period. When it comes to the demand configuration, the capacity of each period is defined based on the length of the periods (L_t) and processing times of the machines (p_m). Accordingly, the external demand value of each period d_t is randomly generated by following formulas:

$$Cap_t = L_t / \sum_{m=1}^{N} (p_m) \tag{3.111}$$

$$d_t \in [0, \sum_{\tau=1}^{t} Cap_\tau - \sum_{\tau=1}^{t-1} d_\tau] \tag{3.112}$$

Results and Discussion

Numerical experiments are implemented on generated data and the results are displayed on Table 3.11 and Table 3.12. In Table 3.11, the size of the tested instances are summarized briefly.
N represents the number of the machines and T stands for the number of the periods. To highlight the complexity of the improved model the number of the binary variables, total number of variables and the number of the constraints are presented for each problem sizes. As it can be observed in Table 3.11, when the size of the instance increases, the number of the variables and the constraints increase dramatically.

In Table 3.12, for each problem size, 5 different instances are generated randomly. The computation time is limited by 1 hour as in the studies of (Masmoudi et al. [2015]; Ramezanian et al. [2013b]. In Table 3.12, the instances which are solved within 3600s are solved to the optimality. It is found that for the instances with 5 machines the optimum solution is obtained. For the instances composed of 7 machines and 7 periods, in most cases, they are solved to the optimality within defined time limit. However, for relatively larger instances, CPLEX is not able to reach the optimum solution within 1 hour. It is obviously seen that, the results shown in Table 3.12 prove the increasing complexity based on increasing problem size demonstrated in Table 3.11.

The developed model can help the customers for many purposes. They can define the production configuration that can satisfy external demand and minimize the production and energy related costs. So far, any relation is built between the required energy and the energy purchasing procedure in real life, except introducing α_t, which is the maximum

Table 3.11: Problem sizes

N	T	Nu.Binary Variables	Nu.Variables	Nu.Constraints
5	5	751	857	1999
5	7	1053	1201	2801
5	10	1506	1717	4004
7	7	2157	2361	6500
7	10	3084	3375	9290
10	7	4548	4836	16406
10	10	6501	6912	23444
10	15	9756	10372	35174

Table 3.12: Solution performance of P_1

N_T	Instances	CPU(s)	N_T	Instances	CPU(s)
N5_T5	Ins_1	1,59	N7_T10	Ins_1	>3600
	Ins_2	0,48		Ins_2	>3600
	Ins_3	0,4		Ins_3	>3600
	Ins_4	3,04		Ins_4	>3600
	Ins_5	0,93		Ins_5	>3600
	Average	1,288		Average	>3600
N5_T7	Ins_1	20,99	N10_T7	Ins_1	>3600
	Ins_2	12,69		Ins_2	>3600
	Ins_3	30,02		Ins_3	>3600
	Ins_4	8,25		Ins_4	>3600
	Ins_5	19,79		Ins_5	>3600
	Average	18,348		Average	>3600
N5_T10	Ins_1	1096,5	N10_T10	Ins_1	>3600
	Ins_2	245,8		Ins_2	>3600
	Ins_3	2889,65		Ins_3	>3600
	Ins_4	564,57		Ins_4	>3600
	Ins_5	507,46		Ins_5	>3600
	Average	1060,796		Average	>3600
N7_T7	Ins_1	389,2	N10_T15	Ins_1	>3600
	Ins_2	>3600		Ins_2	>3600
	Ins_3	92,77		Ins_3	>3600
	Ins_4	79,55		Ins_4	>3600
	Ins_5	61,29		Ins_5	>3600
	Average	844,562		Average	>3600

power amount that can be supplied by supplier, to the model. With this approach, the peak power demand is limited to a certain value, therefore, the production configuration is generated by considering the capacity constraint based on energy availability.

However, instead of setting the production plan according to the limited power defined by energy supplier, industrial customers can choose the best capacity option that can cover the power need of the production. In other words, they can define their own power limit according to their production plan which is formed based on the external demand. Based on this idea, it can be summarized that in the current model (P_1), maximum power (α_t) for each period t (t=1,...,T) is a data of the problem. In the next section, it becomes a decision variable.

3.4 Single Item Lot Sizing Problem by Considering Capacity Contract Selection Problem

As all the other service providers, one of the main objectives of the energy supplier is to satisfy the demand of the customers. The producers of the other commodities can balance the demand and production with a effective production and stock management.

The main difference of the energy from the raw materials is that it is hard to store at a large scale. Due to this characteristic of the energy, it must be produced as it is demanded or a perfect balance must be built with the power demand of the customers and the generated energy. Such a balance can be built with an effective and realistic generation planning. To plan their energy generation as covering the demand of the customers, energy supplier should know the demand in advance or forecast as close as future power demand of their customers.

To set the planning targets on the accurate data, they offer capacity options to their customers, therefore, they aim to get the information about the peak power demand of their customers in advance by reaching an agreement on a certain amount and to foresee the excessive usage or under usage cases easier according to the power amount contracted for better management. On the customers' side, the problem of selecting the best capacity option which can cover the system's need arises. In this section, the bridge between the contract capacity selection decisions and production planing decision is built.

3.4.1 Energy and Demand Charging Scheme

A typical electricity bill is composed of two principal charges: *Energy Charge* which is based on kilowatt hours, with the unit price varying by peak, medium and off-peak and *Capacity Charge* which is determined by kilowatts per month based on maximum demand (in 15 minutes average) during the Time-Of-Use (TOU) period [Chen and Liao, 2011].

Along with the above mentioned electricity pricing strategy, energy suppliers offer different capacity contract options to their customers. When the power demand of the customers exceeds beyond the tolerance interval which is defined according to the amount of the contracted power and certain tolerance ratio, it has been mentioned as *volume tolerance* in the Chapter 2, since it might cause changes in planning of generation or transmission procedures of the energy, the energy suppliers can penalize their customers and the calculated penalty costs are also added on the electricity bill. To evade the penalty costs, the customers must be sure that the maximum demand calculated during the 15-minutes interval in production facility will not exceed the contracted power value over a given month and cover the energy need of the manufacturing system. Similarly, an agreement on a capacity option which is higher than the power need of the system causes paying for unused energy. Therefore, the industrial customers must select the best capacity option which can realize the production plan, reduce energy costs and increase the energy efficiency by considering all the objectives and constraints of the production system.

International Renewable Energy Agency (IRENA) reported that the renewables increasingly provide electricity at costs competitive with, or lower than, fossil-based power. It is expected that solar and wind electricity costs to 2020 presages the lowest costs yet seen for these modular technologies. Recently increasing awareness for the ecological concerns of the nations, growing investments in the renewable generation and storage technologies and optimistic previsions for the deployment of the renewable sources had been explained in the Chapter 2.

By considering this progress, instead of having the production systems relying on a traditional energy source, generating the best energy mix of the renewable and the traditional ones will be crucial important in the future. Based on this motivation, the renewable energy sources are introduced to the energy purchasing procedure in our model.

3.4.2 Problem Statement & Objective

In this study, the single item capacitated lot sizing problem for flow shop configuration is studied by integrating energy capacity selection problem. For the production configuration, a flow shop manufacturing system composed of N machines and N buffers is considered as shown in Figure 3.1.

Customers are offered the capacity options for three types of energy sources (wind, solar and traditional) and asked to make the optimum energy mix that can cover the need of their production system. In this study, two types of renewable energy sources are considered in the energy mix but the model can be generalized by taking into account more renewable energy sources.

The purpose of the developed model is to determine the optimum production quantities to be produced on each machine and in each period and to identify the required maximum power demand by minimizing the production, holding, set-up and energy costs and synchronizing the power demand of the system with the capacity contract options offered by the energy supplier.

3.4.3 Assumptions

It is possible to divide the assumptions into two groups: Production related assumptions, energy related assumptions.

Production related assumptions are kept the same as in the model of Masmoudi et al. [2017a]:

— A single product is considered.

— The production plan is elaborated for a horizon of T periods (t=1,...,T).

— The lengths (L_t), the external demand (d_t) to be met, and electricity prices (Co_t) form the characteristics of each period.

— The external demand is deterministic, known in advance and must be satisfied at the end of each period, that is, backlogging is not considered.

— The first machine is never starved and the last machine is never blocked at each period.

— A machine m can only start the production when all the quantity to be produced ($x_{m,t}$) is available at the output of the previous machine.

— For each machine, a single set-up is allowed in each period and in case of setting-up, related set-up cost is applied.

When it comes to the energy supplier side assumptions, they can be ordered as follows:

— Three types (k=3) of energy sources (traditional, wind, solar) are considered.

— All the energy sources are supplied by and purchased from energy supplier, that is, the on-site generation mechanism is out of the context.

— Since all types of energy sources are provided by energy supplier, their prices are defined according to the tariffs fixed by the energy suppliers.

— Time-Of-Use (TOU) rates electricity pricing strategy is applied.

— Two patterned Time-Of-Use (TOU) tariff is used, accordingly, a day is composed of the successive ON (higher electricity price) and OFF (lower electricity price) periods.

— The capacity options can be proposed in two forms: The customers might be asked to choose any value in an interval or an option among certain number (R_k) of capacity options (which are not necessary equal for all sources) offered by the energy suppliers for each type of energy sources k and the customer can choose most appropriate one. In this thesis, the mathematical model is developed for two cases. These two versions of the options are named as *The Continuous Capacity* and *The Discrete Capacity*.

The Assumptions for The Continuous Capacity

- The lower (P_k^{min}) and upper bounds (P_k^{max}) of the amount of energy which are supplied are defined by the energy supplier for each type of energy sources *k=1,...,K*.
- A unit power cost $Vcost_k$ is defined by the energy supplier for each type of energy source *k*.
- The customers can choose the capacity value (P_k^{opt}) within this interval.

The Assumptions for The Discrete Capacity

- A certain number (R_k) of capacity options (which are not necessary equal for all sources) are offered by the suppliers for each type of energy sources *k=1,...,K*.
- The proposed options constitute the energy contract vectors $V_k = V_1, ..., V_{R_k}$ for each type or energy sources *k=1,...,K*.
- The main characteristic of each option (*l=1,...,*R_k) for each energy sources (*k=1,...,K*) is its subscription fee ($Vcost_{k,l}$).
- The customers are obliged to choose one option from each type of energy sources.

The Assumptions for Two Versions of the Capacity Options

- A tolerance interval is defined which allows the customers to have a deviation within a certain percentage (β) from the contracted capacity. This percentage is assumed to be 10% above and below of the contracted power value. As long as the required power remains inside this interval, the fixed capacity charged is calculated for electricity bills. In case of surpassing the tolerance levels, the power amount outside of the tolerance interval is penalized with penalty cost (℧) which is also determined by the energy provider.
- The customers are not allowed to switch the agreed option to another one. So, it is assumed that the production system is subject to the same power option for the whole planning horizon.
- The total contracted capacity ($V_{k,l}$), (*k=1,...,K; l=1,...,*R_k) or (P_k^{opt})(*k=1,...,K*) for each energy sources k must cover the needs of the production system and minimize the energy and production costs.

In the following section, two mathematical models are presented by considering the listed assumptions for the two versions of capacity options.

Table 3.13: List of parameters and variables

Parameters	
N	Number of machines
T	Number of periods
K	**Number of energy sources**
ϕ_m	The power of the machine *m=1,...,N*
p_m	Unit processing time for machine *m=1,...,N*
Co_t	The price of electricity during period *t=1,...T.*
$\psi_{m,t}=\phi_m.p_m.Co_t$	Unit electrical consumption cost of machine *m=1,...N* at period *t=1,...T*
h	holding cost per unit
$w_{m,t}$	Setup cost of machine *m=1,...N* in period *t=1,...T*
d_t	External demand at period *t=1,...T*
L_t	Length of period *t=1,...T*
M	A large number
β	**Tolerance ratio over the contracted capacity**
P_k^{min}	**The lower bound of the capacity interval for energy source k=1,...,K**
P_k^{max}	**The upper bound of the capacity interval for energy source k=1,...,K**
$Vcost_k$	**Unit power cost for energy source *k=1,...,K***
$\mho$	**Penalty cost**
Decision variables	
$x_{m,t}$	Quantity produced by machine *m=1,...N* in period *t=1,...T.*
$I_{m,t}$	Inventory level of machine *m=1,...N* at the end of period *t=1,...T.*
$C_{m,t}$	Completion time of machine *m=1,...N* in period *t.*
$S_{m,t}$	Starting time of machine *m=1,...N* in period *t=1,...T.*
α_t	**The power demand during period *t=1,...T*.**
P_k^{opt}	**The defined capacity by the customer for the energy source of *k=1,...,K*.**
AC_t	$max(0,(\alpha_t-\sum_{k=1}^{K}(P_k^{opt}))$ **The energy used above the sum of the contracted capacity in period *t=1,...T.***
BC_t	$max((\sum_{k=1}^{K}(P_k^{opt})-\alpha_t),0)$ **The energy used below the sum of the contracted capacity in period *t=1,...T*.**
	Binary variables
$y_{m,t}$	A binary variable, equal to 1 if machine *m=1,...,N* run in period *t=1,...,T*, 0 otherwise.
$v_{m,t}$	A binary variable, equal to 1 if the quantity $x_{m,t}$ is available in buffer *m-1* at the beginning of period *t*, 0 otherwise. *m=2,...N, t=1,...T*
$f_{m,r,t}$	A binary variable, equal to 1 if $C_{r,t} > C_{m,t} - x_{m,t}.p_m$, 0 otherwise. *m=1,...N, r=1,...N,* $m \neq r$, *t=1,...T*
$g_{m,r,t}$	A binary variable, equal to 1 if $C_{m,t} \geq C_{r,t}$, 0 otherwise. *m=1,...N, r=1,...N,* $m \neq r$, *t=1,...T*
$A_{m,r,t}$	A binary variable, equal to 1 if there is an overlap between machine m and r in period t, 0 otherwise. *m=1,...N, r=1,...N,* $m \neq r$, *t=1,...T*
$ws_{m,r,t}$	A binary variable, equal to 0 if there is at least one machine r' ($1 \leq r' < r$) which overlaps with machine m but does not overlap with machine r in period t, 1 otherwise. *m=1,...N, r=1,...N,* $m \neq r$, *t=1,...T*
$z_{m,t}$	**A binary variable, equal to 1 for the maximum power demand** (α_t) **for period *t=1,...,T*, otherwise 0.**

3.4.4 Mathematical Model for The Case of The Continuous Capacity _P_2

Notations

The parameters and the decision variables of the problem are presented in Table 3.13. In addition to the previously improved model P_1, the parameters and variables displayed in bold are introduced for the model P_2 where it is considered that the continuous capacity option is offered to the customers.

Since the currently presented model P_2 is developed by integrating capacity selection problem to the previously improved model P_1, due the the production structure, general and initial conditions are mostly the same, instead of repeating the formerly presented constraints only newly developed ones will be presented. For better sense, the constraints which are the same in two models are clearly addressed with their numbers.

$$\begin{aligned} P_2: \quad Minz = & \sum_{t=1}^{T} \sum_{m=1}^{N} (\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) \\ & + \sum_{k=1}^{K} (Vcost_k.P_k^{opt}) \\ & + \sum_{t=1}^{T} \sum_{k=1}^{K} (\mho.(AC_t + BC_t)) \end{aligned} \tag{3.113}$$

The objective function (3.113) can be explained in three folds:

The first part of the objective function computes electricity consumption cost based production cost. In the study of Masmoudi et al. [2017a], the electricity consumption cost (\$/KWh) is normalized by multiplying it with the required power for processing one unit of product (KWh) and the production cost is defined as $\psi_{m,t}$=$\phi_m.p_m.Co_t$. In this model, the same formula is kept for the production cost in order to integrate the electricity cost in the production cost. The first part of the objective function is completed by adding the holding costs and set-up costs.

The second part figures out the total power cost according to the amount of agreed power capacity.

The last part calculates penalty costs which may occur in case of exceeding tolerance interval of the sum of the contracted capacity.

For the purpose of production/inventory/demand balance the constraints (3.57),(3.58) and (3.59) are kept as they are in model P_1.

To satisfy the vertical interaction between the machines, the constraints (3.60 -3.63) are used as they are in the model. The constraints (3.64-3.71) which are developed for defining the positions of the machines and the overlapping machine groups are also used as they are in model P_1. When it comes to defining the peak power demand, the constraint (3.72) is replaced with the following constraints:

$$\alpha_t \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (A_{m,r,t}.ws_{m,r,t}.\phi_r) \quad \forall m = 1,...,N, t = 1,...,T \tag{3.114}$$

$$\phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (A_{m,r,t}.ws_{m,r,t}.\phi_r) \geq \alpha_t - (1 - z_{m,t}).M \quad \forall m = 1,...,N, t = 1,...,T \tag{3.115}$$

$$\sum_{m=1}^{N} (z_{m,t}) = 1; \qquad \forall t = 1,...,T \tag{3.116}$$

Constraint (3.114) computes the maximum power demand in period t. Since the upper bound of α_t is not fixed in constraint (3.114), constraints (3.115) and (3.116) are introduced to the model in order to fix the maximum power demand in period t. The main idea behind the constraints (3.115) and (3.116) will be detailed after presenting the constraints on contract selection since they have a strong link.

The following step is to build the bridge between the power demand of the system and the offered capacity options in the market. To do so, the following constraints are developed by taking into account β% volume tolerance:

$$P_k^{min} \leq P_k^{opt} \leq P_k^{max} \quad \forall k = 1,...,K \tag{3.117}$$

$$AC_t + (1+\beta).\sum_{k=1}^{K} (P_k^{opt}) \geq \alpha_t \quad \forall t = 1,...,T \tag{3.118}$$

$$(1-\beta).\sum_{k=1}^{K} (P_k^{opt}) - BC_t \leq \alpha_t \quad \forall t = 1,...,T \tag{3.119}$$

The constraints (3.117) guarantee the customers to select a value within the specified range given by the energy supplier. In the constraints (3.118) and (3.119), it is aimed that the sum of the contracted amount of capacities for each type of energy sources ($\sum_{k=1}^{K}(P_k^{opt})$) must cover the power demand of the system (α_t). When the demand exceeds the upper or lower limits (defined by β) of the sum of the contracted power, excess quantity is penalized with defined penalty cost ($\mho$).

In Figure 3.9, an example is given to clarify the penalizing procedure. In this example, it is assumed that the tolerance interval is 10%. According to this assumption, in case the customer reaches an agreement for 15 KW energy. As long as the peak power demand stays between the 16,5 KW and 13,5 KW the customer is not penalized. Otherwise, penalty

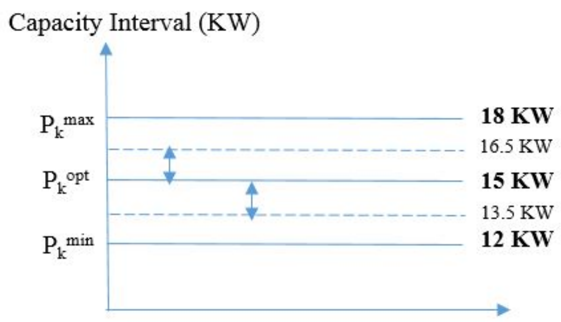

Figure 3.9: An example for contract options and penalty-free interval

charge is calculated and added on the energy charge and capacity charge while computing the total charge for electricity bills.

As it is promised before, we would like to explain the philosophy behind the constraints (3.115) and (3.116). For better sense, let's remember the computation of power demand for the configuration in Figure 3.7. There are two overlapping machine groups. While the first group requires 18 KW energy, the second group which composes of first and fourth machine needs 13 KW energy. Since the right hand side of the constraint (3.114) computes the values of 18KW and 13 KW, it is expected to found α_t must be 18 KW. However, when the constraints (3.118) and (3.119) are introduced to the model, since the value of α_t is not fixed and any value for upper bound of α_t is not defined, the value of α_t is defined based on the penalized amounts. In other words, since the objective function imposes the model to minimize the total amount which will be penalized $(AC_t + BC_t)$, the values of AC_t, BC_t have a significant effect on defining the value of α_t. If the value of α_t is not fixed, even though the real power demand of the system is 18 KW, when AC_t is forced to be 0 and the total contracted amount is found 18KW, the α_t becomes equal to 19,1 and this value does not violate any of the constraints of (3.114) or (3.119).

Whereas, the capacity amounts (P_k^{opt}) must be defined according to the fixed and defined exact power demand α_t. To achieve this, the constraints (3.115) and (3.116) are introduced to the model, thus, the value of α_t is fixed and accordingly excessive or low power usage are penalized.

For the initial and general conditions the constraints (3.74)-(3.84) and (3.86) are used as they are in P_1. Additionally, the constraint (3.120) which builds the relation between the power demand and state of the machine is introduced to the current model P_2. By rearranging the (3.121) and describing the general conditions for the newly presented variables α_t, AC_t and BC_t in constraint (3.122), the model P_2 which aims to integrate the continuous capacity selection problem to the single-item capacitated lot sizing problem is completed.

$$\alpha_t \leq M. \sum_{m=1}^{N} y_{m,t} \quad \forall t = 1,...,T \tag{3.120}$$

$$\begin{gathered} y_{m,t}, v_{m,t}, f_{m,r,t}, g_{m,r,t},, A_{m,r,t}, ws_{m,r,t}, z_{m,t} \in \{0,1\} \\ \forall m = 1,...,N, r = 1,...,N, t = 1,...,T \end{gathered} \tag{3.121}$$

$$\alpha_t, BC_t, AC_t \geq \ 0 \quad \forall t = 1,...,T \tag{3.122}$$

The model can be a useful model for the manufacturing companies who target the minimum power consumption.

The model P_2 can be used as a useful decision support tool for manufacturing companies that have set specific targets for minimum renewable energy use and who also announce environmentally friendly production in various marketing strategies. However, in practical life applications, capacity options are mostly offered to the customers as certain discrete values and they are asked to choose a value that best meets the power requirements of their production systems. Some example power contract options offered by EDF is presented in Table 2.2 and Table 2.3 in the Chapter 2. Based on this motivation, in the following section, another model (P_3) that considers the discrete capacity options is developed and a representative illustrative example is presented.

3.4.5 Mathematical Model for The Case of The Discrete Capacity _P_3

Notations

Since the model P_3 is improved based on the model P_2, to avoid from repeating, we prefer to present only newly introduced variables and constraints in this section. For the model P_3, the notations which are displayed in Table 3.13 are used by reforming. In the parameters section, the parameters P_k^{min} and P_k^{max} are replaced with the parameters R_k and $V_{k,l}$ since the capacity interval is discretized and discrete contract options are given by the energy supplier for each type of energy sources. The unit power cost $Vcost_k$ is removed and instead of it $Vcost_{k,l}$ which is the subscription fee corresponding to each option ($V_{k,l}$) for each energy source k is used. The variable P_k^{opt} which is proposed to define the amount of required capacity is changed to $P_{k,l}$ due to a certain option is selected among offered ones. Lastly, the definition of the variables AC_t and BC_t are redefined by calculating the amount of the power that will be penalized according to the sum of the contracted options.(Table 3.14)

Table 3.14: List of parameters and variables

Parameters	
R_k	Number of contract options for energy source of *k=1,...K*
$V_{k,l}$	Contract option *l=1,...*R_k for energy source of *k=1,...,K.*
$Vcost_{k,l}$	Subscription fee for option *l=1,...*R_k of energy source *k=1,...,K.*
Decision variables	
	Binary variables
$P_{k,l}$	A binary variable, equal to 1 if option l (l=1,...R_k) is chosen for energy source k (k=1,...K), otherwise 0.
AC_t	$max(0,(\alpha_t - \sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}))$ The energy used above the sum of the contracted capacity in period *t=1,...T.*
BC_t	$max((\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l} - \alpha_t),0)$ The energy used below the sum of the contracted capacity in period *t=1,...T.*

Objective function

$$\begin{aligned} P_3: \quad Minz = &\sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) \\ &+ \sum_{k=1}^{K}\sum_{l=1}^{R_k}(Vcost_{k,l}.P_{k,l}) \\ &+ \sum_{t=1}^{T}\sum_{k=1}^{K}(\mho.(AC_t + BC_t)) \end{aligned} \tag{3.123}$$

In the objective function (3.123), the first and the third part of the objective function of the model P_2 shown in 3.113 remain the same, only the second part is rearranged as figuring out the total power cost according to the selected capacity options.

The constraints (3.117-3.119) that are proposed to define required power for each type of energy source k in the model P_2 are replaced with the following constraints:

$$AC_t + (1+\beta).\sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) \geq \alpha_t \quad \forall t = 1,...,T \tag{3.124}$$

$$(1-\beta).\sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - BC_t \leq \alpha_t \quad \forall t = 1,...,T \tag{3.125}$$

$$\sum_{l=1}^{R_k}(P_{k,l}) = 1 \quad \forall k = 1,...,K \tag{3.126}$$

The constraints (3.124) and (3.125) introduce the contract vectors V_k including contract options for different energy sources to the model and establish a relationship between the maximum energy demand in period t and the contract values $V_{k,l}$. When the demand exceeds the upper or lower limits (defined by β) of the sum of the contracted power, excess quantity is penalized with defined penalty cost (℧). The constraints (3.126) force the customers to choose one power option from each type of energy sources.

Illustrative Example

To highlight the impact of the proposed model, an illustrative example (N3_T5) is presented. For the purpose of giving a better insight, the instance which is used to illustrate the model of Masmoudi et al. [2017a] in Section 3.2.5 is tested for the developed model. A planning period composed of five periods (T=5) and three machines (N=3) is considered. The same periods, machines related data are used which are displayed in Table 3.2 and Table 3.3. Additionally, data for contract options which are inspired from the real life, are added to data set. As it can be observed in Table 3.15 three type of energy sources are offered to the customers and the price of renewable energy sources are assumed in this instances to be more expensive than the traditional source.

Table 3.15: Contract options

Trad.	*Vcost($)*	Solar	*Vcost($)*	Wind	*Vcost($)*
6 KW	50	3 KW	75	3 KW	62.5
9 KW	55	4 KW	82.5	4 KW	68.75
12 KW	80	5 KW	120	5 KW	100
15 KW	90	6 KW	135	6 KW	112.5
18 KW	100	7 KW	150	7 KW	125
24 KW	200	8 KW	300	8 KW	250
36 KW	250	9 KW	375	9 KW	312.5

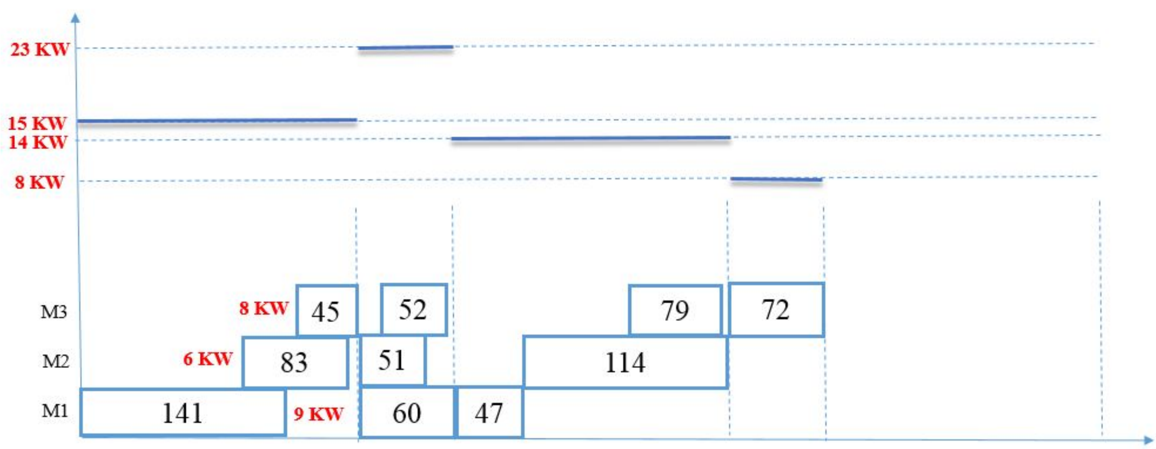

Figure 3.10: The manufacturing configuration obtained by the model of Masmoudi et al. [2017a]

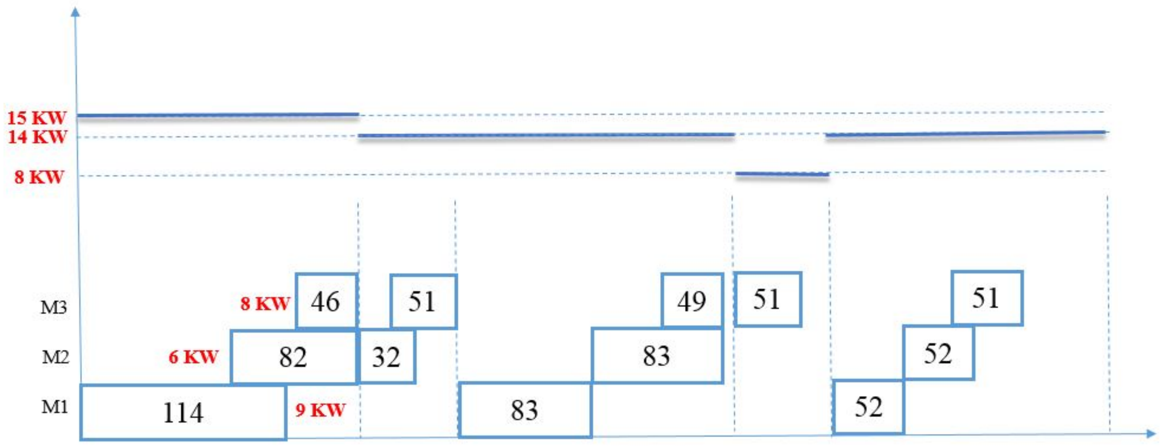

Figure 3.11: The production plan with contract selection constraints (traditional+renewable source)

When the capacity selection problem with multiple energy sources is introduced to the planning problem (P_3), the mathematical model yields that agreement on 6 KW for traditional energy, 3KW for solar and 4 KW for wind energy sources is the optimum energy mix to realize a plan which satisfies the external demand. If the power configuration in Figure 3.10 is compared with the power configuration in Figure 3.11 where the capacity selection problem is introduced, it is explicitly seen that in Figure 3.11, the power configuration is more balanced and realistic in terms of power supply. With the developed model, the customer can observe how much they can derive from the contracted power, and correspondingly, how much penalty cost they will pay. Since the sum of the contracted power is 13 KW energy; as long as the power demand stays between 14,3 and 11,7, the customer is not penalized. In Table 3.16, AC represents the usage of above the tolerance interval while BC stands for the use of energy which is below the sum of the contracted options. For example, since the peak power demand is 15 KW in the first period in Figure 3.11, the power used above the tolerance interval is computed as 0.7 KW (=15-14.3).

Table 3.16: Penalized amounts according to the contracted power options

period	1	2	3	4	5
AC (KW)	0,7	0	0	0	0
BC (KW)	0	0	0	3,7	0

3.4.6 Computational Experiments

In this section, the developed model P_3 is solved by CPLEX 12.6 on an Intel Core i7 with 2.7 GHz and 8 GB RAM on different sizes of instances. To be able to benefit from the CPLEX solver, the non-linear components in the proposed model are linearised as they are explained in Section 3.3.4. For the sake of convenience, the data set which is used for testing the model of Masmoudi et al. [2017a] is kept the same. Since the developed model introduced the capacity selection problem, the E_t^{max} is removed from the model and data set. Due to the subscription fee of the each power option is considered, the power is not priced according to the period. As a result of this set, the price of power θ_t in period t (t=*1,...,T*) is also removed from the data set, too.

Results and Discussion

The performance results of the developed model are displayed on Table 3.17 and Table 3.18. As it is presented for the improved version of the model of Masmoudi et al. [2017a], in Table 3.17, the size of the tested instances are summarized briefly. N represents the number of the machines and T stands for the number of the periods. To emphasize the complexity of the developed model the number of the binary variables, total number of variables and the number of the constraints are presented for each problem sizes. When the number of the variables and the constraints of the developed model is compared with the complexity in Table 3.11, it is seen that the constraints proposed for the capacity selection and the other constraints added to improve the model make the problem even more difficult. As it can be observed in Table 3.17, when the size of the instance increases, the number of the variables and the constraints increases dramatically.

For each problem size, 5 different instances are generated. The computation time is limited by 1 hour (Masmoudi et al. [2015]; Ramezanian et al. [2013b]). In Table 3.18, the instances which are solved within 3600s are solved to the optimality. It is found out that while the instances composed of 5 machines and 10 periods can be solved to the optimality within 1 hour in the previous model where contract selection problem is not introduced in Table 3.12, the CPLEX solver can not reach the optimality within 1 hour for some of the instances N5_T10 when they are tested with the proposed model where the capacity selection problem is combined with the single item lot sizing problem (see, Table 3.18). The results of the instances composed of 7 machines and 7 periods can be interpreted in the same way. In the previous model (P_1) while the instances are solved to the optimality in most cases, the number of the instances which can not reach the optimality in the time limit increases when they are tested with the latter proposed model (P_3). For relatively larger instances, as in the previous model, CPLEX can not reach the optimum solution within the time limit. The increasing number of the instances which can not reach the optimality within the time limit, proves the increasing complexity of the proposed model. To deal with the computational burden of the developed model, appropriate heuristic approaches will be implemented and presented in the Chapter 5.

Table 3.17: Problem sizes of P_3

N	T	Binary Variables	Variables	Constraints
5	5	827	943	2387
5	7	1151	1313	3343
5	10	1637	1868	4777
7	7	2283	2501	7406
7	10	3255	3566	10583
10	7	4716	5018	18068
10	10	6732	7163	25187
10	15	10092	10738	38732

Table 3.18: Solution performance of P_3

N_T	Instances	CPU(s)	N_T	Instances	CPU(s)
N5_T5	Ins_1	5,991	N7_T10	Ins_1	>3600
	Ins_2	3,962		Ins_2	>3600
	Ins_3	10,967		Ins_3	>3600
	Ins_4	9,204		Ins_4	>3600
	Ins_5	6,412		Ins_5	>3600
	Average	7,307		Average	>3600
N5_T7	Ins_1	68,64	N10_T7	Ins_1	>3600
	Ins_2	14,243		Ins_2	>3600
	Ins_3	92,212		Ins_3	>3600
	Ins_4	134,988		Ins_4	>3600
	Ins_5	43,664		Ins_5	>3600
	Average	70,749		Average	>3600
N5_T10	Ins_1	>3600	N10_T10	Ins_1	>3600
	Ins_2	1413,59		Ins_2	>3600
	Ins_3	>3600		Ins_3	>3600
	Ins_4	875,78		Ins_4	>3600
	Ins_5	2862,93		Ins_5	>3600
	Average	2470,46		Average	>3600
N7_T7	Ins_1	>3600	N10_T15	Ins_1	>3600
	Ins_2	>3600		Ins_2	>3600
	Ins_3	1501,8		Ins_3	>3600
	Ins_4	>3600		Ins_4	>3600
	Ins_5	>3600		Ins_5	>3600
	Average	3180,36		Average	>3600

3.5 Conclusion

In this chapter, firstly the mathematical model developed by Masmoudi et al. [2017a] is improved to be able to define exact power need of the production system. A mixed integer non-linear model and its linear equivalent are presented for the solution of the single item lot sizing problem for flow shop configurations by integrating the power capacity selection problem. With the developed mathematical model it is aimed to minimize production and energy costs by considering production and energy purchasing constraints.

The principal contribution of this chapter is to combine optimum energy contract selection problem with the lot sizing problem. Hence, the proposed model identifies optimum production quantities for each period and each machine. The obtained optimum production plan is synchronized with the capacity options offered by the energy supplier. Another contribution is to insert the renewable energy sources into capacity selection procedure. Therefore, the proposed model will be more beneficial for the industrial customers in the upcoming years to achieve the targets defined by governments for encouraging renewable energy usage.

After testing the proposed model on different sizes of instances, it is seen that when the size of the instance increases, the computational burden of the problem increases, too. To deal with this difficulty, it is necessary to apply appropriate heuristic approaches to obtain optimum or near optimum results in a reasonable time for the large size instances.

Chapter 4

Single Item Lot Sizing Under Renewable Energy Uncertainty

Contents

4.1 Introduction

According to the report of U.S. Energy Information Administration, it is expected that energy consumption in non-OECD countries increases 41% between 2015 and 2040 in contrast to a 9% increase in OECD countries (EIA [2017]). When the balance between the energy sources is examined, it is seen that the world's energy need mainly relies on the fossil fuels which are responsible for the increasing carbon emission. The projected increase in energy need and changing climate conditions lead the governments to seek more sustainable and clean ways for energy generation. There is no doubt energy generation from the renewable energy sources is the best option to protect the environment and meet the energy need of the nations. In recent years, governments invest considerable amount of money on renewable energy generation technologies, announce target levels to promote the integration of renewable energy sources and provide some certain incentives to encourage individual or commercial consumers to use greater amount of renewable energy sources. In accordance with this worldwide trend, it can be said that the renewable energy sources will get the fastest growing share in the energy consumption of the world.

It is a fact that the industrial sector, which includes mining, manufacturing, agriculture, and construction, accounts for the largest share of energy consumption of any end-use sector, accounting for more than 50% over the entire projection period (EIA [2017]). Considering this fact, it can be said that if the conventional energy sources supplied to the industrial customers are diversified with the renewable ones; while the energy reserves of the world can be used more efficiently, environmental targets can be achieved significantly by declining carbon emission levels.

Increasing the use of renewable energy sources is not only a matter in the agenda of the states. In recent years, there is a notably growing awareness for the environmental-friendly produced productions in the society. While the customers support the companies that conduct their production activities based on clean energy sources and will to purchase the products of these companies, the companies that do not take responsibility for preventing the global warming from becoming worse and remain insensitive to this issue are easily protested in today's social media era by the customers. By increasing the use of renewable energy, companies can both get rid of the tax burden imposed by the government on carbon emissions, and they can enjoy the best of both worlds by using this transition as a marketing strategy. They can announce the share of the clean energy sources in their total energy consumption to draw the attention of the customers and enhance their market while contributing to achieve global sustainability targets defined for the efficient use of the energy sources.

Despite all these positive outcomes of usage of renewable energy sources, the deployment of renewable sources shows a slow progress. As the responsible of this reality, the intermittent and random nature of the renewable energy sources can be referred. Since the renewable energy sources do not promise reliable and constant energy supply, this characteristic discourages, especially, the industrial customers who need the continuity of the energy supply to sustain the production activities.

When the uncertainty issue is handled from the energy producers' perspective, there is no doubt that the availability of the renewable energy sources must be predicted as accurate as possible and energy supply must be planned accordingly. When the availability of the renewable energy sources is forecasted precisely, the energy producers can plan energy supply more accurately and decrease the probability of any energy curtailment on the consumer side. When the previous studies related to renewable energy generation are examined, it is seen that the studies deal with the uncertainty modelling of the renewable energy sources have the greatest share. The main purpose of the applied uncertainty modelling methods is to measure the impact of uncertain input parameters on the system output parameters. The main difference between them is the used approach to describe the uncertainty of input parameters (Aien et al. [2016]). The studies of Aien et al. [2016] and Talari et al. [2017] can be reviewed for the classification of the uncertainty modelling techniques of renewable energy sources.

In this chapter, instead of measuring the impact of the uncertain input on the renewable power generation which is quite useful approach for the energy producers' side, it is aimed to give an insight to industrial customers while making decision for the optimum contract selection under renewable energy uncertainty. With this purpose, different types of probabilistic constraints are proposed by taking into account the probable curtailments in the supply of the renewable energy sources. The developed probabilistic constraints are merged with the previously studied single item lot sizing problem. Thus, it is targeted to select the contract capacity according to the stochastic nature of the weather-dependent renewable sources.

This chapter is organized as follows: In Section 4.2, the deterministically developed single item capacitated lot sizing problem which is studied in Chapter 3 is recalled and related notations and assumptions are renewed. In Section 4.3, the proposed probabilistic constraints are classified and explained in a general frame. In Section 4.4, to evaluate the cost of the disturbance in the supply of the renewable energy sources, probabilistic objective functions are proposed in a general manner as it is done for the probabilistic constraints. In Section 4.5, developed constraints and objective functions are studied with the consideration of exponential distribution. Section 4.6 includes illustrative examples conducted according to developed probabilistic models. Section 4.7 concludes this chapter with some remarks and perspectives.

4.2 Modelling of the Uncertainty of the Renewable Energy Sources

4.2.1 Problem Statement & Objective

In the probabilistic-constrained model, as in the Chapter 3, the single-item capacitated lot sizing problem for flow shop configuration is studied by integrating energy capacity selection problem under renewable energy uncertainty. The same production configuration which is composed of N machines and N buffers is considered (Figure 3.1).

The purpose of the proposed models is to determine the optimum production quantities to be produced on each machine and in each period and to identify the required maximum power demand by minimizing the production, holding, set-up and energy costs by synchronizing the power demand of the system with the capacity contract options including energy sources that can not be guaranteed to be fully supplied by the energy supplier.

4.2.2 Assumptions

In Chapter 3, the deterministic model is presented with two groups of assumptions: Production Related Assumptions and Energy Related Assumptions. Since the probabilistic model is developed for the same type of production configuration, the production related assumptions are completely kept as they are in the deterministic model (P_3). That's why, production related constraints are not mentioned here one more time. Energy related assumptions are carried to the probabilistic models with a few adds and drops. When the energy related assumptions, in the discrete case, are recalled:

— The use of K types of energy sources (traditional, wind, solar) is assumed.

— All the energy sources are supplied by and purchased from energy supplier, that is, the on-site generation mechanism is out of the context.

— Since all types of energy sources are provided by energy supplier, their prices are defined according to the tariffs fixed by the energy suppliers.

— A given number (R_k) of capacity options (which are not necessary equal for all sources) can be offered by the suppliers for each type of energy sources $k=1,...,K$.

— The R_k proposed options constitute the energy contract vectors $V_k = V_{k,1},...,V_{k,R_k}$ for each type of energy sources.

— The main characteristic of each option ($l=1,...R_k$) for each energy sources ($k=1,...K$) is its subscription fee ($Vcost_{k,l}$).

— The customers are obliged to choose one option from each type of energy sources.

— The customers are not allowed to switch the agreed option to another one during the planning horizon, so, it is assumed that the production system is subject to the same power option for the whole planning horizon.

— The sum of the contracted capacity ($V_{k,l}$) for each energy sources k must cover the needs of the production system and minimize the energy and production costs.

— The main difference between the previously developed deterministic model and the models that are proposed in this section is that, the availability of the renewable energy sources is assumed stochastic and defined with a given distribution.

In the following sections, the uncertainty aspect of the renewable energy sources is integrated into the capacitated single-item lot sizing problem by merging the probabilistic constraints and objective functions with the deterministic model P_3 . Before merging the developed probabilistic constraints with the deterministic model, it is necessary to retouch the deterministic model developed in Section 3.4.5 to make it ready to link with the probabilistic constraints. Therefore, firstly, the deterministic model (P_3) which is developed for the single-item lot sizing problem for flow shop systems with capacity selection problem is presented with some retouches and this adapted model is named PS_0.

4.2.3 Mathematical Model_PS_0

Since the previously developed model P_3 is considered as the basis of the developed probabilistic models in this chapter, to give better sense, the notations of the model P_3 in which discrete contract capacities are integrated to the single-item lot sizing problem are used for the adaptation of the model P_3. To avoid from repetition, we refer the readers to Table 3.13 and Table 3.14.

$$PS_0: \quad Min z = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) \\ + \sum_{k=1}^{K}\sum_{l=1}^{R_k}(Vcost_{k,l}.P_{k,l}) \tag{4.1}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120- 3.122)
the constraints for peak power calculation: (3.114)-(3.116)
the constraints for contract capacity selection: the constraints (3.124) and (3.125) are replaced with the following constraint:

$$\sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) \geq \alpha_t \quad \forall t = 1,...,T \tag{4.2}$$

and constraint (3.126) is kept as it is.

The main difference between the deterministic model P_3 and the currently introduced model PS_0 is that the concept of penalizing the amount consumed above and below of the contracted capacity option is left out of the context. Accordingly, the last part of the objective function of the model P_3 is withdrawn and the basis of the objective function of the probabilistic-constrained models, which will be discussed later, is constructed as in 4.1. Since the production related constraints are the same with the constraints of the model P_3, instead of repeating them , they are recalled by addressing the numbers of the constraints. This approach is applied for the other common constraints with the model P_3.

Thus, the mathematical model which constitutes the basis of the probabilistic constrained models presented in this chapter is completed. In the following section, firstly, developed probabilistic constraints are presented. After explaining the proposed probabilistic constraints in detail, in the subsequent section, the objective functions which are developed based on the cost rising from the unavailability of the renewable energy sources will be detailed.

4.3 Developed Probabilistic Constraints

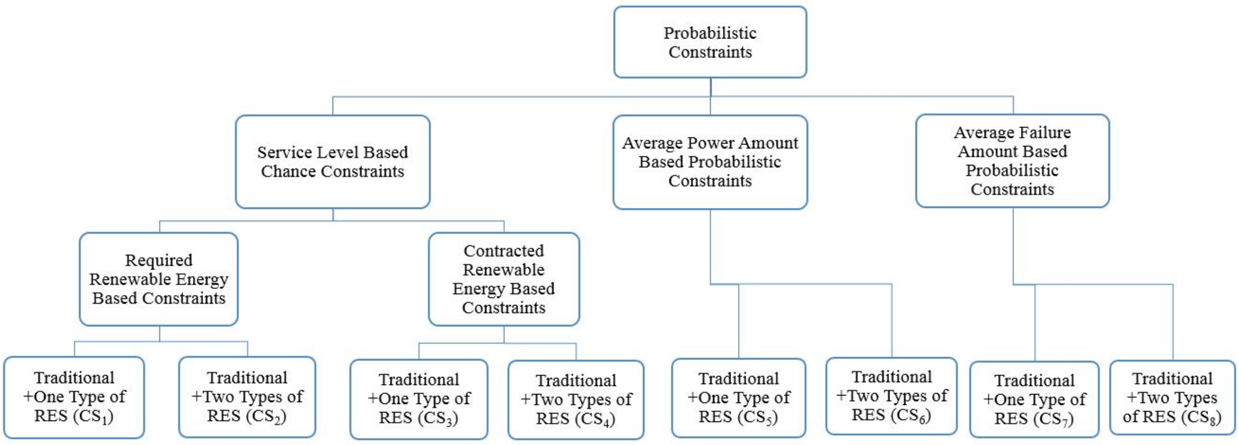

Figure 4.1: Classification of developed probabilistic constraints

In this section, we propose three types of probabilistic constraints to model the stochastic nature of the availability of the renewable energy sources (Figure 4.1):
—Service Level Based Chance Constraints
—Average Power Amount Based Probabilistic Constraints
—Average Failure Amount Based Probabilistic Constraints

In the first group of constraints, chance constraint programming approach is used and the risk in the supply of renewable energy sources is transformed into the risk in the realization of the planned production activity by introducing *service level* of industrial customers. Therefore, the proposed models allow the customers to mix renewable and traditional sources according to the agreed service level and present a strong decision making tool to cope with uncertain and risky characteristic of renewable energy sources.

In the second group of constraints, the randomness in the availability of the renewable energy sources is reflected to the model as the expected value of the availability.

Lastly, in the third group of constraints, the expected value of the amount that might not be met according to contracted option is calculated and optimum contract options are selected by considering expected failure.

In Figure 4.1, the energy mixes which are composed of the traditional energy source and one type of renewable energy source (RES); traditional energy source and two types of renewable energy sources are considered for each type of probabilistic constraint. The numbers are assigned to each of the proposed models and constraints, respectively, like PS_1, PS_2 and CS_1, CS_2 etc. to make them easier to follow in the following sections.

In the next section, developed service level based chance constraints are explained clearly. These constraints are established by considering two cases: When the probability of meeting the required renewable energy source is investigated in the first case and in the second version, when the probability of having at least the amount of renewable energy as agreed in the contract is compared with the promised service level. Before going into details, a short brief will be given about the chance constraint programming.

4.3.1 Service Level Based Chance Constraints

Chance constraint programming which is also known as probabilistic programming was firstly introduced by Charnes and Cooper [1959, 1963] to deal with the linear models including uncertain features. Since then, it has been extensively used for the solution of several types of problems. Recently, Najafi et al. [2017] developed a model with chance constraints for blood inventory management by considering supply and demand uncertainties. Liu and Zhang [2018] applied chance constraint programming for disassembly scheduling problem with random yields and demands. Kınay et al. [2018] modelled the shelter site location problem under demand uncertainty by using chance constraint programming, Noorizadegan and Chen [2018] implemented probabilistic constraints for capacitated vehicle routing problem with demand uncertainty. Gicquel and Cheng [2018] studied joint chance constrained programming approach for the single-item capacitated lot sizing problem with stochastic demand. Ramezanian and Saidi-Mehrabad [2013] addressed lot sizing and scheduling problem of a flow shop system with capacity constraints, sequence-dependent setups, uncertain processing times and uncertain multi-product and multi-period demand. The evolution of the uncertain parameters is modeled by means of probability distributions and chance constrained programming.

In particular, chance constraint programming has been applied for energy management problems. For a detailed technical study on chance constraint programming in energy management, it is recommended to review the work of Van Ackooij [2013]. When some of the prominent studies are examined, it is seen that Kamjoo et al. [2014] benefited from chance constraints to determine the optimal size of hybrid renewable energy system components by considering uncertainties in renewable energy sources. Vergara-Dietrich et al. [2017] formulated chance constraints to deal with uncertainties for the optimal energy management of a micro grid with renewable energy generation and hybrid storage technologies. Beraldi et al. [2017] implemented chance constraint programming for energy procurement problem by taking into account uncertain energy prices in the market and energy needs of the large size customers. Mühlpfordt et al. [2018] studied chance constrained modelling for optimal power flow dependent from any specific probability distribution.

In the study of Miller and Wagner [1965], the mathematical model of a probabilistic linear programming problem is formulated as follows:

$$\mathrm{M}axZ = cx \tag{4.3}$$

$$\mathrm{A}x \leq b, \tag{4.4}$$

$$x_j \geq 0, \tag{4.5}$$

and to the set S of chance constraints

$$\mathrm{Prob}(a_i x \leq \flat_i) \geq \delta_i, \quad \forall i \in \mathrm{S} \tag{4.6}$$

As it is familiar from the classical linear programming models, x is the n-dimensional column vector that we wish to find. c and a_i are the n-dimensional row vectors which correspond to constants and A is the m×n matrix and b is the n-dimensional column vector. $\flat_i$ is the random variable and δ_i is the defined probability value, that is, $0 \leq \delta_i \leq 1$.

From this starting point, chance constraints are developed to handle the random availability of the renewable energy sources. In this study, two types of service level based chance constraints are proposed in a similar fashion by considering the use of one type of renewable source and two types of renewable energy sources.

Case 1: Required Renewable Energy Based Constraints

CS_1**: Traditional Energy and One Type of Renewable Energy Source Consumption**

In this first case, it is assumed that the manufacturer consumes traditional energy source and one type of energy source (solar or wind for instance). The developed model takes into account the random availability of renewable energy source and defines best energy mix which can cover the system need by considering this randomness. To do so, the manufacturer defines a service level (*SL*) which is also assumed as minimum probability for the availability of renewable energy source. In other words, the probability of available renewable energy (X_s) is greater than the required amount of energy must be at least the specified *SL* to satisfy the targeted service level. This idea is translated to the following chance constraint:

$$\text{Prob}(X_s \geq \text{the required renewable energy quantity to satify the production}) \geq SL \quad (4.7)$$

where;
SL: minimum service level defined by industrial customer
X_s: random variable of the available quantity for solar energy source

In deterministic model, α_t is the decision variable which defines the total power need of each period depending on the production planning to satisfy the demand. The sum of the contracted energy capacities for each type of energy sources must cover the total power demand.

If the constraint (4.2) in PS_0 is recalled with the notations $k = s$ for solar and $k = tr$ for traditional:

$$\sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) \geq \alpha_t \quad \forall t = 1, ..., T \quad (4.8)$$

$$\Longleftrightarrow \sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \geq \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) \quad \forall t = 1, ..., T \quad (4.9)$$

the minimum amount of required renewable energy for period t can be expressed as $\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})$. Accordingly, the primitive version of the chance constraint in (4.7) is reformulated as follows:

$$P(X_s \geq \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \geq SL \qquad \forall t = 1,...,T \tag{4.10}$$

$$\Longleftrightarrow 1 - P(X_s < \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \geq SL \qquad \forall t = 1,...,T \tag{4.11}$$

$$\Longleftrightarrow P(X_s < \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \leq 1 - SL \qquad \forall t = 1,...,T \tag{4.12}$$

Thus, in (4.12), the first service level based chance constraint which considers the combination of the traditional energy source with one type of renewable source is obtained.

CS_2: Traditional Energy and Two Types of Renewable Energy Sources Consumption

The proposed first chance constraint (4.12) can be improved in a similar way for the customers who prefer to mix traditional energy source with two types of renewable energy sources (solar and wind for instance). From this starting point, similar to the constraint (4.12), probabilistic constraint including service level is constructed for the mix of traditional and two types of renewable energy sources as follows:

$$P(X_s + X_w < (\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}P_{tr,l})) \leq 1 - SL \tag{4.13}$$

where;
X_s: Random variable of solar energy source.
X_w: Random variable of wind energy source.

To simplify, in the following formulations, let the amount of required renewable energy source be $Q_t = (\alpha_t - \sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})$. So, the constraint (4.13) can be reformulated as follows:

$$P(X_s + X_w < Q_t) \leq 1 - SL \tag{4.14}$$

As it can be seen in constraint (4.14), the left hand side of the inequality includes the sum of the two random variables. In probability theory, the distribution of the sum of two independent non negative random variables arises the *convolution*.

Definition 5.1: Let X and Y be two continuous independent and non-negative random variables with density functions *f(x)* and *g(y)*, respectively. Let the sum of the two random variables be $Z = X * Y$ where $*$ is used to signify the convolution operation. The probability density function of Z is obtained by convolution operation which is defined as follows:

$$(f * g)(z) = \int_{-\infty}^{\infty} f(z-y)g(y)d_y \tag{4.15}$$

$$= \int_{-\infty}^{\infty} g(z-x)f(x)d_x \tag{4.16}$$

In the left hand side of inequality in (4.14), the sum of the two continuous random variables are computed the given convolution-product formula in (4.15). In Section 4.5, the developed constraints will be exemplified by taking into account exponential distribution for the random variables.

In the following section, second version of the developed service level based constraints are detailed by taking into account the same energy mixes which are discussed in the Case 1.

Case 2: Contracted Renewable Energy Based Chance Constraints

In Case 1, the risk in the supply of the renewable energy sources is evaluated according to required renewable amount to realize the planned production. It is possible that the customers might not use all the available energy in certain periods. In this version, as an alternative to the Case 1 where the risk is evaluated according to the real renewable energy need of the production system, the risk is evaluated according to the agreed power amount in the contract.

CS_3: Traditional Energy and One Type of Renewable Energy Source Consumption

To develop contracted option based chance constraints, same steps which are followed for the construction of the constraints studied for Case 1 are pursued. The primitive version of the proposed constraint can be defined as follows:

$$\text{Prob}(X_s \geq \text{the contracted quantity for renewable energy source}) \geq SL \qquad \forall t = 1, ..., T \tag{4.17}$$

$$P(X_s \geq \sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})) \geq SL \qquad \forall t = 1, ..., T \tag{4.18}$$

where;
SL: minimum service level defined by industrial customer

X_s: random variable of the available quantity for solar energy source
$\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})$: contracted capacity option for solar energy source

$$\iff 1 - P(X_s < \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})) \geq SL \qquad \forall t = 1,...,T \tag{4.19}$$

$$\iff P(X_s < \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})) \leq 1 - SL \qquad \forall t = 1,...,T \tag{4.20}$$

Therefore, constraint (4.20) gives the chance constraint that evaluates the risk according to the contracted option for the cases in which the traditional energy source is mixed with one type of renewable energy source. In the following section, the same constraint is built for energy mixes which are composed of the traditional and two types of renewable energy sources.

CS_4: **Traditional Energy and Two Types of Renewable Energy Source Consumption**

Previously, the chance constraint for the mix of the traditional and two types of renewable energy sources had been proposed according to the required renewable energy amount. In this case, the probabilistic constraint based on contracted options is developed by tracking the same steps which are applied for the constraint (4.13). Accordingly, the primary constraint can be expressed as follows:

$$\text{Prob}(X_s + X_w \geq \text{total contracted quantity for renewables}) \geq SL \tag{4.21}$$

$$P(X_s + X_w \geq (\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) + \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})) \geq SL \tag{4.22}$$

where
SL: minimum service level defined by industrial customer
X_s: random variable of the available quantity for solar energy source
X_w: random variable of the available quantity for wind energy source
To simplify the following formulations, let the total contracted amount of renewable energy source be;

$$Q_t = \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) + \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}) \tag{4.23}$$

So, the constraint (4.22) can be reformulated as follows:

$$P(X_s + X_w \geq Q_t) \geq SL \tag{4.24}$$

$$\iff P(X_s + X_w < Q_t) \leq 1 - SL \tag{4.25}$$

The left hand side of the constraint (4.25) involves the sum of the two independent random variables as in the constraint (4.14). As it is proposed for the constraint (4.14), it is necessary to apply the convolution operation. As the other constraints, this constraint will be exemplified by considering the exponential distribution for the random variables in Section 4.5.

Therefore, the service level based chance constraints are proposed in the global manner. Now, the second group of constraints which is defined as "*Average Power Amount Based Probabilistic Constraints*" in the Figure 4.1 is explained broadly in the following section.

4.3.2 Average Power Amount Based Probabilistic Constraints

The power generation from solar and wind energy sources depends on the solar irradiation and wind speed, respectively. When the solar power generation is considered, the irradiation value changes continuously from the first hours of the sunrise to the sunset. The same type of fluctuations in solar irradiation can be observed over a season. When it comes to the power generation from the wind energy, it is possible to say that the wind speed diversifies during the day or season. In this constraint, it is aimed to take into account the mean value of the power generation to cope with the stochastic aspect of renewable energy sources. In probability theory, the mean of the random variables are defined as *expected value* and the expected value of a continuous random variable is calculated with the following formula:

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx \tag{4.26}$$

CS_5: Traditional Energy and One Type of Renewable Energy Source Consumption

Even tough the availability of renewable energy sources is uncertain, it is a fact that when the traditional energy source is mixed with the renewable energy sources, sum of the deterministically known traditional power and the expected renewable power generation must cover the energy need of the production system. This idea can be translated as follows:

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l} P_{tr,l}) + E[X_s] \quad \forall t = 1, ..., T \tag{4.27}$$

with;
α_t : the power need during period t.
$\sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})$: Selected capacity option for traditional energy source.
$E[X_s]$: Expected value for solar power generation.

CS_6**: Traditional Energy and Two Types of Renewable Energy Source Consumption**

It is possible to propose the expected value based probabilistic constraint for the customers who aim to combine traditional and two types of renewable energy sources as in the following constraint:

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l} P_{tr,l}) + E[X_s] + E[X_w] \tag{4.28}$$

In constraints (4.27) and (4.28), the randomness of the renewable energy sources can be taken into account in the contract capacity selection procedure by calculating the expected values of the random variables according to the given probability density functions. Therefore, the second group of constraints displayed in in Figure 4.1 are completed.

In the subsequent section, last group of constraints which is built on the the expected failure amount in the supply of the renewable energy sources are developed in a general frame as the other constraints.

4.3.3 Average Failure Amount Based Probabilistic Constraints

When the clients negotiate for the certain capacity options for the renewable energy sources, they must consider that the complete amount of the contracted option might not be supplied due to the random weather conditions. In case of increasing the contracted value, the risk of dissatisfying the whole contracted amount increases and the risky amount which can not be met increases proportionally. In this constraint, the stochastic aspect of the renewable energy sources is taken into account by figuring out the expected failure amount depending on the contracted option.

CS_7**: Traditional Energy and One Type of Renewable Energy Source Consumption**

As it is applied for the previous constraints, firstly, the mix of traditional and one type of renewable energy source is considered and the following constraint is proposed:

$$\alpha_t \leq \sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - \overline{\nabla_s} \quad \forall t = 1,...,T \tag{4.29}$$

where,
α_t : the power need during period t.
$\sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l})$: The sum of the contracted power amount.
$\overline{\nabla_s}$: Average failure amount based on the contracted power for the solar energy.
The failure amount ∇_s for solar energy can be defined as follows:

$$\nabla_s = \begin{cases} \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - X_s & X_s \leq \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}); \\ 0 & X_s > \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}); \end{cases}$$

where;
$\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})$: Contracted amount for solar energy source.
X_s: Random availability of solar energy source.

By inspiring from the definition of the average value of random variables in (4.26), defined average failure amount can be calculated as follows:

$$\overline{\nabla_s} = \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} (\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - X_s) f(x)dx \tag{4.30}$$

$$\iff \overline{\nabla_s} = \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) f(x)dx - \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.f(x)dx \tag{4.31}$$

$$\iff \overline{\nabla_s} = \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} f(x)dx - \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.f(x)dx \tag{4.32}$$

After obtaining the average failure amount ($\overline{\nabla_s}$) by the formula in (4.32), the constraint (4.29) can be transformed to the following expression:

$$\alpha_t \leq \sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - [\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} f(x)dx - \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.f(x)dx] \quad \forall t = 1,...,T \tag{4.33}$$

Therefore, the contract options can be selected by taking into account the risky amount to meet for renewable energy sources via the constraint (4.33).

CS_8: **Traditional Energy and Two Types of Renewable Energy Source Consumption**

When the same constraint is proposed for the cases in which traditional energy source is blended with the two types of renewable sources, similar to the constraint (4.29), the following constraint can be proposed:

$$\alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - \overline{\nabla_s} - \overline{\nabla_w} \quad \forall t = 1, ..., T \tag{4.34}$$

where;
α_t : the power need during period t.
$\sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l})$: The sum of the contracted power amount.
$\overline{\nabla_s}$: Average failure amount based on the contracted power for the solar energy.
$\overline{\nabla_w}$: Average failure amount based on the contracted power for the wind energy.

The proposed constraint in (4.34) is expanded by following the same steps with the aforementioned case in which only traditional and one type of renewable energy source are mixed. Accordingly, the expected failure amount for wind energy source is formulated as follows:

$$\overline{\nabla_w} = \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} (\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l}) - X_w) f(x) dx \tag{4.35}$$

$$\Longleftrightarrow \overline{\nabla_w} = \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} \sum_{l=1}^{R_w} (V_{w,l}.P_{w,l}) f(x) dx - \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} X_w.f(x) dx \tag{4.36}$$

$$\Longleftrightarrow \overline{\nabla_w} = \sum_{l=1}^{R_w} (V_{w,l}.P_{w,l}) \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} f(x) dx - \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} X_w.f(x) dx \tag{4.37}$$

The final version of the constraint (4.34) becomes:

$$\begin{aligned} \alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - [\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})} f(x) dx - \int_0^{\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})} X_s.f(x) dx] \\ -[\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l}) \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} f(x) dx - \int_0^{\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l})} X_w.f(x) dx] \quad \forall t = 1, ..., T \end{aligned} \tag{4.38}$$

Thus, after presenting the constraints CS_7 and CS_8 in Figure 4.1, three types of probabilistic constraints have been proposed by considering the two types of energy mixes. In the following section, the cost of the probable failures in the supply of the renewable energy sources are evaluated and the two types of objective functions are proposed for this purpose.

4.4 Developed Objective Functions

In this section, two types of objective functions are presented. In the first type, penalty cost depending on the the failure probability is taken into consideration and added to the classical production and energy purchasing costs. In the second type of objective function, directly the expected failure amount in the supply of the renewable energy sources is penalized and considered as additionally costs in the objective function.

The main philosophy behind the applying penalty cost is that, when there is a failure in the meeting of the required renewable energy source, the customer compensates the failure amount with the traditional energy sources to be able to sustain the production activities. In other words, as the excessive amount of use of the energy sources are penalized in the deterministic models presented in the previous chapter, excessive amount of traditional energy source is penalized in the probabilistic models presented in this chapter.

Starting from the first type, developed objective functions are detailed in the following sub sections.

4.4.1 Type 1: Penalizing The Probability of Failure

If the required amount of renewable energy is not fully met, the industrial customers may experience loss of production which can cause unsatisfied demand or meet the missing amount of renewable source with the traditional energy sources in order to maintain production activities without interruption. However, in case of increasing the use traditional energy source, carbon emission level increases correspondingly and the customers might face some sanctions to reduce it. In order to avoid such undesirable situations, it is considered to penalize the probability of the failure of the renewable energy source as follows:

$$\text{OF.1.1}: \quad \text{M}inz = \sum_{t=1}^{\text{T}} \sum_{m=1}^{\text{N}} (\psi_{m,t} x_{m,t} + h\text{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\text{R}_k} \sum_{k=1}^{\text{K}} (\text{V}cost_{k,l}\text{P}_{k,l}) + \sum_{t=1}^{\text{T}} \gamma.\text{P}(\text{X}_s < \alpha_t - \sum_{l=1}^{\text{R}_{tr}} (\text{V}_{tr,l}.\text{P}_{tr,l})) \tag{4.39}$$

where:

γ: Penalty cost

X_s: Random availability of solar energy source.

$\alpha_t - \sum_{l=1}^{\text{R}_{tr}} (\text{V}_{tr,l}.\text{P}_{tr,l})$: Required amount for renewable energy source.

Thus, the objective function including the cost of failure probability is obtained.It is possible to apply same idea for the objective function of the models which are considering the mix of traditional and two types of energy sources. This time, the expected failure cost can be expressed, as in:

$$\text{OF.1.2}: \quad \text{M}inz = \sum_{t=1}^{\text{T}} \sum_{m=1}^{\text{N}} (\psi_{m,t} x_{m,t} + h\text{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\text{R}_k} \sum_{k=1}^{\text{K}} (\text{V}cost_{k,l}\text{P}_{k,l}) + \sum_{t=1}^{\text{T}} \gamma.\text{P}(\text{X}_s + \text{X}_w < \alpha_t - \sum_{l=1}^{\text{R}_{tr}} (\text{V}_{tr,l}.\text{P}_{tr,l})) \tag{4.40}$$

where:

γ: Penalty cost

X_w: Random availability of wind energy source.

X_s: Random availability of solar energy source.

$\alpha_t - \sum_{l=1}^{\text{R}_{tr}} (\text{V}_{tr,l}.\text{P}_{tr,l})$: Required amount for renewable energy source.

Therefore, the failure probability based objective function for the cases in which two types of renewable energy sources are mixed with the traditional source is obtained.

As it can be observed, as long as the sum of the availability of the renewable sources is less than the required renewable energy amount, the penalty cost is charged in addition to the other costs in the objective function. The objective function attained in (4.40) involves the sum of the two continuous random variables. It had been explained that the product of convolution must be calculated to obtain the probability density function of the sum of the two continuous random variables. In Section 4.5, the proposed objective function in (4.40) will be enhanced by considering exponential distribution.

If it is desired to consider the probability of failure according to the contracted capacity value of renewable energy sources instead of taking into account required renewable energy, as it is considered for the *Contracted Renewable Energy Based Chance Constraints* in Section 4.3.1, the versions of the objective function Type I which are presented in (4.39) and (4.40) can be reformulated as follows:

$$\text{OF.1.1.}a: \quad Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l})$$
$$+ \sum_{t=1}^{T}\gamma.\mathrm{P}(\mathrm{X}_s < \sum_{l=1}^{R_s}(\mathrm{V}_{s,l}.\mathrm{P}_{s,l})) \qquad (4.41)$$

and for the use of two types of renewable energy sources:

$$\text{OF.1.2.}a: \quad Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l})$$
$$+ \sum_{t=1}^{T}\gamma.\mathrm{P}(\mathrm{X}_s + \mathrm{X}_w < \sum_{l=1}^{R_s}(\mathrm{V}_{s,l}.\mathrm{P}_{s,l} + \sum_{l=1}^{R_w}(\mathrm{V}_{w,l}.\mathrm{P}_{w,l})) \qquad (4.42)$$

After presenting the objective function Type I, we can go through the second type of objective function.

4.4.2 Type 2: Penalizing The Failure Amount of Renewable Energy

The idea of objective function Type II is to directly penalizing the average amount of failure. It is obvious that as long as the the value of contracted option increases, the average amount of failure increases correspondingly. So, magnitude of failure amount is related to the contracted option and undoubtedly the renewable energy generation potential of the location of the generators. By linking all these ideas, the following objective function for the use of one type of renewable energy source with traditional source is proposed:

$$\text{OF.2.1}: \quad Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l})$$
$$+ \sum_{t=1}^{T}\gamma.\overline{\nabla_s} \qquad (4.43)$$

where,

γ : Penalty cost per unit.

$\overline{\nabla_s}$: Average failure amount based on contracted option for solar energy.

The idea applied for the mix of traditional and one type of renewable energy source can be implemented for the cases including the use of traditional energy source and two types of renewable energy sources as follows:

$$\text{OF.2.2}: \quad \mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) + \sum_{t=1}^{\mathrm{T}} \gamma.\overline{\nabla_s} + \sum_{t=1}^{\mathrm{T}} \gamma.\overline{\nabla_w} \tag{4.44}$$

Two types of objective functions have so far been proposed to deal with the uncertainty of the renewable energy sources. As the reader can realize, the developed constraints and the objective functions are presented in a global manner without specifying any probability distribution for the random variables. Therefore, it is aimed to present a general view to be able to tailor the proposed probabilistic constraints and the objective functions to the any given probability distribution for the random variables.

In the following section, the constructed probabilistic constraints (4.12),(4.14),(4.20),(4.25),(4.27),(4.28),(4.33),(4.38) and the objective functions (4.39)-(4.44) will be studied by considering a specific probability distribution, exponential distribution in our case, and mathematical models that take into account the stochastic nature of the renewable energy sources for the single-item lot sizing problem will be generated by merging the probabilistic constraints and the newly developed objective functions.

4.5 The Case Study Using the Exponential Distribution

In this part, the proposed constraints are expanded depending on the exponential distribution.

The availability of renewable energy resources is directly affected by their natural fluctuations, which can be presented as probability distributions Cai et al. [2009].

In the literature, the most widely used probability distribution for modelling the wind power generation is Weibull distribution. However, it is possible to come across the studies that implement Rayleigh distribution function as in the study of Gazijahani et al. [2018].

When it comes to the solar power generation, the most popular distribution used for modelling the stochastic solar power generation is Normal distribution. Beta distribution can be referred to the secondly most widely used distribution to model solar power generation. The study of Nikmehr and Ravadanegh [2016] is one of the examples that apply Beta distribution for modelling the solar power generation. For further detail, we refer the reader to the review of Mavromatidis et al. [2018]. They summarize the most commonly employed probability distribution functions for the characterization of the renewable energy sources in their study.

As Gazijahani et al. [2018] pointed out in their study, the wind power generation extremely appertain to wind speed and the solar power generation is dependent on the solar radiation and environment temperature. To model the wind energy availability, the first task is to generate wind speed samples by Weibull distribution which is a mathematical idealization of the distribution of wind speed over time (Nikmehr and Ravadanegh [2016], then these samples are transformed to power output by using "wind speed–power" curve.

The same approach is conducted for the solar power generation. In this case, the solar radiation is modelled via Beta distribution Nikmehr and Ravadanegh [2016] or Normal distribution as in the study of Tran and Smith [2019] and the power generation is computed by using the curve of "radiation-power".

In our study, we look for the probability of meeting the required renewable energy source by the energy supplier. To do so, it is required to model the uncertainty based on the "probability-power demand" curve. Since the power need increases, the risk not to meet the required power amount increases (see, Figure 4.2). Moreover, in recently published study of Kun et al. [2018], it is proved that, the "probability-power" distribution follows the exponential distribution in the case of wind speed is 2m/s. Based on this consideration:

- It is assumed that both of the random variables follow exponential distribution with the parameters λ_s and λ_w independently.
- Since the expected value of average generation of wind and solar energy sources are generally different, it is assumed that $\lambda_s \neq \lambda_w$.
- The values of λ solely depends on the type of the used renewable energy. Thus, for a renewable energy type, λ is the same for all periods.

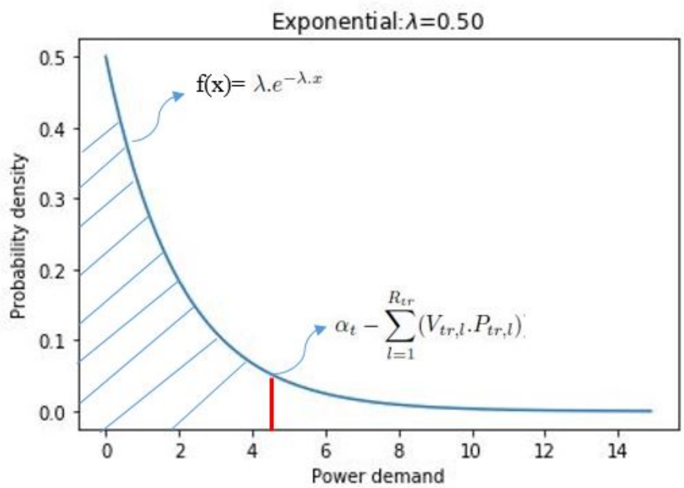

Figure 4.2: “Power Demand-Probability" relation according to the exponential distribution

To calculate the area under the curve in Figure 4.2, it is necessary to recall probability density function of the exponential distribution. It is known that when a continuous random variable X follows exponential distribution with parameter λ, its probability density function is defined as follows:

$$f(x) = \begin{cases} \lambda.e^{-\lambda.x} & x \geq 0; \\ 0 & x < 0; \end{cases}$$

In this section, the probabilistic constraints and the objective functions which have been presented in an a general manner in the previous section are expanded by considering the given definition of the probability density function of the exponential distribution.

4.5.1 Service Level Based Chance Constraints

Case 1: Required Renewable Energy Based Constraints

CS_1: Traditional Energy and One Type of Renewable Energy Source Consumption

Firstly, the service level based chance constraints will be tailored to the exponential distribution starting from the constraint (CS_1). After obtaining the equivalence of the constraint, it is merged with the model PS_0. Let's recall the constraint (CS_1) defined in (4.12):

$$P(X_s < \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \leq 1 - SL \qquad \forall t = 1, ..., T \tag{4.45}$$

The constraint (4.12) is illustrated in Figure 4.2 by assuming that the random variable (X_s) follows the exponential distribution. Based on the probability density function, the constraint (4.45) including random variable X_s which depicts the random availability of solar energy source with the parameter of λ_s can be transformed to:

$$\Longleftrightarrow \int_0^{\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})} f(x)dx \leq 1 - SL \qquad \forall t = 1, ..., T \tag{4.46}$$

$$\Longleftrightarrow 1 - e^{[-\lambda_s.(\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})]} \leq 1 - SL \qquad \forall t = 1, ..., T \tag{4.47}$$

$$\Longleftrightarrow -\lambda_s.(\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \geq ln(SL) \qquad \forall t = 1, ..., T \tag{4.48}$$

$$\Longleftrightarrow \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) \geq \frac{ln(SL)}{\lambda_s} + \alpha_t \qquad \forall t = 1, ..., T \tag{4.49}$$

Hence, the first constraint (CS_1) which is developed based on the required renewable energy is obtained by considering service level (*SL*) of industrial customer. The adaptation of the deterministic model (PS_0) developed for the single-item lot sizing problem with the capacity selection can be combined with the constraint (4.49) to take into account the random nature of the renewable energy source for the cases in which one type of renewable energy source is mixed with the traditional one as follows:

$$PS_1: \quad \text{Min } Z \tag{4.50}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraints for contract capacity selection: (3.126),(4.2)

$$\sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) \geq \frac{ln(SL)}{\lambda_s} + \alpha_t \qquad \forall t = 1,...,T \tag{4.51}$$

Thus, the model PS_1 is completed. In the following subsection, the same constraint is disclosed by considering the use of two types of renewable energy sources.

CS_2**: Traditional Energy and Two Types of Renewable Energy Sources Consumption**

To deal with the uncertain nature of the renewable energy sources in the cases which two types of renewable energy sources are mixed with the traditional one, the constraint (4.13) have been developed according to the required renewable energy sources. Let's recall the proposed constraint (4.13):

$$P(X_s + X_w < (\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}P_{tr,l})) \leq 1 - SL \qquad \forall t = 1,...,T \tag{4.52}$$

where;
X_s: Random variable of solar energy source.
X_w: Random variable of wind energy source.

For simplicity, the right hand side of the constraint have been translated as $Q_t = (\alpha_t - \sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})$ and the constraint have been reformulated as follows:

$$\iff P(X_s + X_w < Q_t) \leq 1 - SL \qquad \forall t = 1,...,T \tag{4.53}$$

When it comes to the left side of the inequality, it has been explained that it is necessary to obtain the convolution product for the probability density function of the sum of the two independent random variables. For better sense, let's remember the given formulation of the convolution:

$$(f * g)(z) = \int_{-\infty}^{\infty} f(z-y) g(y) d_y \tag{4.54}$$

In our case study, it is assumed that the random variables follow the exponential distributions. The convolution of the two exponential distribution is studied by Oguntunde et al. [2014] comprehensively. Inspiring from their study, let's consider a random variable X following the exponential distribution with the parameter λ_1 and another random variable Y following the exponential distribution with parameter λ_2 and $Z = X + Y$ has the following probability density function:

$$h(z) = \int_0^z \lambda_1 . e^{(-\lambda_1(z-y))} \lambda_2 . e^{(-\lambda_2(y))} d_y \tag{4.55}$$

$$\iff h(z) = \lambda_1 \lambda_2 . e^{(-\lambda_1 z)} \int_0^z e^{(\lambda_1 - \lambda_2) y} d_y \tag{4.56}$$

$$\iff h(z) = \lambda_1 \lambda_2 . e^{(-\lambda_1 z)} [\frac{e^{(\lambda_1 - \lambda_2) z} - 1}{\lambda_1 - \lambda_2}] \tag{4.57}$$

$$\iff h(z) = (\frac{\lambda_1 \lambda_2}{\lambda_1 - \lambda_2}) [e^{(-\lambda_2 z)} - e^{(-\lambda_1 z)}] \tag{4.58}$$

After obtaining the convolution function, left part of the chance constraint (4.53) can be rewritten as:

$$P(X_s + X_w < Q_t) = \int_0^{Q_t} (\frac{\lambda_1 \lambda_2}{\lambda_1 - \lambda_2}) [e^{(-\lambda_2 z)} - e^{(-\lambda_1 z)}] d_z \qquad \forall t = 1, ..., T \tag{4.59}$$

$$\iff P(X_s + X_w < Q_t) = \frac{\lambda_1 . (1 - e^{-\lambda_2 . Q_t}) - \lambda_2 (1 - e^{-\lambda_1 . Q_t})}{\lambda_1 - \lambda_2} \qquad \forall t = 1, ..., T \tag{4.60}$$

Then, the equivalence of the constraint (4.53) becomes:

$$\frac{\lambda_1 . (1 - e^{-\lambda_2 . Q_t}) - \lambda_2 (1 - e^{-\lambda_1 . Q_t})}{\lambda_1 - \lambda_2} \leq 1 - SL \qquad \forall t = 1, ..., T \tag{4.61}$$

with the notations λ_s, λ_w as parameters of the laws:

$$\frac{\lambda_s (1 - e^{-\lambda_w . Q_t}) - \lambda_w (1 - e^{-\lambda_s Q_t})}{\lambda_s - \lambda_w} \leq 1 - SL \qquad \forall t = 1, ..., T \tag{4.62}$$

$$\frac{\lambda_s(1-e^{-\lambda_w.(\alpha_t-\sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})})-\lambda_w(1-e^{-\lambda_s(\alpha_t-\sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})})}{\lambda_s-\lambda_w} \leq 1-SL \qquad \forall t=1,...,T \quad (4.63)$$

The obtained equivalence in (4.63) of the proposed chance constraint (4.13) can be combined with the adapted deterministic model PS_0 as it is done for the previously presented model PS_1 as follows:

$$PS_2: \quad \text{Min } Z \tag{4.64}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraint for contract capacity selection: (3.126),(4.2)

$$\frac{\lambda_s(1-e^{-\lambda_w.(\alpha_t-\sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})})-\lambda_w(1-e^{-\lambda_s(\alpha_t-\sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})})}{\lambda_s-\lambda_w} \leq 1-SL \qquad \forall t=1,...,T \tag{4.65}$$

As it is applied in PS_1, all the constraints of PS_0 are kept as they are and the constraint (4.63) is added to the model PS_0, then, the new model that takes into the randomness of the two types of renewable energy sources while selecting the contract capacity under the production constraints is built.

Thus far, the first type of the proposed service level chance constraints, which calculates the probability of the availability according to the real renewable energy need of the system, is tailored to the exponential distribution.

In the following section, the second type of constraint under the same cap, which is constructed according to the contracted amount of renewable energy source will be expanded to the exponential distribution.

Case 2: Contracted Renewable Energy Based Chance Constraints

CS_3**: Traditional Energy and One Type of Renewable Energy Source Consumption**

In the Case 2, the probability of the availability of the renewable energy sources have been calculated based on the contracted power option for the renewable sources. As in the previously studied Case 1, the mix of one type of renewable energy source and traditional source has been considered and the constraint (4.20) have been proposed:

$$P(X_s < \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})) \leq 1-SL \qquad \forall t = 1,...,T \tag{4.66}$$

where;
SL: minimum service level defined by industrial customer
X_s: random variable of the available quantity for solar energy source
$\sum_{l=1}^{R_s} V_{s,l}.P_{s,l}$: contracted capacity option for solar energy source

Based on the given definition of probability density function of the exponential distribution, the constraint (4.66) is transformed as follows:

$$\int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} f(x)dx \leq 1-SL \qquad \forall t = 1,...,T \tag{4.67}$$

$$\Longleftrightarrow 1-e^{[-\lambda_s.(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})]} \leq 1-SL \qquad \forall t = 1,...,T \tag{4.68}$$

$$\Longleftrightarrow e^{[-\lambda_s.(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}))]} \geq SL \qquad \forall t = 1,...,T \tag{4.69}$$

Therefore, the equivalence of the proposed chance constraint is obtained:

$$\Longleftrightarrow \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) \leq \frac{ln(SL)}{-\lambda_s} \qquad \forall t = 1,...,T \tag{4.70}$$

When the constraint (4.70) is converged with the deterministic model PS_0, the promised model which takes into account the probability of the availability of the renewable energy source according to the contracted amount of energy is constructed as follows:

$$PS_3: \quad \text{Min } Z \tag{4.71}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraint for contract capacity selection: (3.126),(4.2)

$$\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) \leq \frac{ln(SL)}{-\lambda_s} \qquad \forall t = 1,...,T \tag{4.72}$$

In the following section, the second version of the same constraint which is proposed for the cases in which the customers prefer to blend two types of renewable energy sources with the traditional one is adapted according to the exponential distribution.

CS_4**: Traditional Energy and Two Types of Renewable Energy Source Consumption**

The constraint (4.25) has been developed for integrating the uncertainty aspect to the deterministic model for the aforementioned purpose. To work out the equivalence of the presented probabilistic constraint, let's recall it first:

$$P(X_s + X_w < Q_t) \leq 1 - SL \qquad \forall t = 1,...,T \tag{4.73}$$

where;
X_s: Random variable of solar energy source.
X_w: Random variable of wind energy source.
Q_t has been defined as follows: $Q_t = \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) + \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})$

The left hand side of the constraint (4.25) involves the sum of the distributions of two independent random variables as in the constraint (4.14). To get the probability density function of the sum of the continuous random variables on the left hand side of the inequality in (4.73), the convolution product has been calculated in (4.60) as follows:

$$P(X_s + X_w < Q_t) = \frac{\lambda_1.(1-e^{-\lambda_2.Q_t}) - \lambda_2(1-e^{-\lambda_1.Q_t})}{\lambda_1 - \lambda_2} \tag{4.74}$$

the equivalence of the constraint (4.25) with the parameters of the distributions λ_s, λ_w is obtained:

$$\frac{\lambda_s(1-e^{-\lambda_w.Q_t}) - \lambda_w(1-e^{-\lambda_s Q_t})}{\lambda_s - \lambda_w} \leq 1 - SL \qquad \forall t = 1,...,T \tag{4.75}$$

In summary, the constraint (4.25) differs from its pair (4.14) which is proposed for the Case 1 in terms of the definition of Q_t. Therefore, the new model is built:

$$PS_4: \quad \text{Min } Z \tag{4.76}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraint for contract capacity selection: (3.126),(4.2)

$$\frac{\lambda_s(1-e^{-\lambda_w(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})+\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}))})-\lambda_w(1-e^{-\lambda_s(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})+\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}))})}{\lambda_s-\lambda_w} \leq 1-SL \qquad \forall t=1,...,T \tag{4.77}$$

Therefore, all the proposed service level based chance constraints are expanded by considering the exponential distribution for the random variables. In the subsequent section, the second group of constraints which is defined as "*Average Power Amount Based Probabilistic Constraints*" displayed in Figure 4.1 and studied in Section 4.3.2 are converted to their equivalences with the exponential distribution consideration.

4.5.2 Average Power Amount Based Probabilistic Constraints

In the constraints proposed in this group, it is aimed to integrate the uncertain nature of the renewable energy in the form of the average value of the random variables. While presenting the general form of the constraint in Section 4.3.2, the following formula has been given

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx \tag{4.78}$$

to calculate the mean of the random variables. By applying the defined formula in (4.78), the expected value of the random variable x that follows the exponential distribution with the parameter λ is:

$$\iff E(x) = \int_{-\infty}^{\infty} x(\lambda.e^{-\lambda.x})dx \tag{4.79}$$

$$\iff E(x) = \frac{1}{\lambda} \tag{4.80}$$

For the mix of the traditional energy source with one type of renewable energy source and two types of renewable energy sources, the constraints (4.27) and (4.28) have been proposed, respectively:

$$\alpha_t \leq \sum_{l=1}^{R_{tr}}(V_{tr,l}P_{tr,l}) + E[X_s] \qquad \forall t=1,...,T \tag{4.81}$$

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l} P_{tr,l}) + E[X_s] + E[X_w] \qquad \forall t = 1, \ldots, T \tag{4.82}$$

where;

α_t : the power need during period t.

$\sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})$: Selected capacity option for traditional energy source.

$E[X_s]$: Expected value for solar power generation.

$E[X_w]$: Expected value for wind power generation.

Based on the calculated expected value in (4.80) the equivalence of the constraints (4.27) and (4.28) are acquired by taking into account the λ_s and λ_w as the parameters of distributions as follows:

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) + \frac{1}{\lambda_s} \qquad \forall t = 1, \ldots, T \tag{4.83}$$

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) + \frac{1}{\lambda_s} + \frac{1}{\lambda_w} \qquad \forall t = 1, \ldots, T \tag{4.84}$$

When the proposed constraint is blended with the presented mathematical model, two more mathematical models (PS_5) and (PS_6) which can help decision makers who need to define optimum production lot sizes which can satisfy the demand and minimize the related costs under renewable energy uncertainty can be :

$$PS_5: \quad \text{Min } Z \tag{4.85}$$

subject to:

the production related constraints: (3.57-3.71)

the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)

the constraint for contract capacity selection: (3.126)-(4.2)

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) + \frac{1}{\lambda_s} \qquad \forall t = 1, \ldots, T \tag{4.86}$$

and

$$PS_6: \quad \text{Min } Z \tag{4.87}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraint for contract capacity selection: (3.126)-(4.2)

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) + \frac{1}{\lambda_s} + \frac{1}{\lambda_w} \qquad \forall t = 1, ..., T \tag{4.88}$$

Hence, the general form of the second group of constraints which are developed by taking into account expected power amount of the renewable energy sources are improved according to the exponential function.

In the following section, the last group of constraints are enhanced in the similar fashion and the attained equivalences of the previously proposed constraints are merged with the retouched deterministic model (PS_0). The last two models PS_7 and PS_8 are presented.

4.5.3 Average Failure Amount Based Probabilistic Constraints

In this group of constraints, it has been aimed to calculate the expected amount of renewable energy that might not be supplied by the energy supplier due to the uncertain nature of the weather-dependent sources. Therefore, the customers can constitute their energy mix which must cover the power need of the system by taking into account the risky amount of energy. For the customers who prefer to combine the traditional energy source with one type of renewable energy, the constraint (4.33) has been developed. Let's recall it to expand:

$$\alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - [\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} f(x)dx - \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.f(x)dx] \tag{4.89}$$

$$\forall t = 1, ..., T$$

When the function *f(x)* in constraint (4.89) is replaced with the probability density function of the exponential distribution, we obtain:

$$\iff \alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - [\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} (\lambda_s.e^{-\lambda_s.x})dx \tag{4.90}$$
$$- \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.(\lambda_s.e^{-\lambda_s.x})dx] \quad \forall t = 1, ..., T$$

After the integration procedure, the equivalence of the constraint (4.89) is obtained as follows:

$$\alpha_t \leq \sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - [(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})}}{\lambda_s})] \quad \forall t = 1,...,T \tag{4.91}$$

The constraint which has been proposed for the use of the traditional energy source with the two types of renewable sources with the same purpose can be converted in the same way and the following constraint is acquired:

$$\begin{aligned}\alpha_t \leq \sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - [(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})}}{\lambda_s})] \\ -[(\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}) - \frac{1}{\lambda_w} + \frac{e^{-\lambda_w * \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})}}{\lambda_w})] \quad \forall t = 1,...,T\end{aligned} \tag{4.92}$$

When the developed constraints are integrated to the adapted deterministic model (PS_0), since the sum of the contracted capacity is already considered in (4.89), the constraint (4.2) in the model PS_0 becomes redundant. That's why, different from the previously presented models including probabilistic constraints, instead of directly adding the developed probabilistic constraint, the constraint (4.2) is removed and the expanded constraint (4.91) and (4.92) are added to PS_0 to construct the last models PS_7 and PS_8 as follows:

$$PS_7: \quad \text{Min } Z \tag{4.93}$$

subject to:
the production related constraints: (3.57-3.71)
the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraint for contract capacity selection: (3.126)

$$\alpha_t \leq \sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - [(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})}}{\lambda_s})] \quad \forall t = 1,...,T \tag{4.94}$$

and

$$PS_8: \quad \text{Min } Z \tag{4.95}$$

subject to:
the production related constraints: (3.57-3.71)

the initial and general conditions constraints: (3.74-3.84) and (3.86),(3.120-3.122) the constraints for peak power calculation: (3.114)-(3.116)
the constraint for contract capacity selection: (3.126)

$$\alpha_t \leq \sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - [(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})}}{\lambda_s})]$$
$$-[(\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}) - \frac{1}{\lambda_w} + \frac{e^{-\lambda_w * \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})}}{\lambda_w})] \quad \forall t = 1,...,T \tag{4.96}$$

Therefore, all the proposed probabilistic constraints have been expanded by considering the exponential distribution for the random variables which represent the availability of renewable energy sources. The equivalences of the constraints have been merged with the adaptation (PS_0) of the deterministic model developed (P_3) for the single-item lot sizing problem for flow shop systems with capacity selection consideration in the previous section.

To build the stochastic models, as the last step, the equivalences of the proposed objective functions will be obtained in the next section.

4.5.4 Developed Objective Functions

Two types of objective functions have been proposed to evaluate the cost of the failure in the supply of the renewable energy sources. In this section, they will be recalled and worked out with the consideration of the exponential distribution.

Type 1: Penalizing The Probability of Failure

Let's remember the first objective function (4.39) which is proposed to calculate the cost of the probability of failure:

$$Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l})$$
$$+ \sum_{t=1}^{T}\gamma.P(X_s < \alpha_t - \sum_{l=1}^{R_{tr}}(V_{tr,l}.P_{tr,l})) \tag{4.97}$$

where,
γ: Penalty cost
X_s: Random availability of solar energy source.
$\alpha_t - \sum_{l=1}^{R_{tr}}(V_{tr,l}.P_{tr,l})$: Required amount for renewable energy source.

The last part of the objective function calculates the penalty costs when the availability of the renewable source is less than renewable energy need of the system. Since this part is the same with the constraint developed in (4.45) for the model PS_1, the objective function can be reformulated as follows:

$$\mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma. \int_0^{\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})} f(x)dx \tag{4.98}$$

by considering λ_s as parameter, objective function given in (4.98) becomes ready for the integration:

$$\mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma. \int_0^{\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})} (\lambda_s.e^{-\lambda_s.x})dx \tag{4.99}$$

After the integration, the equivalence of the developed objective function is obtained:

$$\mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma.(1 - e^{[-\lambda_s.(\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})]}) \tag{4.100}$$

For the cases in which the traditional energy source is blended with two types of renewable sources, the objective function given in (4.40) has been proposed:

$$\mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma.\mathrm{P}(\mathrm{X}_s + \mathrm{X}_w < \alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})) \tag{4.101}$$

The sum of the distributions of two random variables has been studied previously for the constraint (4.13) and after applying the convolution, it has been transformed to the equation (4.60). With the parameters λ_s and λ_w, the equivalence in (4.60) can be used for penalizing the failure probability and the following objective function is constructed for the mix of the traditional energy and two types of renewable energy sources:

$$\begin{aligned}\mathrm{M}inz = &\sum_{t=1}^{\mathrm{T}}\sum_{m=1}^{\mathrm{N}}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k}\sum_{k=1}^{\mathrm{K}}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l}) \\ &+ \sum_{t=1}^{\mathrm{T}}\gamma.\frac{\lambda_s.(1-e^{-\lambda_w.(\alpha_t-\sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})}) - \lambda_w(1-e^{-\lambda_s.(\alpha_t-\sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})})}{\lambda_s-\lambda_w}\end{aligned} \tag{4.102}$$

Q_t: $\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})$: Required amount of renewable energy source.

Specifically for this type of constraint, we would like to draw the attention of the readers to the expression $(\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l}))$ which calculates the required amount of renewable energy. Since the objective function forces to minimize the total cost, to prevent $(\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l}))$ to take any negative value, the objective function in (4.100) is formulated in an alternative way by assigning a new variable $\mathrm{Q}_t = (\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l}))$ and introducing new constraints which can guarantee Q_t is positive. Accordingly, the objective function (4.100) becomes:

$$\begin{aligned}\mathrm{M}inz = &\sum_{t=1}^{\mathrm{T}}\sum_{m=1}^{\mathrm{N}}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k}\sum_{k=1}^{\mathrm{K}}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l}) \\ &+ \sum_{t=1}^{\mathrm{T}}\gamma.(1-e^{-\lambda_s.\mathrm{Q}_t})\end{aligned} \tag{4.103}$$

Similarly, the objective function displayed in (4.102) which has been developed for the mix of the two types of energy sources is reformulated as follows:

$$\begin{aligned}\mathrm{M}inz = &\sum_{t=1}^{\mathrm{T}}\sum_{m=1}^{\mathrm{N}}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k}\sum_{k=1}^{\mathrm{K}}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l}) \\ &+ \sum_{t=1}^{\mathrm{T}}\gamma.\frac{\lambda_s.(1-e^{-\lambda_w.\mathrm{Q}_t}) - \lambda_w(1-e^{-\lambda_s.\mathrm{Q}_t})}{\lambda_s-\lambda_w}\end{aligned} \tag{4.104}$$

and the following constraints are added to the model:

$$\mathrm{Q}_t \geq 0 \qquad \forall t = 1,\ldots,\mathrm{T} \tag{4.105}$$

$$\mathrm{Q}_t \geq \alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}}(\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l}) \qquad \forall t = 1,\ldots,\mathrm{T} \tag{4.106}$$

Therefore, the equivalences of the objective functions in (4.100) and (4.101) are obtained in (4.103) and (4.104). By replacing the current objective functions of the previously presented models PS_1, PS_2, PS_3, PS_4, PS_5, PS_6, PS_7, PS_8 with the objective functions presented in (4.103) and (4.104) and adding the constraints (4.105) and (4.106), the cost of the probability of the failure can be considered in the objective function of the models.

Type 2: Penalizing The Average Failure Amount of Renewable Energy

In the second type of objective function, the expected failure amount is penalized directly. Let's recall the proposed objective functions for the combination of the traditional source with the one type of renewable energy source and two types of renewable sources, respectively:

$$\begin{aligned} Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) \\ + \sum_{t=1}^{T}\gamma.\overline{\nabla_s} \end{aligned} \tag{4.107}$$

$$\begin{aligned} Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) \\ + \sum_{t=1}^{T}\gamma.\overline{\nabla_s} + \sum_{t=1}^{T} + \gamma.\overline{\nabla_w} \end{aligned} \tag{4.108}$$

where,

γ : Penalty cost per unit.

$\overline{\nabla_s}$: Average failure amount based on contracted option for solar energy.

$\overline{\nabla_w}$: Average failure amount based on contracted option for wind energy.

Expected failure amount of the renewable energy sources has been studied before in the form of constraint. The equivalence of the constraint (4.29) has been obtained in (4.91) and the expected value has been calculated as follows:

$$\nabla_s = [(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})}}{\lambda_s})] \tag{4.109}$$

By replacing the $\overline{\nabla_s}$ and $\overline{\nabla_w}$ in the objective functions (4.107) and (4.108) with the formula of expected value displayed in (4.109), the expected failure amount based objective functions are acquired as follows:

$$\begin{aligned} Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) \\ + \sum_{t=1}^{T}\gamma.[(\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})}}{\lambda_s})] \end{aligned} \tag{4.110}$$

$$\begin{aligned} Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(\mathrm{V}cost_{k,l}\mathrm{P}_{k,l}) \\ + \sum_{t=1}^{T}\gamma.[(\sum_{l=1}^{R_s}(\mathrm{V}_{s,l}.\mathrm{P}_{s,l}) - \frac{1}{\lambda_s} + \frac{e^{-\lambda_s * \sum_{l=1}^{R_s}(\mathrm{V}_{s,l}.\mathrm{P}_{s,l})}}{\lambda_s})] \\ + \sum_{t=1}^{T}\gamma.[(\sum_{l=1}^{R_w}(\mathrm{V}_{w,l}.\mathrm{P}_{w,l}) - \frac{1}{\lambda_w} + \frac{e^{-\lambda_w * \sum_{l=1}^{R_w}(\mathrm{V}_{w,l}.\mathrm{P}_{w,l})}}{\lambda_w})] \end{aligned} \tag{4.111}$$

The expanded objective functions (4.110) and (4.111) can be used by substituting the current objective functions of the presented models which include probabilistic constraints.

So far, the equivalences of the proposed probabilistic constraints and the objective functions have been obtained with the exponential distribution consideration. In the subsequent section, the Mixed Integer Non-Linear Programming models which are built by combining the proposed constraints and the objective functions will be tested on a small size instance and the results are analyzed in detail.

4.6 Numerical Study

In this section, with the aim of validation of the proposed models, different combinations of the proposed constraints and objective functions are tested on an illustrative example and the results are discussed in detail. Since the proposed models involve non linear components, they are solved by LINGO 18.0 on an Intel Core i7 with 2.7 GHz and 8 GB RAM. In the numerical example, three machines (N=3) are considered and the planning horizon is split into three periods (T=3). The machine and period related data which are generated according to the data generation procedure that is explained in Section 3.3.5, are given in Table 4.1 and Table 4.2. In Table 4.3, contract options for different types of energy sources which are offered by energy supplier and corresponding prices are given. In this example, it is assumed that the traditional energy sources are more expensive than the renewable energy sources. Therefore, it is aimed to constitute a trade-off between the *costly-reliable* and *cheaper - less reliable* options.

Table 4.1: Time related data of Instance N3_T3

Period (t)	1	2	3
d_t *(piece)*	53	47	75
L_t *(min)*	1080	360	1080
Co_t *($/KWh)*	0,16	0,08	0,16
w_1, t *($)*	74	52	91
w_2, t *($)*	64	89	99
w_3, t *($)*	57	96	75

Table 4.2: Machine related data of Instance N3_T3

machine(m)	1	2	3
ϕ_m(KW)	8	9	7
p_m (min)	5	6	6

Table 4.3: Contract options

Trad.	*Vcost($)*	Solar	*Vcost($)*	Wind	*Vcost($)*
3 KW	75	2 KW	30	3 KW	20
6 KW	82,5	4 KW	35	5 KW	25
9 KW	120	6 KW	40	7 KW	30
12 KW	135	8 KW	50	11 KW	40
15 KW	150	10 KW	60	13 KW	50
18 KW	300	12 KW	85	15 KW	75
24 KW	375	14 KW	120	17 KW	100

As it is pointed out before, the main parameter describing the stochastic nature of the renewable energy sources is λ_s , used for solar energy and λ_w, used for wind energy. In Figure 4.3 and Figure 4.4, different availability levels of the wind and solar energy sources are displayed. Accordingly, it can be said that when the λ_w values are equal to 0.04 and 0.02 wind energy source is pretty reliable, however, when the λ_w is equal to 0.2, the wind energy source is less reliable. The high reliability levels such as λ_w=0.04 or 0.02 are introduced to the instance intentionally, in order to analyze the behaviour of the model while selecting the best contract options when the reliability of the renewable source is nearly same with the deterministic case.

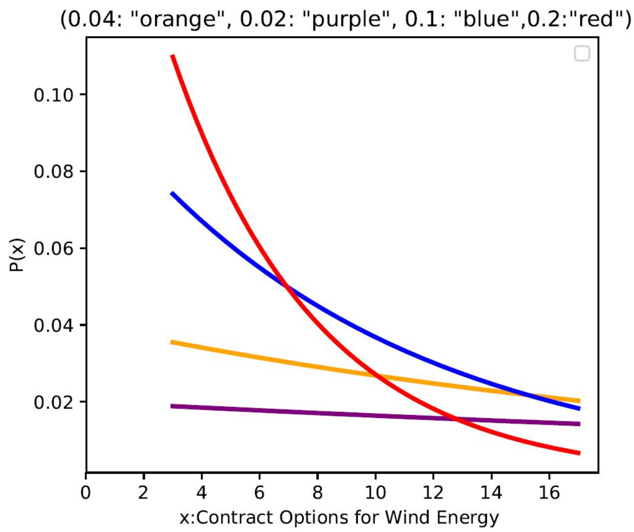

Figure 4.3: Reliability levels to contract options of wind energy

The reliability to the contract options of solar energy in Figure 4.4 can be interpreted in the same way. While the λ_s= 0.75 and λ_s=1, promise the less reliability, under the weather conditions where the availability of solar energy is expressed with λ_s=0.1, the solar energy becomes more reliable for the end-users. The numerical study is implemented by con-

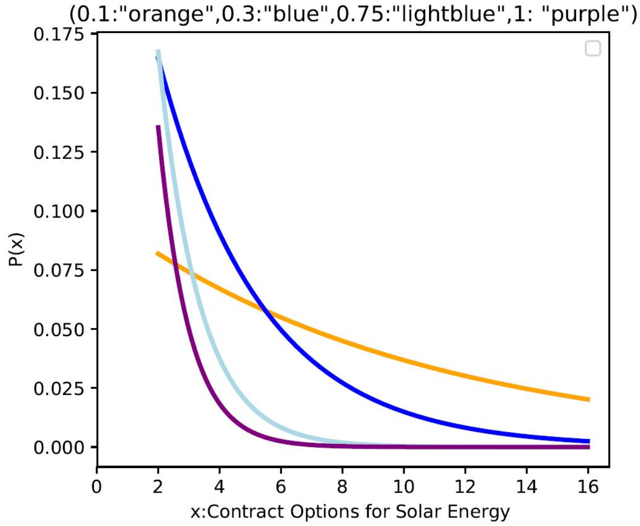

Figure 4.4: Reliability levels to contract options of solar energy

sidering the different λ_w and λ_s values which are displayed in Figure 4.3 and Figure 4.4. Each of the developed constraints is combined with the proposed any of the two types of objective functions and the instance given in Table 4.2 and Table 4.3 is tested for each of the constructed models.

Service Level Based Models with Objective Function Type I, One Type of RES and Traditional Mix

The Model Obtained with The Objective Function Type I (OF.1.1) and Model PS_1

First of all, the objective function Type I is integrated to the model PS_1 and the results are presented in Table 4.4. Accordingly, in the objective function, the cost of the probability of failure is added to the production and energy related costs. Therefore, it is aimed to find the best production and energy mix configurations which can satisfy promised service level by taking into account the probability of meeting the required renewable energy. In Table 4.5 and Table 4.6, the results of the model in which the objective function Type I and the model PS_3 are shown. In Figure 4.5 the production configuration of the models $\mathrm{PS}_1, \mathrm{PS}_3, \mathrm{PS}_5, \mathrm{PS}_7$ which are merged with the objective function Type I is illustrated.

In Table 4.4, the first noticeable result is that as long as the service level is increased, the manufacturer tend to mix the renewable energy source with more traditional energy source to be on the safe side. This tendency can be clearly observed in the results of the model where the service level is assumed 0.99. As it can be seen in the Table 4.4, since the λ_w=0.04 or λ_w=0.02 guarantee more reliability, the customer can choose more renewable energy sources compared to the less reliable circumstances where the λ_w=0.2 or λ_w=0.1. While the customer can guarantee to realize the production with 50% (SL=0.5), by mixing

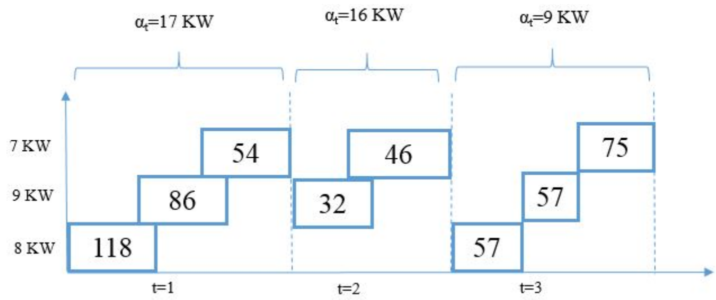

Figure 4.5: The production configuration of objective function Type 1+PS_1,PS_3, PS_5,PS_7

Table 4.4: The results of the model PS_1+ objective function OF.1.1

Service Level	λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
SL=0.5	0.2	15-3	1210.7	15
	0.1	12-5	1202.8	11
	0.04	6-11	1166.07	13
	0.02	6-11	1162.46	30
SL=0.9	0.2	18-3	1355.59	19
	0.1	18-3	1355.59	33
	0.04	15-3	1206.75	19
	0.02	12-5	1197.31	21
SL=0.99	0.2	18-3	1355.59	20
	0.1	18-3	1355.59	21
	0.04	18-3	1355.59	21
	0.02	18-3	1355.59	19

15 KW traditional and 3 KW wind sources under λ_w=0.2, he can satisfy the same service level by mixing 6 KW traditional and 11 KW wind source when the λ_w is changed to 0.04. The results for the other service levels can be interpreted in the same way.

Table 4.5: The results of the model PS_3+ objective function OF.1.1.a

Service Level	λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
SL=0.5	0.2	15-3	1219.12	<1
	0.1	12-5	1207.39	<1
	0.04	6-11	1168.77	<1
	0.02	6-11	1164.01	<1
SL=0.9	0.2	No feasible		
	0.1	No feasible		
	0.04	No feasible		
	0.02	12-5	1198.44	5
SL=0.99	0.2	No feasible		
	0.1	No feasible		
	0.04	No feasible		
	0.02	No feasible		

The Model Obtained with The Objective Function Type I (OF.1.1.a) and Model PS_3

The second version of the first proposed service level based constraint is built on the probability of meeting the contracted power (PS_3). This constraint is more rigid than the first version (PS_1). The stiffness of the constraint is proved by the results of the numerical test shown in Table 4.5. First noticeable result is that when the 0.5 service level is guaranteed by the manufacturers, they negotiate for the same mixes with the first type of constraint however, accept to pay more. Because, according to the changing constraint the cost of the failure probability is changed from :

$$Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) \\ + \sum_{t=1}^{T}\gamma.P(X_s < \alpha_t - \sum_{l=1}^{R_{tr}}(V_{tr,l}.P_{tr,l})) \tag{4.112}$$

To:

$$Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) \\ + \sum_{t=1}^{T}\gamma.P(X_w < \sum_{l=1}^{R_{tr}}(V_{w,l}.P_{w,l})) \tag{4.113}$$

In other words, the customer purchase the rigidness by paying more. The other observable result, while the production is feasible under service level 0.9 and 0.99 when the objective function is applied to the model PS_1 (Table 4.4), when it comes to the results of the model PS_3 (Table 4.5), it is not possible to realize the production by guaranteeing the service level 0.99. The service level 0.9 can be satisfied only the reliability of wind energy source is significantly increased like to 0.02 the manufacturer can satisfy the demand with the confidence of 0.90% by mixing the 12 KW traditional and 5 KW wind energy sources.

To give a better insight to the manufacturers, in Table 4.6, it is sought for the maximum service level under given reliability levels of the renewable sources. So, the handled instance is tested different service levels between 0.5 and 0.9 such as 0.6, 0.7 and 0.8. In the end, it can be said that the service level which certainly can not be guaranteed is 0.99. The manufacturer can satisfy the demand of the customers by mixing the different amount of energy options by promising the other service levels. It can be pointed out that when the service level is increased incrementally, the less reliable conditions (λ_w=0.2, λ_w=0.1) make the realizing the production impossible.

Average Power Amount Based Models with Objective Function Type I, One Type of RES and Traditional Mix

Table 4.6: The results of the model PS_3+ objective function OF.1.1.a (continued)

Service Level	λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
SL=0.60	0.2	No feasible	1219.12	<1
	0.1	12-5	1207.39	<1
	0.04	6-11	1168.77	<1
	0.02	6-11	1164.01	<1
SL=0.70	0.2	No feasible		
	0.1	15-3	1213.36	<1
	0.04	15-3	1208.98	<1
	0.02	6-11	1164.01	<1
SL=0.8	0.2	No feasible		
	0.1	No feasible		
	0.04	12-5	1201.02	<1
	0.02	6-11	1164.01	<1

In Table 4.7, the service level is left out of the context and the uncertainty in the availability of the renewable energy source is handled by considering the expected availability of the renewable energy source. The objective function Type I (OF.1.1) is merged with the probabilistic model PS_5. The results in Table 4.7 clearly show that, as it can be observed in the results shown in Table 4.5 and Table 4.6, increasing reliability allows the manufacturers to generate energy mix with more renewable energy source.

Table 4.7: The results of the model PS_5+ objective function OF.1.1

λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
0.2	12-5	1207.41	16
0.1	12-5	1202.82	49
0.04	6-11	1166.07	15
0.02	6-11	1162.46	25

The other outcome of the test is that the expected availability based constraint is softer than the service level based chance constraint whose results are exhibited in Table 4.4. To explain the difference between them in a better way, the case where λ_w=0.2 can be reviewed. In Table 4.4, when the objective function Type I (OF.1.1) is combined with PS_1, the following probabilistic constraint plays a role:

$$\sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) \geq \frac{ln(SL)}{\lambda_s} + \alpha_t \qquad \forall t = 1,...,T \tag{4.114}$$

The existence of service level imposes to the model to choose a value which is greater than 13,535 as in the following:

$$\sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) \geq \frac{-0,693}{0,2} + \alpha_t \qquad \forall t = 1, ..., T \tag{4.115}$$

where ln(0,5)=0,693 and α_1=17 KW as in the Figure 4.5 for period *t=1*. So, traditional energy is selected as 15 KW. However, when the expected availability based constraint is applied for the conditions where λ_w=0.2:

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) + \frac{1}{\lambda_w} \qquad \forall t = 1, ..., T \tag{4.116}$$

$$\alpha_t \leq \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}) + 5 \qquad \forall t = 1, ..., T \tag{4.117}$$

The model combines the available renewable energy with the less traditional energy source and covers the power need of the machines.

Average Failure Amount Based Models with Objective Function Type I, One Type of RES and Traditional Mix

Lastly, the objective function Type I (O.F.1.1) is integrated to the model PS_7. If the customer prefers to negotiate with the energy supplier according to expected failure amount of the renewable energy options, he can reach an agreement with the energy supplier by purchasing more renewable energy source compared to the other types of constraints as shown Table 4.8. As it can be observed in the other propositions, as long as the reliability of the wind energy source is increased, the customer can purchase less traditional source by relying on the renewable energy option since the increasing reliability leads to less amount of the expectation in the failure. This approach of the model can be be seen when the λ_w is changed from 0.2 to 0.1; from 0.04 to 0.02.

Table 4.8: The results of the model PS_7+ objective function OF.1.1

λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
0.2	15-3	1210.7	19
0.1	12-7	1207.82	24
0.04	9-11	1200.77	19
0.02	6-13	1172.46	23

After integrating the objective function Type I with the developed probabilistic models, the given instance is tested by merging the objective function Type II with the same models (PS_1, PS_3, PS_5, PS_7). Different from the objective function Type I, instead of average cost of the probability of failure, the cost of expected amount of failure in renewable energy source is added to the production and power subscription costs in the objective function. In Table 4.9, Table 4.10, Table 4.11, Table 4.12 and Table 4.13 the obtained results are presented. The production configuration shown in Figure 4.5 does not change.

Service Level Based Models with Objective Function Type II, One Type of RES and Traditional Mix

Since the tested mathematical models are the same (PS_1) in Table 4.4 and Table 4.9 except the objective functions, comparing the results of two models gives perfect sense to compare the impact of the two different types of objective functions. The most noticeable result is that the model produces same contract values with the higher costs compared to the costs in Table 4.4 for the service levels 0.9 and 0.99. When it comes to the service level 0.5, the manufacturer has the tendency to generate the energy mix with the smaller amount of wind energy sources compared to the model in Table 4.4. The main idea behind this behaviour of the model is that under a given reliability level, an increase in the amount of the contracted wind energy source causes an increase in the the expected failure amount, too.

Let's consider the case λ_w=0.04. Can the model tested in Table 4.9 choose the values 6 and 11 when the reliability λ=0.04 as in the Table 4.4 when SL=0.5? If the model tested in Table 4.9 had selected the values of 6 and 11 KW for traditional and wind energy sources respectively, under λ_w=0.04, as in the Table 4.4, the cost of the expected rupture would be:

$$Minz = \sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}x_{m,t} + hI_{m,t} + w_{m,t}y_{m,t}) + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) + \sum_{t=1}^{T}\gamma.[(\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}) - \frac{1}{\lambda_w} + \frac{e^{-\lambda_w * \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})}}{\lambda_w})] \quad (4.118)$$

(it is known that the same production configuration is obtained with two models, so the production cost is the same)

$$Minz = ... + \sum_{l=1}^{R_k}\sum_{k=1}^{K}(Vcost_{k,l}P_{k,l}) + \sum_{t=1}^{T}\gamma.[(\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l}) - \frac{1}{\lambda_w} + \frac{e^{-\lambda_w * \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})}}{\lambda_w})] \quad (4.119)$$

Where $(V_{w,l}.P_{w,l})$=11 KW, the expected amount of failure would be 2.1 KW $[11 - \frac{1}{0,04} + \frac{e^{-0,04*11}}{0,04} = 2,1]$ and for penalty cost per unit of failure is γ=10\$, the total penalty cost would be 63 $ for three periods and the total energy cost combining the 11 KW wind energy with the 6KW traditional source would be 185.5$ by adding the subscription costs and penalty cost. (=82.5+40+63).

However, if 5 KW wind energy ($V_{w,l}.P_{w,l}$) is combined with the 12 KW traditional source since the expected rupture is 0.46 under λ_w=0.04, the cost of mix 12 KW traditional and 5 KW renewable source would be 173.8$ (=135+25+13.8). The answer of the question is; yes, both options satisfy the service level based chance constraint proposed in the model PS_1. However, the penalizing the expected failure amount (objective function Type II) is more vigorous than the penalizing the probability of failure (objective function Type I) and tries to choose less renewable based energy mixes.

Table 4.9: The results of the model PS_1+ objective function OF.2.1

Service Level	λ_w	Contract Values(Tr-W)	Objective Value	CPU(s)
SL=0.5	0.2	15-3	1227.91	6
	0.1	15-3	1217.83	6
	0.04	12-5	1209.63	11
	0.02	6-11	1191.86	6
SL=0.9	0.2	18-3	1377.91	11
	0.1	18-3	1367.83	9
	0.04	15-3	1210.78	12
	0.02	12-5	1202.84	5
SL=0.99	0.2	18-3	1377.91	9
	0.1	18-3	1367.83	7
	0.04	18-3	1360.78	4
	0.02	18-3	1358.23	5

In Table 4.10 and Table 4.11, the instance is analyzed as it is done in Table 4.5 and Table 4.6. The current constraint is altered with service level constraint based on the contracted power (PS_3) and the model turns the similar results in terms of the realization of the production. The maximum service level that can be satisfied is searched as in the Table 4.6, similar to the previous model, it is found out that until the service level is 0.99, it is possible to satisfy the external demand of the customers under some reliability levels of the renewable energy sources Table 4.11.

Average Power Amount Based Models with Objective Function Type II, One Type of RES and Traditional Mix

In Table 4.12, the results of the model that is built by combining the objective function Type II (OF.2.1) with the model including the average availability constraints (PS_5) are given. By comparing the results in Table 4.7, the impact of the objective function Type II can be observed clearly. In Table 4.7, where the probability of failure is penalized, the

Table 4.10: The results of the model PS_3+ objective function OF.2.1.a

Service Level	λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
SL=0.5	0.2	15-3	1227.91	<1
	0.1	15-3	1217.83	8
	0.04	12-5	1209.63	13
	0.02	6-11	1191.86	6
SL=0.9	0.2	No feasible		
	0.1	No feasible		
	0.04	No feasible		
	0.02	12-5	1202.84	8
SL=0.99	0.2	No feasible		
	0.1	No feasible		
	0.04	No feasible		
	0.02	No feasible		

Table 4.11: The results of the model PS_3+ objective function OF.2.1.a (continued)

Service Level	λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
SL=0.60	0.2	No feasible		
	0.1	15-3	1217.83	8
	0.04	12-5	1209.63	8
	0.02	6-11	1191.86	5
SL=0.70	0.2	No feasible		
	0.1	15-3	1217.83	<1
	0.04	12-5	1209.63	10
	0.02	6-11	1191.86	6
SL=0.8	0.2	No feasible		
	0.1	No feasible		
	0.04	12-5	1209.63	6
	0.02	6-11	1191.86	6

model has more tendency to generate the energy mix with greater amount of renewable energy sources when the reliability is not that much high (λ_w=0.1 or λ_w=0.2). However, the second type of objective function keeps the customer on the safer side by combining the traditional energy source with the less amount of renewable sources.

Table 4.12: The results of the model PS_5+ objective function OF.2.1

λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
0.2	15-3	1227.91	4
0.1	15-3	1217.83	7
0.04	12-5	1209.63	14
0.02	6-11	1191.86	6

Average Failure Amount Based Models with Objective Function Type II, One Type of RES and Traditional Mix

In this group, the model based on the expected failure amount constraint (PS_7) is merged with the Objective Function Type II (OF.2.1) and the results are presented in Table 4.13. The similar test is conducted when the same model is combined with the objective function Type I (OF.1.1) and the results are shown in Table 4.8. When the results of two tables are compared, it is seen that when failure amount is penalized in the objective function, even though the reliability of the wind energy source is increased, the model turns the least failure risk option and always combines the 3KW energy with 15 KW traditional energy source.

Table 4.13: The results of the model PS_7+ objective function OF.2.1

λ_w	Contract Values (Tr-W)	Objective Value	CPU(s)
0.2	15-3	1227.91	<1
0.1	15-3	1217.83	<1
0.04	15-3	1210.78	<1
0.02	15-3	1208.23	<1

Up until now, the developed constraints and objective functions are tested on the given instance by considering the use of traditional and one type of energy sources (PS_1, PS_3, PS_5 and PS_7).

In the following, the models that are built by combining the objective functions Type I and Type II with the models PS_2, PS_4, PS_6, PS_8 which take into account the mix of the traditional, wind and solar energy sources are tested on the same instance. The reliability levels for wind energy source are kept as in the Figure 4.3, for the solar energy source the λ_s values shown in Figure 4.4 are considered. The models PS_2, PS_4, PS_6, PS_8 which are developed for the cases in which the customers prefer to mix the traditional energy source with two types of renewable sources are relatively more complicated than the models proposed for the traditional and one type of renewable source combinations (PS_1, PS_3, PS_5, PS_7). The complexity of the developed models causes the longer computation times. Since a quite small size instance is considered, the computation time is limited to 10 minutes in our tests. If the model reaches a solution within the time limitation, the computation time is taken as it is and given in the following tables, otherwise, the model is stopped at the end of time limit and the found solution is used as the reference objective value for the further analysis.

Service Level Based Models with Objective Function Type I, Two Types of RES and Traditional Mix

The first glaring result in Table 4.14, in most cases, the constructed model can not reach optimum solution at the end of time limit and the reference solutions are displayed. Another significant result is that, as long as the service level is increased for the same level of reliability of the renewable sources, the customers prefer to subscribe for more traditional energy source to satisfy the promised service level. This outcome has been discussed in detail when the cases in which the traditional energy source is mixed with only one type of renewable source.

To get better comprehension, interpreting some of the cases which are generated based on the different reliability levels of renewable energy sources (represented by different λ_s and λ_w values) would be useful for the readers.

Let's look at the the case where SL=0,5 closer in Table 4.14. When λ_s=0.1 and λ_w=0.02 the customer can reach an agreement for 6 KW traditional, 6 KW for solar and 5 KW for wind energy sources. If the case where the reliability is lower such as λ_s=0.3 and λ_w=0.2, as a natural result of this case, the customer tends to create a mixture based on higher proportion of traditional energy sources and prefers to buy 12KW traditional source with 2 KW solar and 3 KW wind energy sources. We can interpret another cases in a similar

Table 4.14: The results of the model PS_2+ objective function O.F.1.2

Service Level	λ	Contract Values (Tr-S-W)	Objective Value	CPU(s)
SL=0.5	λ_s=0.1 λ_w=0.04	6-6-5	1186.01	600
	λ_s=0.1 λ_w=0.02	6-6-5	1184.65	193
	λ_s=0.3 λ_w=0.2	12-2-3	1226.56	600
	λ_s=0.3 λ_w=0.1	9-6-3	1222.46	600
	λ_s=0.3 λ_w=0.02	6-4-7	1185.98	177
	λ_s=0.75 λ_w=0.02	6-6-5	1186.78	106
SL=0.9	λ_s=0.1 λ_w=0.04	9-6-3	1217.19	600
	λ_s=0.1 λ_w=0.02	6-6-5	1184.65	147
	λ_s=0.3 λ_w=0.2	15-2-3	1241.681	600
	λ_s=0.3 λ_w=0.1	15-2-3	1240.75	600
	λ_s=0.3 λ_w=0.02	9-4-5	1217.29	231
	λ_s=0.75 λ_w=0.02	12-2-3	1226.64	88
SL=0.99	λ_s=0.1 λ_w=0.04	15-2-3	1239.85	600
	λ_s=0.1 λ_w=0.02	15-2-3	1239.78	600
	λ_s=0.3 λ_w=0.2	24-2-3	1881.54	600
	λ_s=0.3 λ_w=0.1	24-2-3	1881.54	600
	λ_s=0.3 λ_w=0.02	15-2-3	1239.92	600
	λ_s=0.75 λ_w=0.02	18-2-3	1437.62	600

way where the reliability of the wind energy is increased. Under the same service level

(SL=0.5), when the reliability of solar energy is kept the same (λ_s=0.3) but the reliability of wind source is increased gradually such as λ_w=0.2, λ_w=0.1 or λ_w=0.02. The results show that in parallel, with the increase in reliability of wind energy, the traditional energy source has a smaller proportion of the energy mix (from 12 KW to 6 KW) and solar and wind energy sources balance each other. This behaviour of the model can be easily observed for the other service levels. When the service level is increased to 0.9 and the reliability of the renewable energy sources quite low such λ_s=0.3 and λ_w=0.2, the production configuration changes slightly (Figure 4.6). When the service level is risen to 0.99, 24 KW is chosen for the traditional energy source, the configuration changes as in Figure 4.7, thus, the customer can conduct the production activities in a safer way.

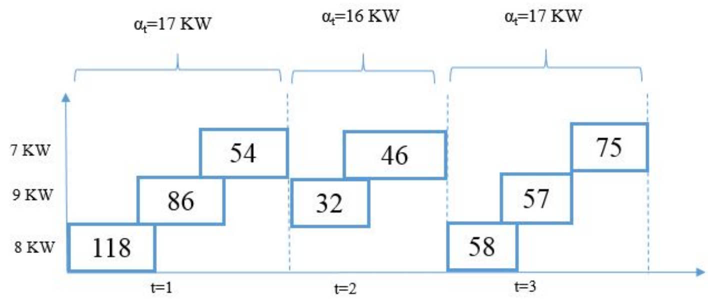

Figure 4.6: The production configuration of the model PS_2 + OF.1.2, $\lambda_s = 0.3$, λ_w=0.2, SL=0.9

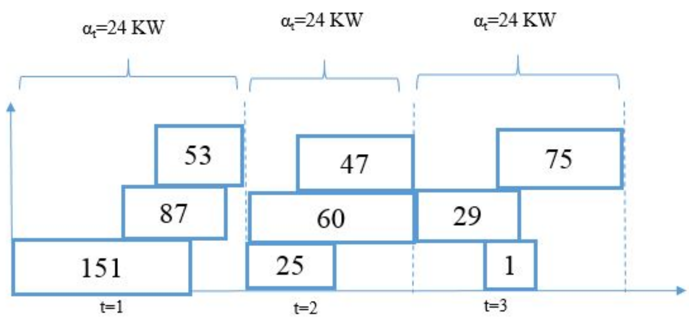

Figure 4.7: The production configuration of the model PS_2 + OF.1.2, $\lambda_s = 0.3$, λ_w=0.2, SL=0.99

In Table 4.15, the results of the model PS_4 with the objective function Type I are presented. The similar study has been conducted for its pair where the traditional energy source is mixed with one type of renewable source (PS_3) and the results have been shown in Table 4.5 and Table 4.6. Similar to the results in Table 4.4 and Table 4.5, while the model is tested with the model PS_2 it is possible to realize the production under the SL=0.9 and SL=0.99, the production seems infeasible when the probability of the availability of the renewable energy sources is considered based on the contracted options (PS_4) in Table 4.15. It is possible to see the effect of the high level of reliability under SL=0.9. Even though, the production is infeasible in most cases under the SL=0.9, when the reliability of the any of the renewable source is relatively higher than the other cases such as λ_w=0.04 or 0.02, the production becomes realizable under the given conditions.

Table 4.15: The results of the model PS_4 +objective function OF.1.2.a

Service Level	λ	Contract Values(Tr-S-W)	Objective Value	CPU(s)
SL=0.5	λ_s=0.1 λ_w=0.04	6-6-5	1187.54	88
	λ_s=0.1 λ_w=0.02	6-4-7	1185.49	60
	λ_s=0.3 λ_w=0.2	12-2-3	1230.87	15
	λ_s=0,3 λ_w=0.1	12-2-3	1226.64	30
	λ_s=0.3 λ_w=0.02	6-4-7	1187.37	89
	λ_s=0.75 λ_w=0.02	6-6-5	1188.35	70
SL=0.9	λ_s=0.1 λ_w=0.04	12-2-3	1221.78	33
	λ_s=0.1 λ_w=0.02	6-4-7	1185.49	37
	λ_s=0.3 λ_w=0.2	No feasible sol		
	λ_s=0.3 λ_w=0.1	No feasible sol		
	λ_s=0.3 λ_w=0.02	12-2-3	1221.98	21
	λ_s=0.75 λ_w=0.02	12-2-3	1222.72	13
SL=0.99	λ_s=0.1 λ_w=0.04	No feasible sol		
	λ_s=0.1 λ_w=0.02	No feasible sol		
	λ_s=0.3 λ_w=0.2	No feasible sol		
	λ_s=0.3 λ_w=0.1	No feasible sol		
	λ_s=0.3 λ_w=0.02	No feasible sol		
	λ_s=0.75 λ_w=0.02	No feasible sol		

Average Power Amount Based Models with Objective Function Type I, Two Types of RES and Traditional Mix

When the objective function Type I is combined with the model PS_6 (Table 4.16), average power amount based probabilistic constraint softens the model and the model produces the same energy mix in most cases. However, when a case where the reliability of solar and wind energy sources are quite low compared to the others, λ_s=0.3 and λ_w=0.2 is considered, the proportion of the traditional source is increases to 9 KW from 6 KW.

Table 4.16: The results of the model PS_6 +objective function OF.1.2

λ	Contract Values (Tr-S-W)	Objective Value	CPU(s)
λ_s=0.1 λ_w=0.04	6-6-5	1186.01	600
λ_s=0.1 λ_w=0.02	6-6-5	1184.65	176
λ_s=0.3 λ_w=0.2	9-4-5	1226.39	600
λ_s=0.3 λ_w=0.1	6-6-5	1193.93	196
λ_s=0.3 λ_w=0.02	6-6-5	1185.98	84
λ_s=0.75 λ_w=0.02	6-6-5	1186.78	64

Average Failure Amount Based Models with Objective Function Type I, Two Types of RES and Traditional Mix

The objective function Type I is integrated with the probabilistic model PS_8 and the results are shown in Table 4.17. The expected failure amount of the renewable energy sources is considered while selecting the capacity options in the models PS_7 and PS_8. As it is interpreted for the model PS_7 where the same constraint is used for the traditional and one type of renewable energy sources in Table 4.8, when the two types of the renewable energy sources are blended with the traditional source, as long as the reliability of the renewable energy sources is increased, the proportion of the renewable energy sources increases since the expected failure amount decreases. Thus, the customers can rely on the renewable energy sources more Table 4.17. Other noteworthy result in Table 4.17, the renewable energy sources compensate each other quite well. Let's look at the case where λ_s=0.1 and the λ_w=0.04 or λ_w=0.02 closer . When the reliability of wind energy is raised from 0.04 to 0.02, the customer can choose the same option for the wind energy source (11 KW) but increasing reliability of the wind energy source allows the customers to depend on the less solar energy and they can choose smaller option for solar energy source.

Table 4.17: The results of the model PS_8+ objective function OF.1.2

λ	Contract Values (Tr-S-W)	Objective Value	CPU(s)
λ_s=0.1 λ_w=0.04	6-4-11	1196.01	600
λ_s=0.1 λ_w=0.02	6-2-11	1189.65	37
λ_s=0.3 λ_w=0.2	12-4-5	1236.56	600
λ_s=0.3 λ_w=0.1	12-2-5	1229.06	600
λ_s=0.3 λ_w=0.02	6-2-11	1190.98	44
λ_s=0.75 λ_w=0.02	6-2-13	1210.19	600

As it is implemented for the models developed for the mix of traditional and one type of renewable energy source (PS_1, PS_3, PS_5, PS_7), the objective function Type II is combined with the models proposed for the energy mixes based on two renewable energy sources PS_2, PS_4, PS_6, PS_8 and tested on the same instance. The results are presented in Table 4.18, Table 4.19, Table 4.20 and Table 4.21.

Service Level Based Models with Objective Function Type II, Two Types of RES and Traditional Mix

The objective function Type II has been developed based on penalizing the average failure amount. In Table 4.14, the same model PS_2 has been tested with the objective function Type I. To provide better insight about the impact of the objective functions, a comparison the results in Table 4.14 and Table 4.18 will be effective for the reader. For better analysis, let's recall the related constraint:

$$\frac{\lambda_s(1-e^{-\lambda_w.(\alpha_t-\sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})}) - \lambda_w(1-e^{-\lambda_s(\alpha_t-\sum_{l=1}^{R_{tr}} V_{tr,l}P_{tr,l})})}{\lambda_s-\lambda_w} \leq 1-SL \qquad \forall t=1,...,T \tag{4.120}$$

When the case where SL=0.5, λ_s=0.1 and λ_w=0.02 in Table 4.14 and Table 4.18 is examined, choosing the 6 KW for traditional energy source satisfies the constraint (4.120). (The same production configuration is obtained in Figure 4.5.) However, in Table 4.14 traditional energy source is mixed with 6 KW solar and 5 KW wind energy while it is mixed with 4 KW solar and 7 KW wind energy source in Table 4.18. Because the combination of 4 KW solar and 7 KW wind energy is less costly than the mix of 6 KW solar and 5 KW wind energy which are chosen when the objective function Type I is considered.

When the availability is reduced to λ_s=0.3 and λ_w=0.1, the model tends to select the smallest options like 2 KW for solar energy and 3 KW for wind energy source since the failure risk is high under the conditions where the reliability level is low. However, when the reliability level is increased for the wind energy source (λ_w=0.02), since the risk of failure decreases, customer can compose the energy mix with with more renewable energy source like selecting 11 KW option for wind energy source.

When the high service level including cases are reviewed, even though the reliability levels are high, due to the service level constraint recalled in (4.120), the model tends to combine energy sources with the smallest renewable energy portions to generate the safer energy configurations.

Generally speaking, it can be said that the objective function Type II is more sensitive than the objective function Type I to the increase in the reliability of the renewable energy sources. Let's take the example the case where SL=0.5 λ_s=0.3 and λ_w=0.1 and the reliability of the wind energy is boosted to the λ_w=0.02. When objective function Type I is performed, it is seen that in Table 4.14 the energy mix changes from 9 KW,6 KW and 3 KW for traditional, solar and wind energy sources,respectively to 6 KW , 4 KW and 7 KW. When it comes to Table 4.18, the options change from 12, 2, and 3 KW for traditional, solar and wind respectively to the 6, 2, 11. The increase in the reliability of the wind energy source shows a more aggressive reaction when the same model is integrated with the objective function Type II.

In Table 4.19, the results of the model built by combining the objective function Type II and the PS_4 are given. As it is commented before, this version of the service level based chance constraint shows more rigidness. This behaviour can be observed in the results of

Table 4.18: The results of the model PS_2+ objective function OF.2.2

Service Level	λ	Contract Values(Tr-S-W)	Objective Value	CPU(s)
SL=0.5	λ_s=0.1 λ_w=0.04	6-4-7	1231.02	50
	λ_s=0.1 λ_w=0.02	6-4-7	1218.22	77
	λ_s=0.3 λ_w=0.2	12-2-3	1257.79	46
	λ_s=0.3 λ_w=0.1	12-2-3	1247.71	69
	λ_s=0.3 λ_w=0.02	6-2-11	1236.75	94
	λ_s=0.75 λ_w=0.02	6-2-11	1250.79	37
SL=0.9	λ_s=0.1 λ_w=0.04	12-2-3	1231.4	30
	λ_s=0.1 λ_w=0.02	6-4-7	1218.22	68
	λ_s=0.3 λ_w=0.2	15-2-3	1272.79	29
	λ_s=0.3 λ_w=0.1	15-2-3	1262.71	26
	λ_s=0.3 λ_w=0.02	12-2-3	1238.11	40
	λ_s=0.75 λ_w=0.02	12-2-3	1252.16	41
SL=0.99	λ_s=0.1 λ_w=0.04	15-2-3	1246.4	25
	λ_s=0.1 λ_w=0.02	15-2-3	1243.85	64
	λ_s=0.3 λ_w=0.2	18-2-3	1422.79	29
	λ_s=0.3 λ_w=0.1	18-2-3	1412.71	88
	λ_s=0.3 λ_w=0.02	15-2-3	1253.11	15
	λ_s=0.75 λ_w=0.02	18-2-3	1417.16	73

the cases in which the service level is considered as 0.9 and 0.99. Previously mentioned more renewable energy sensitive attitude of the objective function Type II can be seen in the case of PS_4 when the results in Table 4.19 are compared to the results in Table 4.15.

Average Power Amount Based Models with Objective Function Type II, Two Types of RES and Traditional Mix

By following the same order with the tests applied for the objective function Type I, in Table 4.20, the model PS_6 is performed by integrating the objective function Type II to the model. When the results are compared with the results in Table 4.16, it is seen that objective function Type II imposes the model to benefit from the increasing reliability levels of the renewable energy sources since the risk of the failure decreases. That's why, in case of considering the objective function Type II, customers generate their energy mix with higher proportion of renewable energy sources especially the reliability level is safe enough such as λ_w=0.02.

Table 4.19: The results of the model PS_4+ objective function OF.2.2.a

Service Level	λ	Contract Values(Tr-S-W)	Objective Value	CPU(s)
SL=0.5	λ_s=0.1 λ_w=0.04	6-4-7	1231.02	600
	λ_s=0.1 λ_w=0.02	6-4-7	1218.22	600
	λ_s=0.3 λ_w=0.2	12-2-3	1257.79	21
	λ_s=0.3 λ_w=0.1	12-2-3	1247.71	260
	λ_s=0.3 λ_w=0.02	6-2-11	1236.75	600
	λ_s=0.75 λ_w=0.02	6-2-11	1250.79	600
SL=0.9	λ_s=0.1 λ_w=0.04	12-2-3	1231.4	285
	λ_s=0.1 λ_w=0.02	6-4-7	1218.22	600
	λ_s=0.3 λ_w=0.2	No feasible sol		
	λ_s=0.3 λ_w=0.1	No feasible sol		
	λ_s=0.3 λ_w=0.02	12-2-3	1238.11	23
	λ_s=0.75 λ_w=0.02	12-2-3	1252.16	11
SL=0.99	λ_s=0.1 λ_w=0.04	No feasible sol		
	λ_s=0.1 λ_w=0.02	No feasible sol		
	λ_s=0.3 λ_w=0.2	No feasible sol		
	λ_s=0.3 λ_w=0.1	No feasible sol		
	λ_s=0.3 λ_w=0.02	No feasible sol		
	λ_s=0.75 λ_w=0.02	No feasible sol		

Table 4.20: The results of the model PS_6+ objective function OF.2.2

λ	Contract Values (Tr-S-W)	Objective Value	CPU(s)
λ_s=0.1 λ_w=0.04	6-4-7	1231.02	15
λ_s=0.1 λ_w=0.02	6-4-7	1218.22	15
λ_s=0.3 λ_w=0.2	12-2-3	1257.79	9
λ_s=0.3 λ_w=0.1	12-2-3	1247.71	9
λ_s=0.3 λ_w=0.02	6-2-11	1236.75	11
λ_s=0.75 λ_w=0.02	6-2-11	1250.79	10

Table 4.21: The results of the model PS_8+ objective function OF.2.2

λ	Contract Values (Tr-S-W)	Objective Value	CPU(s)
λ_s=0.1 λ_w=0.04	15-2-3	1246.4	<1
λ_s=0.1 λ_w=0.02	6-2-11	1227.48	<1
λ_s=0.3 λ_w=0.2	15-2-3	1272.79	<1
λ_s=0.3 λ_w=0.1	15-2-3	1262.71	<1
λ_s=0.3 λ_w=0.02	6-2-11	1236.75	<1
λ_s=0.75 λ_w=0.02	12-2-5	1261.77	<1

Average Failure Amount Based Models with Objective Function Type II, Two Types of RES and Traditional Mix

Lastly, the model PS_8 which includes expected failure amount based constraint is merged with the objective function Type II in Table 4.21. It is obviously seen that in parallel to the increase in the reliability of the renewable sources, their portion increases in the energy mix as it is discussed in detail before. To evaluate the effect of the objective functions Type I and Type II on the same model, it is necessary to compare the results in Table 4.17 and Table 4.21. The results show that, penalizing the expected failure amount costs more than penalizing the probability of the failure, the energy mixes are generated with less amount of renewable energy source to avoid from the penalty charge sourcing from the the renewable energy amount that can not be satisfied.

Therefore, in this section, all the developed probabilistic constraints and the objective functions have been expanded with the exponential distribution consideration for the random variables that represent the availability of the renewable energy sources. To evaluate the proposed models, the equivalences of the models and the objective functions which are obtained based on the exponential distribution, are tested on a small size instance and the results are discussed to give better insight to the customers who intend to use the developed models.

4.7 Conclusion

In this chapter, three groups of probabilistic constraints and the appropriate objective functions to the constraints are developed to deal with the uncertain nature of the renewable energy sources during the power purchasing procedure. Firstly, the developed constraints are presented in a general manner. Then, they are expanded with the consideration of exponential distribution. The obtained equivalences of the proposed constraints and the objective functions are merged by creating various combinations with the mathematical model presented for the single-item lot sizing problem with capacity selection aspect. The obtained MINLP models are tested on a small size instance and the results are discussed comprehensively.

In our study, the probabilistic mathematical models are proposed based on the exponential distribution consideration. As it is cited before, Kun et al. [2018] generated the some irregular distributions of "wind power-probability" relation by using the curve of "wind speed-power". The similar study can be conducted for the solar power probability modelling. The obtained distribution functions, regardless if they are regular distributions such as Weibull, Normal etc. or irregular ones, can be used to integrate the uncertainty of the renewable energy sources into lot sizing problems by tailoring them into the probabilistic constraints proposed in this thesis.

Even though, the models are tested on small size of instance, it is seen that in some cases the model can not reach any optimum solution after 10 minutes. When the models are tested on the instances which are composed of five machines, especially for the cases two types of renewable energy sources are mixed with the traditional energy source, it is seen that the models can not reach any solution after one hour. To deal with this complexity of the models, Fix-and-Relax heuristic is proposed to solve the problem in the next chapter.

Chapter 5

Solution Approaches

Contents

5.1 Introduction

It has been proven by Florian et al. [1980] and Bitran and Yanasse [1982] that the single item capacitated lot sizing problem (CLSP) is NP-hard for general objective functions. (Problems with concave cost functions and no capacity limits (Wagner and Whitin [1958]) or constant capacities (Florian and Klein [1971]), lot sizing with convex cost functions and no set-up cost are solvable in polynomial time (Jans and Degraeve [2007])). Due to the NP-hard characteristic of the single-item CLSP, it is too difficult to solve most real life instances to the optimality by commercial optimization solvers. As it can be observed in the computational experiments implemented in the previous section, when the single-item CLSP is combined with capacity selection problem, CPLEX can not reach the optimum solutions for most of the medium size instances including five machines and ten periods (N5_T10) or seven machines and seven periods (N7_T7). When it comes to the relatively larger size instances, CPLEX is not capable of solving the problem to the optimality within 1 hour time limit.

To implement developed mathematical model for the real life instances, since the commercial solvers can not meet the need, most likely larger size real life instances can be solved by appropriate heuristic solution approaches that can provide high quality solutions in reasonable time periods. These solution approaches have been detailed by referring to related papers in the state of art in this thesis.

With the emergence of off-the-shelf MIP-solvers in the late nineties, MIP-based heuristics started to be used to solve MIP models and in the beginning of the 2000s they are started to be applied for the lot sizing problems (Absi and van den Heuvel [2019]). In this section, one of the most commonly used MIP-based heuristics, Fix-and-Relax heuristic, is proposed to solve the developed single-item CLSP with capacity selection problem in affordable computation times by obtaining good quality solutions.

This chapter is organised as follows: In Section 5.2, the previous studies in which Fix-and-Relax heuristic is used as solution approaches are reviewed. Section 5.3 presents the general framework of the Fix-and-Relax heuristic and two different relaxation procedures are proposed. The presented (F&R) approaches are tested on several instances for the developed deterministic and probabilistic models in previous chapters and the obtained results are analyzed in Section 5.4. Finally, Section 5.5 concludes this chapter with some perspectives and remarks.

5.2 Literature Review

Fix-and-Relax Heuristic (F&R) was firstly introduced by Dillenberger et al. [1994]. Since then, it has been applied for the solution of different types of problems in different categories such as production planning, inventory management, supply chain management etc. As Turhan and Bilgen [2017] pointed out, application areas of F&R in the literature can be categorized as follows: production planning, lot sizing, scheduling, inventory planning, and supply chain management. Since F&R heuristic is well-suited for lot sizing problems and promises attaining the optimum or near optimum results within a reasonable computational time, it has been executed for different variants of the lot sizing problems up to date.

Clark and Clark [2000] applied F&R heuristic for the capacitated multi-item lot sizing problems when set-up times are sequence-dependent. Stadtler [2003] proposed time-based decomposition to solve the dynamic multi-item multilevel lot sizing problem and introduced overlapping procedure between the successive time intervals which allows to improve lot size decisions of previous iteration in the subsequent iteration. Therefore, it ensures to obtain better quality results for the main problem. Absi [2005] implemented F&R and introduced Double-Fix and Relax heuristic for the solution of capacitated lot sizing problems. Beraldi et al. [2008] compared and analysed the solutions of F&R heuristics with different partition strategies for set of variables for the identical parallel machine lot sizing and scheduling problem with sequence-dependent set-up costs. Akartunali and Miller [2009] studied on (l,S) inequalities for strengthening the formulation of big-bucket problems in order to boost the performance of F&R. Mohammadi and Fatemi [2010] employed two versions of F&R to deal with the computational complexity of lot sizing and sequencing in permutation flow shops with sequence-dependent set-ups. They improved this study by proposing new algorithmic approach of F&R in Mohammadi et al. [2010c]. Ferreira et al. [2009] examined integrated lot sizing and scheduling problem for soft drink industry and compared the performance of several fixing strategies for F&R approach. Toledo et al. [2015] combined F&R and Fix and Optimize and applied to the multi-level capacitated lot sizing problem with backlogging. Masmoudi et al. [2016, 2017b] implemented it for multi-item capacitated lot sizing problem in a flow shop system with energy consideration. Recently published work of Absi and van den Heuvel [2019] analyses the worst case behaviour of Relax-and-Fix heuristics for lot sizing problems.

Giglio et al. [2017] utilized the F&R for the integrated lot sizing and energy-efficient job shop scheduling problem in manufacturing/re-manufacturing systems. Melo and Ribeiro [2017] solved multi-item uncapacitated lot sizing problem with inventory bounds with F&R heuristic based on a rolling horizon time partitioning scheme.

The use of F&R heuristic approach for the solution of the problems (Mohammadi and Fatemi [2010], Mohammadi et al. [2010b],Ramezanian et al. [2013b], Masmoudi et al. [2016, 2017b]) which are quite similar to the problem handled in this thesis and the presented outstanding results motivated the authors to implement F&R heuristic for the developed model in this thesis.

In order to solve the developed model, in the following section, two variants of F&R approach are proposed and their performances are analyzed according to different types of fixing strategies.

5.3 Fix-and-Relax Heuristic

F&R is a constructive type heuristic approach. The main principle of F&R is to decompose the global problem into smaller, tractable, manageable, easier sub-problems than the global one and to solve these sub-problems subsequently by using the information from previously solved ones. As it can be thought for the solution of any type of problem, the aim of the decomposition is to reduce the complexity and consequently computational burden of the original problem.

In F&R procedure, firstly, the integer variables are partitioned into disjoint sets. These sets are generated according to the time intervals and each of these time intervals are called *window*. Each window consists of a certain number of time periods. In the first iteration, the planning horizon is divided into two windows: Observation Window (OW) and Approximation Window (AW). The variables pertaining to OW are as in the original model and the model of AW is a relaxed version of the original one. The obtained partially relaxed model is solved. From the second iteration, the planning horizon is decomposed in three windows: Observation Window (OW), Frozen Window (FW) and Approximation Window (AW). After the model is solved in iteration k, the OW slides through the future, and the decision variables belong to OW at iteration k , which are not in the OW any more at iteration k+1, are fixed to the obtained values at iteration k ,therefore, Frozen Window (FW) is generated. It is possible to apply different fixing strategies for the variables. This solution procedure is repeated subsequently until the end of the planning horizon (Figure 5.1). Algorithm 1 provides the scheme of F&R heuristic.

Algorithm 5.1: The Fix and Relax Algorithm Masmoudi et al. [2016]

k=1;
a_k=1;
b_k=σ;
while b_k <T **do**
    Solve subproblem;
    k=k+1;
    a_k=b_k-δ;
    b_k=b_k+σ-δ;
    if b_k>T **then**
        b_k=T;
    end
end
Solve subproblem;

There are two parameters which have a significant influence on the performance of F&R heuristic: the number of the periods in the observation window (σ_k) and the number of the overlapping periods (δ_k) between OWs of iteration k and iteration k+*1*. There

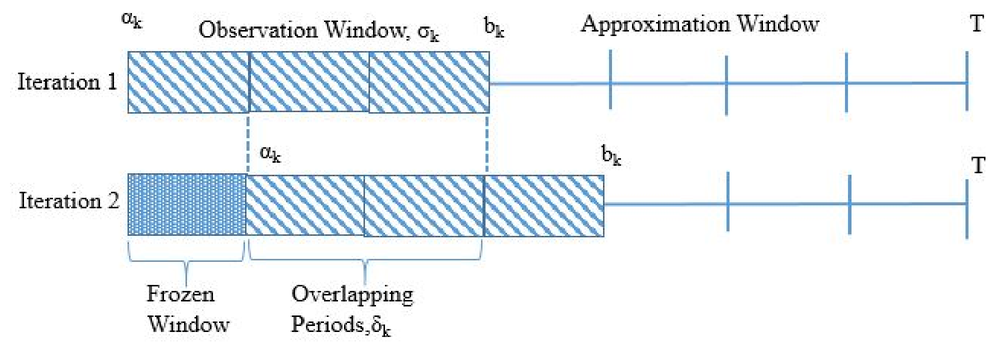

Figure 5.1: F&R heuristic approach

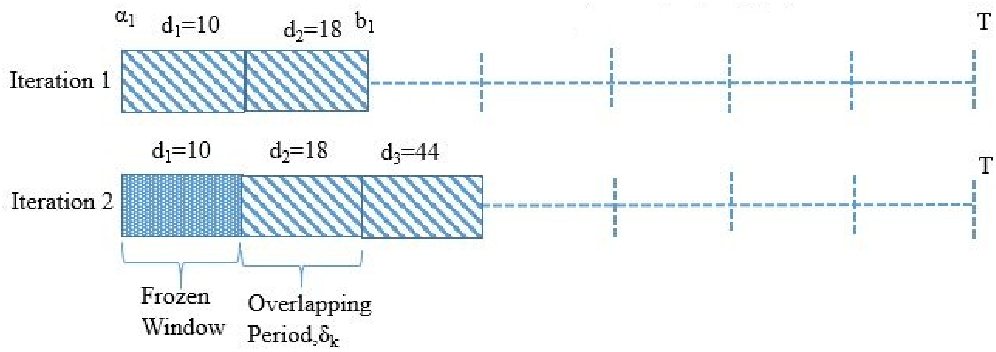

Figure 5.2: The principle of F&R without Approximation Window

is no doubt that the fewer periods in observation window means the fewer integer variables to handle and as a result of this choice, the sub-problem is easier to solve. However, this path increases the number of the sub-problems and iterations. When the observation window is composed of more periods, the complexity of the sub-problems increases. Hence, defining the best size of the observation window has a vital importance to obtain a good performance from F&R heuristic.

After giving detailed information for the outline of F&R heuristic, the proposed versions are now introduced.

5.3.1 F&R without Approximation Window-Myopic Approach

It is obvious that increasing the number of relaxed variables makes the problem easier to solve. However, when the number of relaxed variables is increased, the gap between the obtained solution and optimum solution can increase dramatically. To deal with this issue, we firstly propose to implement F&R heuristic without approximation window. The main idea behind this approach is to solve the sub-problem which is defined for OW by rolling horizon fashion.

The principle of this approach can be observed in Figure 5.2. In the first iteration, only OW including *t=2* periods is considered and the sub-problem is solved according to the related demand scheme $[d_1...d_t]$. In the second iteration, the chosen decision variables are fixed at their current values in the frozen window. The observation window is rolled through the future by keeping the overlapping period(s) (δ_k) between the consecutive observation windows. The sub-problem is solved by taking into account the fixed variables in the frozen window and fresh demand scheme.

One important drawback of this approach is that it is possible to have infeasible solutions. In this approach, the sub-problems do not involve an approximation window. Thus, the demand configuration which belongs to the whole planning horizon is not taken into account and the sub-problems are solved according to the demand configuration related only to the considered OW at each iteration. As a natural consequence of this procedure, the decision variables are determined and fixed only according to the viewed demand values. The variables that have already been fixed in the previous iterations may not meet the refreshed demand configuration in the current or subsequent iterations and such a case produces an infeasible solution. From this perspective, this approach can be named as *myopic approach*. Increasing the visibility of demand configuration can prevent to have infeasible solutions or decreases number of infeasible solutions. To do so, the addressed model is solved F&R heuristic with approximation window.

5.3.2 F&R with Approximation Window

As it is mentioned in the outline of F&R heuristic, one way of solving this NP-hard problem is relaxing some of the variables. In this approach, the model is solved by keeping its original structure and a part of it is relaxed to cope with the shortcoming of the previous version.

In our problem, there are two main decisions to be made:

Optimum production quantity for each period, for each machine,

Optimum energy contract option which covers the needs of the production plan.

The global problem is taken into account for the observation window where lot sizing decisions and energy contract decisions are made, the energy related constraints are pruned off the global problem and it is transformed to a classical lot sizing problem in a flow shop configuration for the approximation window (Figure 5.3). To sum up, energy related variables ($\alpha_{k,t}, P_{k,l}, f_{m,r,t}, g_{m,r,t}, z_{m,t}$) are ignored in approximation window to relax the problem.

5.3.3 Fixing Strategies

As the implemented relaxing strategy has a great influence on the difficulty of the sub-problems, fixing the appropriate variables has a crucial importance on the solution quality of the problem. In this study, three different fixing strategies are tested (Table 5.1).

First of all, it will be useful to disclose the main idea behind the identification of the variables to be fixed. There is no doubt that solving any kind of problem by fixing some

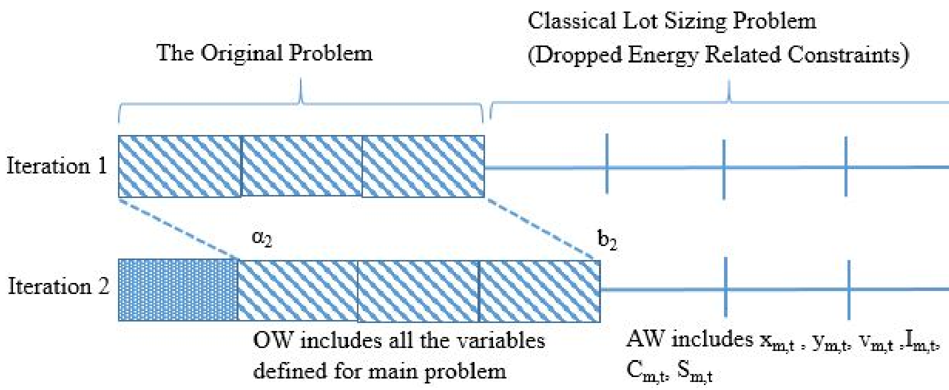

Figure 5.3: The principle of F&R with Approximation Window

Table 5.1: Proposed fixing strategies

Nu.	Fixing Strategy	Variables
1	Production quantity	$x_{m,t}$
2	Machine overlaps	$f_{m,r,t}, g_{m,r,t}, y_{m,t}, v_{m,t}$
3	Set-up decision	$y_{m,t}$

variables at each iteration reduces the computational burden of the problem and the solution can be obtained in an affordable time period.

By following this idea, fixing the production quantity produced by machine m in period t ($x_{m,t}$) is firstly proposed. It is necessary to signify that once the production quantity is fixed, related set-up variables ($y_{m,t}$) are also fixed. Hence, the number of binary variables to be dealt with significantly decreases and the handled sub-problems can be solved easier. This case enables us to attain the solution in a relatively short computational time. However, [Akartunali and Miller, 2009] has remarked, the more variables fixed in a window mean the higher probability we have for infeasibility in later windows.

The proposed second strategy is to fix the machine overlapping. To do so, only the variables ($y_{m,t}, v_{m,t}, f_{m,r,t}, g_{m,r,t}$) are fixed at each iteration. Therefore, it becomes possible to keep the strength of fixing production quantity which is reaching the solution quicker.

Lastly, fixing set-up decision ($y_{m,t}$) which is the most widespread fixing strategy applied in the literature. Different from the second strategy, the position of the machines ($f_{m,r,r}, g_{m,r,t}$) are not fixed. When the machine overlaps and the production quantities ($x_{m,t}$) are left unfixed, the problem has more flexibility to adapt itself to changing subproblem at each iteration.

5.4 Computational Experiments

In this section, the proposed variants of Fix-and-Relax heuristic are implemented for the solution of the deterministic and probabilistic mathematical models which are presented in Chapter 3 and 4 respectively. The proposed models solved by the commercial solvers and the obtained results are compared with the results of the heuristic approach and the performance of the proposed variants is discussed in detail.

5.4.1 Solution of The Deterministic Model P_3

The F&R heuristic is coded on Python 2.7 and the results are compared with results obtained from CPLEX 12.6 on an Intel Core i7 with 2.7 GHz and 8 GB RAM. Five different instances are generated for each problem configuration (N,T). The proposed fixing strategies are applied with different sizes of observation and overlaps to identify the best fixing and partitioning strategy in terms of solution quality and CPU time. Each iteration of F&R solution algorithm is set to 180s for all the instances. The CPU time for global solution is limited with 3600s. When CPLEX is not able to reach optimum solution within 1 hour, the feasible solution attained at the end of this time limit is considered to calculate the GAP (5.1). The average gap is computed with the following equation:

$$GAP = (Z_{F\&R} - Z_{CPLEX}/Z_{CPLEX}) \times 100 \tag{5.1}$$

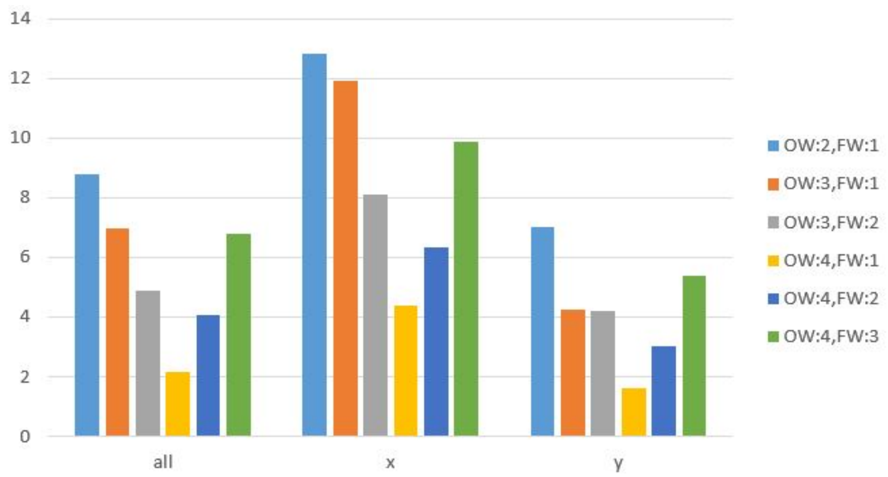

Figure 5.4: The results of average GAP (%) without Approximation Window for different window configurations and fixing strategies

The results of the proposed F&R heuristic without Approximation Window are displayed in Table 5.2 and the performance of the solution method is compared with the performance of CPLEX solver. For each problem size, five different instances are tested and the average CPU time and the GAP levels are shown on the table. As it is indicated before, for each instance the computation time is limited 3600s. For the problem sizes, N5_T5 and N5_T7, five of the five instances reach the optimum solution. When the instances of N5_T10 are tested, three of the instances attain the optimum solution within the defined time limit. When the instances can not reach the optimum solution in 3600s, the solver is stopped and the CPU is considered as 3600s and the obtained solution value is taken into account for calculating the GAP between the CPLEX and F&R approaches.

Table 5.2: The results of the F&R approach without Approximation Window

		CPLEX		OW:2 FW:1		OW:3 FW:1		OW:3 FW:2		OW:4 FW:1		OW:4 FW:2		OW:4 FW:3	
Instance	**Fix Var**	**Avg. CPU.**	**Nu. Opt.**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**
N5T5	y	7,307	5_5	7,15	2,30	15,25	1,36	16,48	2,01	33,30	**0,08**	14,21	1,36	7,14	1,66
	x			1,58	11,73	3,06	3,77	2,26	4,52	7,23	1,75	4,07	2,55	3,41	6,45
	all			2,96	5,87	5,76	0,80	4,27	2,60	16,78	0,96	6,36	1,74	4,06	3,50
N5T7	y	70,749	5_5	63,42	6,11	40,65	1,12	39,19	5,17	137,21	**0,17**	81,90	0,51	79,54	0,56
	x			2,56	15,69	6,74	6,46	3,80	5,53	18,43	3,60	10,45	3,79	8,39	3,43
	all			4,15	3,70	14,79	3,26	9,93	5,16	35,87	0,65	28,41	2,50	25,78	1,45
N5T10	y	2470,46	3_5	227,70	9,23	268,65	3,42	238,38	4,28	323,11	**0,94**	186,04	4,03	154,83	5,25
	x			No.Sol	No.Sol	12,04	11,09	6,26	11,73	39,46	4,83	23,29	4,85	29,54	9,98
	all			57,09	9,98	33,38	5,19	53,93	6,27	152,54	1,49	86,71	3,57	83,07	6,26
N7T7	y	3180,36	1_5	265,48	5,71	457,40	**1,36**	216,74	3,41	525,70	2,57	325,39	1,45	203,67	3,42
	x			7,33	10,38	30,53	16,12	17,58	10,44	128,41	7,43	66,83	10,84	32,25	7,60
	all			16,84	12,46	65,69	7,59	30,91	7,86	317,40	2,82	190,44	5,25	139,06	5,35
N7T10	y	3600,00	0_5	325,14	9,54	873,13	8,02	579,63	8,63	1108,79	**2,99**	566,84	5,15	295,72	8,32
	x			15,30	13,70	80,73	19,31	38,22	15,54	235,10	4,80	142,49	9,85	147,38	11,64
	all			33,42	10,30	109,48	13,78	45,12	9,11	263,21	3,25	170,40	5,47	200,06	5,15
N10T7	y	3600,00	0_5	446,17	9,23	800,00	10,22	603,63	8,73	1003,90	**3,01**	666,84	5,64	362,72	6,01
	x			24,8	12,70	93,21	14,72	58,22	11,46	252,13	3,78	172,95	6,03	249,3	9,45
	all			73,02	10,40	154,23	11,35	75,41	9,86	405,40	3,89	324,44	5,95	209,06	7,63

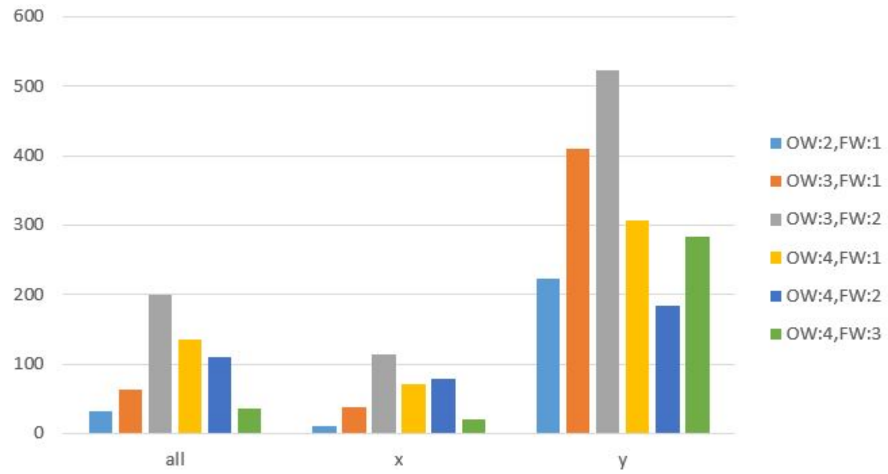

Figure 5.5: The results of average CPU(s) without Approximation Window for different window configurations and fixing strategies

While one of the instances reaches the optimality for the instances composed of 7 machines and 7 periods (N7_T7), none of the N7_T10 and N10_T7 instances reach optimum solution within the time limit by CPLEX.

Each of the 25 instances are tested with three different fixing strategies and different combinations for the sizes of observation window (OW) and frozen window sizes (FW). As it can be seen on the Table 5.2, the tested OW-FW combinations are: 2-1, 3-1, 3-2, 4-1, 4-2, 4-3. The performance of F&R approaches is analysed in terms of two parameters: Obtained Best GAP and Obtained Best CPU. In Table 5.2 the average Best Gap value for each instance is shown in bold. To explain the Table 5.2 in detail, the instance of N7_T7 can be considered. When F&R without Approximation Window is applied on the instances N7_T7, the average of *the obtained best gap* is 1.36% and the proposed approach reaches this solution in average 457,40s when the sub-problem is decomposed into three windows and fixed set-up decision ($y_{m,t}$) in one window at each iteration. The results can be analyzed in the same fashion in terms of computation times.

While the results shown in Table 5.2 display the average values of the obtained best GAP and CPU time, Figure 5.4 and Figure 5.5 present a general picture to evaluate the effect of the size of overlapping periods and the applied fixing strategies. In Figure 5.4 and Figure 5.5, the evaluation is done according to taking into account the average performance of each fixing strategy with each Observation Window (OW) and Frozen Window (FW) configurations on all the instances and the terms *"all"* ,*"y"* and *"x"* correspond respectively, fixing all binary variables, fixing the set-up variable and fixing the production quantity.

The Figure 5.4 shows that, generally, fixing set-up decision ($y_{m,t}$) or fixing the machine overlapping with the set-up variables ($f_{m,r,t}$, $g_{m,r,t}$,$y_{m,r,t}$,$v_{m,r,t}$) produces better solution than the fixing the production quantity ($x_{m,t}$). Since this approach does not allow to see demand of whole planning horizon, it can solve the problem in a more myopic way, therefore, fixing the values according to the low visibility causes huge gaps especially for the instances where the demand scheme fluctuate in further periods. When observation window is kept as greatest possible (4 in our study) and fixing window is defined as smallest possible (1 in our study), this approach always better quality results in terms of *GAP* as displayed in Figure 5.4 or solving the problems according to observation window (OW) is equal to 2, produces worst quality results. This analysis proves the idea of "higher myopic, lower quality."

The Figure 5.5 points out that, in most cases, fixing the production quantity ($x_{m,t}$) reaches the solution of the global problem within a relatively shorter time. It is possible to obtain solutions within 1,5 - 2 min. in average when the production quantity is fixed. However, fixing set-up decision ($y_{m,t}$) requires longest computational times regardless of observation window and frozen window configuration. Even the required computation times seem quite high, it can be seen that the maximum of average CPU time corresponds less than 10 min. So, the proposed solution approach can be regarded as affordable when it is compared to the 1 hour.

The same instances are tested for the F&R with Approximation Window approach. The results are displayed in Table 5.3. The first noticeable result is that F&R with Approximation Window outperforms the F&R without Approximation Window in terms of *GAP* levels. When the results in Table 5.2 and Table 5.3 are compared, it is seen that for all the instances the average gap value is always better than the values obtained from the F&R without Approximation Window. When the maximum average gap is 13% in Figure 5.4, this value decreases to 1.8% when F&R with Approximation is applied (Figure 5.6). When the performance is assessed in terms of the found best gaps between the optimum or referenced results obtained by CPLEX and the results of the heuristic approach, for some of the instances, it is possible to reach even better solution than the solution of CPLEX in a relatively reasonable time (Table 5.3).

In Figure 5.6, it is seen that, when the strategy of fixing production quantity ($x_{m,t}$) is left out of evaluation, in most cases, the gap between the obtained value by applying heuristic approach and the reference value is less than (0.8%). Even though reaching the solution within a less computation time has an advantage (Figure 5.5, Figure 5.7), fixing production quantity ($x_{m,t}$) takes the solution away from the optimality (Figure 5.4,Figure 5.6). In cases where a little longer computation times are affordable, fixing binary variables promises higher quality solutions when compared to the strategy of fixing production quantity.

In terms of the computation time, as it is expected, the problem can be solved within longer time compared to F&R without Approximation Window approach since larger subproblems are handled at each iteration. Similar to the F&R without Approximation Window approach, fixing production quantity, $x_{m,t}$, enables to reach a solution in a shorter time compared to the other fixing strategies.

Therefore, the two variants of F&R heuristic approach are proposed to deal with the complexity of the handled problem and the good-quality results are obtained within the affordable computation times. In the next section, same heuristic approach is employed

Table 5.3: The results of the F&R approach with Approximation Window

	CPLEX			OW:2 FW:1		OW:3 FW:1		OW:3 FW:2		OW:4 FW:1		OW:4 FW:2		OW:4 FW:3	
Instance	**Avg. CPU(s)**	**Nu. Optim.**	**Fix. Var.**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**	**CPU(s)**	**Gap(%)**
N5T5	7,307	5_5	y	10,27	0,17	20,71	**0,08**	10,16	0,17	58,23	**0,08**	17,55	**0,08**	13,51	**0,08**
			x	2,70	0,45	5,25	0,41	3,77	0,41	15,61	**0,08**	12,08	**0,08**	11,46	**0,08**
			all	3,47	0,35	8,06	0,32	4,72	0,32	16,71	**0,08**	12,60	**0,08**	11,70	**0,08**
N5T7	70,749	5_5	y	86,23	0,36	107,84	**0,17**	88,93	0,36	243,43	0,22	99,54	**0,17**	89,49	**0,17**
			x	11,49	1,62	26,66	1,13	19,23	1,55	93,10	0,57	65,65	0,85	58,52	0,67
			all	32,03	0,67	41,67	0,39	26,80	0,45	135,84	0,27	77,70	0,27	71,91	**0,17**
N5T10	2470,46	3_5	y	449,33	-0,10	704,87	**-0,16**	373,60	**-0,16**	818,82	0,25	459,77	-0,10	356,54	1,17
			x	95,89	0,56	226,36	0,37	134,20	0,40	403,81	0,36	259,01	0,16	197,11	0,22
			all	167,50	-0,08	344,13	-0,04	144,88	0,01	597,78	-0,02	403,49	0,16	238,55	0,00
N7T7	3180,36	1_5	y	704,75	1,73	798,23	1,20	482,56	1,63	721,78	2,58	508,47	2,95	360,93	1,88
			x	71,05	1,15	190,21	1,02	134,82	0,90	322,21	**0,83**	209,30	1,03	197,07	0,95
			all	157,08	1,02	365,21	1,14	177,64	0,91	485,90	1,02	365,47	1,29	241,43	1,02
N7T10	3600,00	0_5	y	1347,19	-0,20	1338,87	2,79	797,73	-0,10	1242,32	-1,76	657,50	1,27	489,11	-1,91
			x	448,93	**-2,42**	649,57	-0,23	414,00	0,87	823,35	1,17	418,27	-1,79	299,74	-1,85
			all	736,87	-0,93	1160,26	-1,12	711,28	0,05	1134,56	-0,32	647,72	-2,30	495,15	0,22
N10T7	3600,00	0_5	y	936,98	2,13	No.Sol	No.Sol	427,00	1,68	No.Sol	No.Sol	545,16	1,04	No.Sol	No.Sol
			x	344,78	**-0,44**	587,31	2,40	397,46	6,45	726,25	7,75	398,66	10,71	363,29	9,95
			all	794,56	1,12	806,45	1,93	464,86	0,82	No.Sol	No.Sol	No.Sol	No.Sol	No.Sol	No.Sol

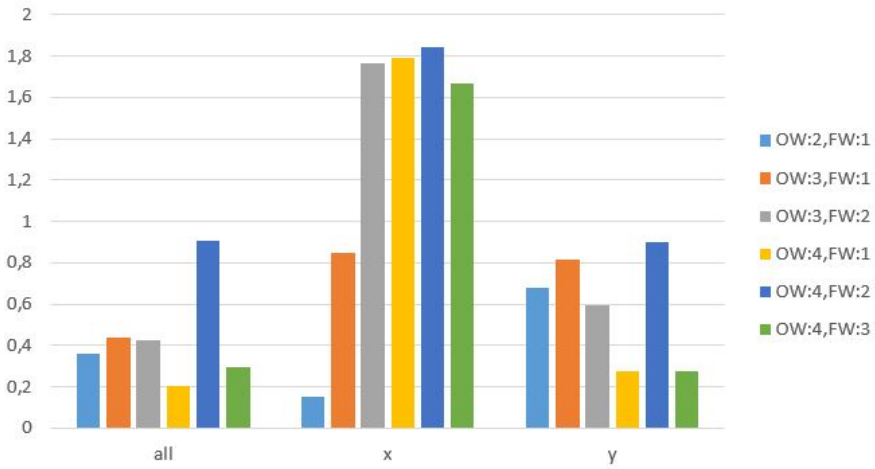

Figure 5.6: The results of average GAP (%) with Approximation Window for different window configurations and fixing strategies

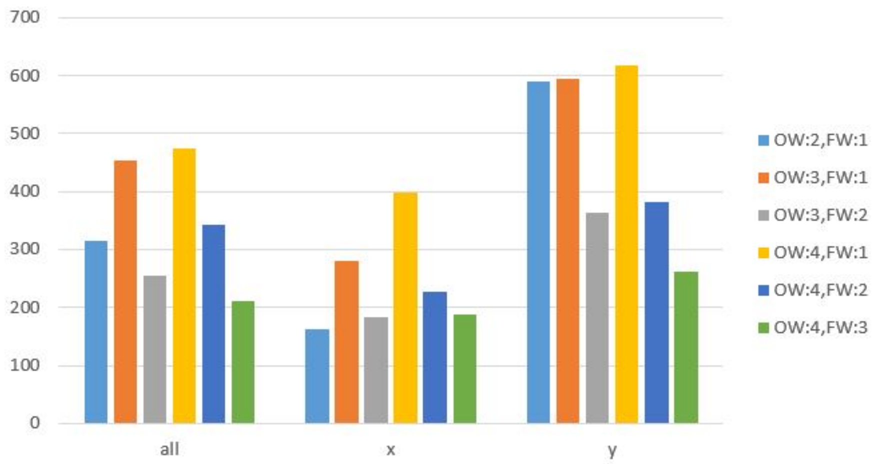

Figure 5.7: The results of average CPU(s) with Approximation Window for different window configurations and fixing strategies

for the solution of the developed probabilistic models in Chapter 4.

5.4.2 Solution of The Probabilistic Models

In Chapter 4, developed probabilistic constraints and the objective functions have been merged with each other and the built mathematical models have been tested on a small size instance composed of 3 machines and 3 periods (N3_T3) by using LINGO 18.0 solver. Therefore, the impact of the integration of the renewable energy uncertainty into the capacity selection procedure has been illustrated.

In this section, it is aimed to get better insight about the difficulty of the problem and the generated models are tested on more instances. While service level based models (PS_1) and (PS_2) are tested on the instances, based on the illustrative study presented in Chapter 4, the service level is considered as 0.5 for all the instances tested in this section. Therefore, it is intended to see the behavior of the models under relatively less rigid case compared to the case in which service level is is considered as 0.9 or 0.99. For the models including the mix of the traditional and one type of renewable energy source, the availability parameter is assumed as λ_s=0.02, for the cases in which two types of renewable energy sources are mixed with traditional energy sources, the parameters of the probability distribution are considered as λ_s=0.3, λ_w=0.02.

When the small size instances (N3_T3) are tested, it is seen that the LINGO solver can reach the optimality within short computational times. The obtained results are displayed in Table 5.4 and Table 5.5. The first noticeable result is that the models including two types of renewable energy sources need more time to reach optimality compared to the models based on the one type of renewable energy source. The other noteworthy result is that the models built with the objective function Type II (OF.2.1 or OF.2.2) can reach the optimum solution in a shorter time than the models built on the objective function Type I (OF.1.1 or OF.1.2).

Overall, since the instances N3_T3 are solvable in reasonable computational times, it is not required to apply the heuristic approach.

Table 5.4: The results of the probabilistic models for the mix of traditional and one type of RES for the instances of N3_T3

	OF.1.1+PS_1		OF.1.1+PS_5		OF.1.1+PS_7	
Instance	LINGO		LINGO		LINGO	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
3-3_1	607,19	3	607,19	3	610,79	60
3-3_2	819,93	36	819,93	36	825,99	219
3-3_3	578,17	3	578,17	3	581,77	13
	OF.2.1+PS1		OF.2.1+PS5		OF.2.1+PS7	
Instance	LINGO		LINGO		LINGO	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
3-3_1	608,68	1	608,68	1	618,28	1
3-3_2	827,74	7	827,74	7	837,35	2
3-3_3	579,65	1	579,65	1	589,26	1

When it comes to the slightly larger instances, the computation time of the LINGO solver is limited with 1 hour. The solution obtained at the end of the time limit is considered as reference solution. When the instances composed of 4 machines and 4 periods (N4_T4) or 5 machines and 5 periods (N5_T5) are tested with the built models, it is seen that the LINGO solver can not reach the optimum solution for a part of the N4_T4 instances (Table 5.6,Table 5.7.) However, when the instances including 5 machines (N5_T5) are solved, the difficulty increases and nearly all the instances can not reach feasible so-

Table 5.5: The results of the probabilistic models for the mix of traditional and two types of RES for the instances of N3_T3

Instance	OF.1.2+PS_2		OF.1.2+PS_6		OF.1.2+PS_8	
	LINGO		LINGO		LINGO	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
3-3_1	634,76	230	634,76	151	634,76	25
3-3_2	843,57	226	843,57	293	845,67	286
3-3_3	605,74	44	605,74	33	605,74	10
Instance	OF.2.2+PS_2		OF.2.2+PS_6		OF.2.2+PS_8	
	LINGO		LINGO		LINGO	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
3-3_1	653,56	37	653,56	2	653,56	2
3-3_2	872,63	45	872,63	19	872,63	1
3-3_3	624,53	80	624,53	1	624,53	1

lutions after 1 hour.

To cope with this difficulty, the Fix-and-Relax heuristic which is proposed for the solution of the deterministic MILP models is used for the solution of the MINLP models. Firstly, it is realized that the difficulty of the handled probabilistic models increases quickly. Based on this observation, it is aimed to decompose the problem into the smallest possible sub-problems and solve the sub-problems iteratively. From this point of view, instead of dropping the certain variables of the problem and handling with a partially relaxed problem, removing the approximation window could generate even more easier and manageable sub-problems. Therefore, it is proposed to solve the probabilistic models via F&R without Approximation Window approach.

As it is pointed out before, the size of sub-problems, so called Observation Window (OW) has an important role for solving the problem with high quality results in affordable computation times. There is no doubt that increasing size of OW generates a trade-off between the solution quality and the CPU time. Based on the several experiments, it has been seen that when the size of OW is considered 2 and the size of the Frozen Window (FW) is assumed equal to 1, the mathematical models can be solved in reasonable time periods. So, for all the experiments conducted on the instances N4_T4 and N5_T5, the same sizes are applied.

When it comes to the fixing strategy, based on the experience from the previous numerical study implemented on the deterministic model, since fixing the set-up decision ($y_{m,t}$) produces higher quality results in terms of the optimaity gap, $y_{m,t}$ variables are fixed in all the instances.

By taking into account all these outcomes and experiences from the previous experiments, F&R heuristic is coded on LINGO 18.0.

The results are displayed in Table 5.6 and Table 5.7. The first outstanding results in Table 5.6 and Table 5.7, the proposed F&R heuristic solves the all N4_T4 instances which can not be solved by LINGO within 1 hour in a shorter time. In some cases, the applied F&R heuristic can reach even better solution than the solution obtained by LINGO solver. This cases are shown in bold in the tables. Similar to the optimality gap, the proposed F&R heuristic outperforms the LINGO solver in terms of computational time. As the reader can realize, for some instances F&R heuristic reaches the optimum solution within a shorter time period than the computation time of LINGO solver.

When the results of the instances N5_T5 are examined, it is seen that even though proposed F&R heuristic approach can solve some of the instances which can not be solved by the LINGO solver within the time limit, most of the N5_T5 instances can not be solved the by heuristic approach.

Table 5.6: The results of the probabilistic models for the mix of traditional and one type of RES for the instances of N4_T4 and N5_T5

Instance	OF.1.1+PS_1				OF.1.1+PS_5				OF.1.1+PS_7			
	LINGO		FR		LINGO		FR		LINGO		FR	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
4-4_1	No sol.	3600	1164,17	1226	1673,37	3600	**1164,2**	917	1712,51	3600	**1174,17**	876
4-4_2	No sol.	3600	1211,51	1163	No sol.	3600	1211,5	1033	No sol.	3600	1242,88	760
4-4_3	No sol.	3600	989,49	343	No sol.	3600	989,49	271	1689,51	3600	**993,67**	586
5-5_1	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600
5-5_2	No sol.	3600	1692,87	3600	No sol.	3600	1385,9	3600	No sol.	3600	No sol.	3600
5-5_3	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600

Instance	OF.2.1+PS_1				OF.2.1+PS_5				OF.2.1+PS_7			
	LINGO		FR		LINGO		FR		LINGO		FR	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
4-4_1	1200,56	492	1200,56	1424	1200,6	501	1200,6	1061	1200,56	29	1212,06	1188
4-4_2	1228,51	1142	1228,51	1179	1228,51	1175	1228,5	957	1228,51	17	1251,97	1048
4-4_3	991,87	387	991,87	384	991,87	396	991,87	609	1003	16	1044,36	986
5-5_1	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	1781,14	181	No sol.	3600
5-5_2	No sol.	3600	1701,78	3600	No sol.	3600	No sol.	3600	1527,67	143	1891,24	3600
5-5_3	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	1603,22	35	No sol.	3600

Table 5.7: The results of the probabilistic models for the mix of traditional and two types of RES for the instances of N4_T4 and N5_T5

	OF.1.2+PS2				OF.1.2+PS6				OF.1.2+PS8			
Instance	LINGO		FR		LINGO		FR		LINGO		FR	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
4-4_1	No sol.	3600	1186,8	885	No sol.	3600	1186,8	1830	No sol.	3600	1197,93	2131
4-4_2	No sol.	3600	1234,2	938	2490,69	3600	1234,2	1851	No sol.	3600	1240,61	1623
4-4_3	1092,72	3600	**1017,26**	942	1415,3	3600	**1017,3**	1711	No sol.	3600	1017,26	2109
5-5_1	No sol.	3600	No sol.	3600	No sol.	3600	1508,2	3600	No sol.	3600	No sol.	3600
5-5_2	No sol.	3600	2009,05	3600	1578,53	3600	1621,6	3600	No sol.	3600	1756,9	3600
5-5_3	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600
	OF.2.2+PS2				OF.2.2+PS6				OF.2.2+PS8			
Instance	LINGO		FR		LINGO		FR		LINGO		FR	
	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)	Obj	CPU(s)
4-4_1	No sol.	3600	1236,36	1698	1236,36	858	1236,4	1440	1236,36	11	1261,9	1549
4-4_2	No sol.	3600	1264,31	2100	1264,31	1078	1264,3	1080	1264,31	27	1305,66	1720
4-4_3	No sol.	3600	1041,7	1380	1041,7	380	1041,7	1209	1041,7	7	1094,2	1451
5-5_1	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	1823,26	279	No sol.	3600
5-5_2	No sol.	3600	1866,79	3600	No sol.	3600	No sol.	3600	1567,48	149	1884,84	3600
5-5_3	No sol.	3600	No sol.	3600	No sol.	3600	No sol.	3600	1645,34	29	No sol.	3600

5.5 Conclusion

Since the problem is NP-Hard, a Fix-and-Relax heuristic is introduced to solve the problem. Two different relaxation procedures are applied and the performance of the solution approach is tested on randomly generated instances. It is seen that the obtained results are quite promising. The applied heuristic approach produces solutions with the optimality gap 0.2% in average for the small problem sizes such as (N5_T5,N5_T7). For the larger instances, it allows to reach better results than the results obtained by commercial solvers within a shorter time.

In the following, one of the proposed variants of F&R heuristic is applied for the solution of probabilistic models which are developed for the single-item lot sizing problem with capacity selection problem under renewable energy uncertainty. It is seen that implemented heuristic approach can solve the relatively small size instances like N4_T4 which can not be solved by commercial solver within 1 hour. However, the instances including 5 machines and 5 periods (N5_T5) are still quite difficult for the presented heuristic approach.

The implemented F&R heuristic might be developed by backtracking procedure to deal with the possibility of facing infeasibility of sub-problems.

Conclusions and Perspectives

Conclusions

The world's energy need mainly relies on the fossil fuels which are responsible for the increased carbon emission. In addition to this side effect, the limited nature of the conventional energy sources rises the concerns about the meeting the energy need of the world. The projected increase in energy consumption and changing climate conditions lead the governments to seek more sustainable and clean ways for energy generation. The manufacturing sector has an important role since it has one of the largest share in the total energy consumption. Based on this fact, increasing the energy efficiency in the industrial area and facilitating the transition from traditional sources to renewable ones, not only contributes to the declining the overall carbon emission levels significantly, but also contributes to achieve the sustainability targets.

The main objective of this thesis is to propose optimization models and solution approaches for the Single-Item Capacitated Lot-Sizing Problem for Flow-Shop Systems by considering the energy availability constraints. To integrate availability of the energy sources to the production planning models, the handled problem is combined with the contract capacity selection problem by inspiring from the real life practices.

Chapter 2 reviews the literature and affirms that the handled problem in this thesis has never been studied before in the literature. In Section 2.4, the lot-sizing studies including uncertain parameters are reviewed and it is seen that, the uncertainty of the availability of the renewable energy sources has never been integrated to the lot sizing problems. In addition to this originality, the application of probabilistic constraints to model the uncertain nature of the renewable energy sources is the another novelty of our study.

In Chapter 3, we present mixed integer linear programming (MILP) models including contract capacity constraints for the handled problem which minimizes the production and energy related costs. Firstly, the model of Masmoudi et al. [2017a] which constitutes the basis of our study is tested on a representative instance and the necessity of the connection with the capacity selection problem is explained briefly. Then, their model is improved in terms of the calculation of the power demand for each period. Then, the contract options are integrated to the improved model in continuous and discrete manner. The proposed models are solved on CPLEX 12.6 solver and it is seen that the model can reach the optimality within the defined time limit for only small size instances. While some of the mid-size instances can reach the optimality, any of the large-size instances can not attain the optimality at the end of the 1 hour. The results show the necessity of an appropriate approximation heuristics to solve the problem.

In the next chapter, the developed model is extended to the uncertain environment and the stochastic nature of the renewable energy sources is taken into account. To model the uncertainty of the renewable energy sources, three types of probabilistic constraints that consider the mix of the traditional energy with one type of renewable energy source and two types of renewable sources are proposed. In coherence with the presented probabilistic constraints, to compute the cost of the failure in the supply of the renewable energy sources, two types of objective functions are developed. The developed probabilistic constraints and objective functions, firstly, are presented in a general frame and after expanded with the assumption of exponential distribution. The obtained equivalences of the probabilistic constraints and objective functions are integrated with the previously developed single-item lot sizing problem. Thus, several models are proposed. The models that are built by different combinations of the proposed constraints and the objective functions are tested on an illustrative instance and it is shown the contract capacity choice of the manufacturers and the production configuration change when the uncertainty of the renewable energy sources are taken into account.

Chapter 5 is devoted to the appropriate solution approaches. Since the problem is NP-Hard, a Fix-and-Relax heuristic is introduced to solve the problem. Two different relaxation procedures are applied and the performance of the solution approach is tested on randomly generated instances. It is seen that the obtained results are quite promising. The applied heuristic approach produces solutions with the optimality gap 0.2% in average for the small problem sizes such as (N5_T5,N5_T7). For the larger instances, it allows to reach better results than the results obtained by commercial solvers within a shorter time. In the following, proposed heuristic is applied for the developed stochastic models. It is seen that implemented heuristic approach can solve the relatively small size instances like N4_T4 which can not be solved by commercial solver within 1 hour. However, the instances including 5 machines and 5 periods (N5_T5) are still quite difficult for the presented heuristic approach.

Overall, this thesis contributes to the field of energy aware production planning optimization.

Perspectives

The study conducted in this thesis, opens several paths for the future researches. We would like to present some of the perspectives that can attract the researchers for the further studies.

Short Term Perspectives

One of the short term targets is to develop effective local search algorithms that can solve the large-size instances within a reasonable computational time with a high quality results. In terms of the application of our study in real life cases where dozens of the machines are run, it has a vital importance.

Long Term Perspectives

In our study, the scaling of the machine speed is left out of the context and the processing time is assumed as constant value. When the machine speed scaling features are integrated to the model, since the power demand configuration changes significantly, the obtained results and the comparison with our model would be interesting study.

In this thesis, the environmental-aware models are constructed based on the cost-minimization approach. Alternatively, the carbon emission levels can be minimized by modelling the same problem with the multi-objective approach. The occurring conflicts between the cost minimization and the carbon emission levels would generate different energy mixtures to subscribe for the customers.

In the Chapter 4, while the stochastic nature of the renewable energy sources is taken into account, the external demand is kept as deterministic. The randomness of the demand can be considered along side with the randomness of the renewable energy sources. Generally speaking, the presented models in this thesis can be enriched with the consideration of other uncertain parameters.

Another perspective is that, the handled problem in this thesis can be joint with the facility location problem. Each region of a country/city has a different characteristic in terms of the renewable energy availability. In this type of joint problem, the consideration of the random availability of the renewable energy sources has more importance and by viewing the availability of the renewable energy sources and the contracted power options, the problem can be formulated as dynamic facility location problem.

Last but not least, in last years, on-site generation applications grow up significantly. Accordingly, Feed-In-Tariffs that award the customers who install the renewable energy generation facilities at their companies or (residents) are deployed. The consideration of the on-site generation and the integration of the amount of the energy generated by their own installation, will change the contracting scheme with the energy supplier.

Annexe A

Résumé étendu en francais

Contents

A.1 Introduction

L'Union Européenne définit des objectifs énergétiques pour 2020, 2030 et 2050 visant à surveiller systématiquement la consommation d'énergie des pays de l'UE. Ces objectifs fournissent un cadre politique cohérent pour les émissions de gaz à effet de serre dans l'Union Européenne, les sources d'énergie renouvelables et l'efficacité énergétique. Les objectifs énergétiques connus pour «Objectifs 20-20-20» pour 2020 définissent les priorités comme suit :

— augmenter la part des énergies renouvelables dans la consommation énergétique de l'UE d'au moins 20%

— réduire les gaz à effet de serre d'au moins 20%

— augmenter l'efficacité énergétique d'au moins 20%

Pour atteindre les objectifs définis, le secteur manufacturier joue un rôle important puisqu'il occupe une des parts les plus importantes dans la consommation totale d'énergie. L'augmentation de la consommation d'énergie renouvelable dans la zone industrielle contribue non seulement à la diminution significative des niveaux globaux d'émissions de carbone, mais facilite également la réalisation des objectifs de durabilité. En d'autres termes, si les sources d'énergie conventionnelles fournies aux clients industriels sont diversifiées avec les énergies renouvelables; bien que les réserves énergétiques mondiales puissent être utilisées plus efficacement, les objectifs environnementaux peuvent être atteints en réduisant considérablement les niveaux d'émissions de carbone.

L'utilisation efficace des ressources dépend fortement des stratégies de planification et d'ordonnancement appropriées, conçues de manière cohérente avec la capacité du système et la disponibilité des ressources. Lorsque les contraintes liées aux ressources sont ignorées, les plans de production générés aboutissent à un échec, entraînant l'augmentation des coûts.

L'énergie diffère des autres ressources d'un système de production en termes de conditions de stockage et d'approvisionnement. La gestion des besoins en énergie d'un système de production nécessite une compatibilité élevée entre le client industriel et le fournisseur d'énergie. Afin de satisfaire l'harmonie entre les deux parties et de contrôler l'équilibre entre l'offre et la demande en énergie, différents tarifs sont proposés aux clients, avec notamment des mécanismes de tarification différents et des options de puissance (capacité).

Il est essentiel de prendre en compte les contraintes et les limites définies par le fournisseur d'énergie pour élaborer des plans de production appropriés, satisfaire l'efficacité et minimiser les coûts énergétiques des systèmes de production.

À ce stade, en plus des questions de planification de la production telles que "Quand et combien doit-on produire?" qui peut être traduit par des «problèmes de dimensionnement de lots» et la deuxième question est «combien, quand et où les ressources doivent être allouées?" qui peut être traduit par "un problème de ordonnoncament", un autre problème se pose aux fabricants : «Laquelle des options de capacité proposées peut couvrir les besoins du système de production? "

En particulier, au cours des dernières décennies, les sociétés ont pris de plus en plus conscience de la nécessité de protéger la planète, de produire ou de consommer le biens / services de manière plus écologique. Remplacer les sources d'énergie traditionnelles qui ont un effet de serre énorme sur la planète par des sources d'énergie naturelles illimitées et propres est devenu l'une des préoccupations majeures de tous les pays.

Dû au fait que les clients industriels ont la plus grande part de la consommation d'énergie et que la grande partie de cette consommation est fortement basée sur les ressources fossiles, le secteur industriel est plus scruté que jamais pour réduire les émissions de carbone. C'est pourquoi les entreprises de fabrication cherchent les moyens de maintenir leurs activités de production de manière plus respectueuse de l'environnement. Évidemment, augmenter l'utilisation des énergies renouvelables les sources peuvent surmonter ce problème.

Aujourd'hui, la part des sources d'énergie renouvelables dans le total de l'électricité achetée est déterminée par les fournisseurs d'énergie. Comme expliqué précédemment, pour atteindre les objectifs de l'UE, les gouvernements encouragent l'utilisation des sources d'énergie renouvelables. Les clients industriels sont confrontés à de nouvelles réglementations visant à réduire leurs émissions de carbone à des niveaux acceptables. Par conséquent, le choix de la meilleure option de capacité pour les sources d'énergie renouvelables aura également une importance vitale.

Cependant, la nature stochastique des sources d'énergie renouvelables découragent les clients industriels qui ont besoin d'un approvisionnement constant en énergie pour réaliser les plans de production sans interruption. La dernière question "Comment les sources d'énergie renouvelables peuvent-elles être intégrées à la procédure d'achat d'énergie en considérant leur nature incertaine?"

Dans cette these, nous combinons trois problèmes d'optimisation et trouvons les réponses aux questions suivantes pour contribuer à accroître l'efficacité énergétique et l'efficacité de la production :

1. Problème de dimensionnement de lot dans un systeme de Flow-Shop
   Quand et combien de produits doit être fabriqué ?
   Comment organiser la production ?
2. Problème de sélection de la capacité contractuelle
   Quelle option de capacité peut réaliser de manière optimale la production planifiée ?
   Comment le meilleur mix énergétique peut-il être généré à partir des options proposées ?
3. Générer le meilleur mix énergétique en cas d'incertitude liée aux énergies renouvelables
   Comment générer le meilleur mix énergétique lorsque la nature stochastique des énergies renouvelables sources d'énergie est considéré ?

L'objectif principal est de développer un modèle d'optimisation permettant de définir les quantités de production optimales, l'attribution des emplois aux machines et l'option de capacité optimale pouvant couvrir les besoins de la production planifiée. Par conséquent, les deux premiers problèmes peuvent être résolus simultanément par le modèle développé.

Le deuxième objectif est d'intégrer la caractéristique stochastique des sources d'énergie renouvelables dans le problème de la sélection de la capacité et de créer un pont entre la procédure de sélection de la capacité et les décisions de dimensionnement des lots dans l'incertitude. Le dernier objectif est de proposer une approche de solution appropriée capable de gérer la complexité du modèle développé et fournir une solution optimale / quasi-optimale dans un temps de calcul raisonnable.

Au cours des dernières décennies, l'intégration de l'énergie aux problèmes de planification de la production a été un sujet brûlant de la littérature et de nombreuses contributions originales ont été publiées. La section suivante présente brièvement les études précédemment réalisées dans le domaine de la planification de la production avec l'aspect de l'énergie.

A.2 Etat de art

L'aspect énergétique peut être pris en compte aux différents niveaux hiérarchiques du processus de prise de décision. Cette hiérarchie est composée de trois niveaux : décisions stratégiques, tactiques et opérationnelles.

Dans cette thèse, l'aspect énergie est pris en compte au niveau tactique et le problème de dimensionnement d'un lot de production est étudié.

Il est possible de classer les études de dimensionnement des lots publiés qui comprennent l'aspect énergétique en deux groupes en fonction de la manière d'intégrer l'aspect énergétique :

— Les études qui visent à limiter les niveaux d'émission de carbone conformément aux différentes réglementations en matière de carbone et à minimiser les coûts opérationnels liés aux coûts écologiques.

— Les études qui visent à minimiser les coûts énergétiques du système de production.

Pour les études combinant problème de dimensionnement de lots et aspect écologique, l'étude de Absi et al. [2013] peut être considérée comme l'une des études pionnières. Ils proposent quatre types de contraintes d'émission de carbone appelées contrainte périodique d'émission de carbone, contrainte cumulative d'émission de carbone, contrainte globale d'émission de carbone et contrainte d'émission de carbone glissante et prouvent que lorsque le problème de dimensionnement de lot est combiné avec les contraintes sauf les contraintes périodiques d'émission de carbone, le problème devient un problème NP-difficile. Les études de Benjaafar et al. [2013], Akbalik and Rapine [2014], Velázquez-Martínez et al. [2014], Helmrich et al. [2015], Zouadi et al. [2015, 2018, 2016] sont quelques exemples parmi d'autres qui traitent des effets environnementaux tout en prenant des décisions concernant le dimensionnement des lots.

Dans cette thèse, nous localisons dans la deuxième catégorie et l'énergie est intégrée au problème de dimensionnement des lots comme ressources du système de production et elle vise à minimiser les coûts liés à l'énergie.

Masmoudi et al. [2015] prennent en compte les coûts de consommation d'énergie et d'électricité et proposent un modèle pour le problème de dimensionnement de lots. Dans leur étude, au lieu de donner un coût de production donné comme dans le problème classique de la taille d'un lot, on calcule un coût de production dépendant du coût de l'électricité et variant d'une période à l'autre. De plus, la demande totale en énergie est calculée pour chaque période et limitée par la quantité maximale d'énergie pouvant être fournie par le fournisseur d'énergie. Le modèle vise à identifier les quantités de production optimales en minimisant les coûts de production et d'énergie. À notre connaissance, l'étude de Masmoudi et al. [2015] est la première tentative combinant de cette manière le problème de dimensionnement de lots et l'aspect énergétique. Après cela, de nombreuses études combinent le problème de dimensionnement de lots avec l'aspect énergétique en visant les coûts de production et d'énergie ont été publiées. Les études de Giglio et al. [2017], Rapine et al. [2018b], Wichmann et al. [2018], Johannes et al. [2019] peuvent être données à titre d'exemple.

Il est un fait que, dans la réalité, les fournisseurs d'énergie peuvent fournir l'énergie à leurs clients avec un certain équilibre. Pour maintenir ce flux d'énergie équilibré, ils négocient avec les clients pour différentes options d'alimentation, y compris différents tarifs, et parviennent à un accord. En s'inspirant des pratiques de la vie réelle, dans cette thèse, le modèle de Masmoudi et al. [2015] est étendu au problème de la sélection optimale de la capacité des contrats d'énergie. Le modèle proposé dans cette thèse vise à identifier la quantité de production optimale qui répond à la demande en tenant compte des contraintes du système et énergétiques et à sélectionner la capacité de contrat énergétique optimale offerte par les fournisseurs en fonction de la configuration de la production. Le modèle proposé prenant en compte les options de capacité offertes par les fournisseurs d'énergie, il vise à synchroniser les besoins en énergie du système de production et les options du marché. Par conséquent, elle satisfait à des plans de production plus réalistes et adaptés aux conditions du fournisseur d'énergie.

La manière conventionnelle de choisir l'option de capacité contractuelle consiste à vérifier les données historiques et à prévoir la demande en énergie de la prochaine période contractuelle. Dans ce cas, étant donné que la décision de sélection de la capacité du contrat est prise sans correspondre à la demande en énergie de la production planifiée avec précision, cette affaire entraîne des insuffisances dans l'utilisation de la quantité d'énergie achetée ou une utilisation excessive d'énergie, et principalement des coûts supplémentaires engendrés par ce type de discordances. À l'avenir, avec l'utilisation accrue des sources d'énergie renouvelables, gérer les opérations de production et de stockage d'énergie et satisfaire l'équilibre entre la demande en énergie et l'alimentation en électricité, en obtenant des données plus précises sur leur demande d'énergie à partir de la clientèle deviendra de plus en plus important.

Malgré l'importance de la procédure de sélection de la capacité contractuelle, peu d'études abordent ce problème avec différentes solutions. Tsay et al. [2001] a appliqué des algorithmes évolutionnaires pour résoudre des problèmes de sélection de contrat optimaux. Lee and Chen [2007] ont mis en œuvre des processus de numérisation qui ont résolu le problème de la sélection des capacités, y compris les taux de durée d'utilisation. Yang and Peng [2012] ont amélioré la méthode de Taguchi, qui intègre la méthode de Taguchi traditionnelle et l'algorithme PSO. Hwang et al. [2009] ont résolu ce problème en mettant en œuvre des algorithmes d'optimisation de CSO (Cat Swarm Optimization) et d'optimisation de PSO (Particle Swarm Optimization). Chen and Liao [2011] a proposé de résoudre le problème avec la programmation linéaire. Point commun de toutes ces études, la capacité contractuelle optimale a été choisie sur la base de données historique de consommation d'énergie en appliquant divers algorithmes heuristiques ou techniques de programmation linéaire.

Cependant, aucune étude ne permet d'établir un lien direct entre les décisions de sélection de contrats d'énergie et les décisions de planification de la production. Notre étude promet de combler ce manque.

Une autre nouveauté de notre étude réside dans le fait que les sources d'énergie renouvelables et leur nature incertaine sont prises en compte lors de la création d'un mix énergétique qui peut couvrir les besoins en énergie du système.

Aloulou et al. [2014] classifient les études de dimensionnement de lots conduites en considérant des paramètres non déterministes en fonction de la demande, du rendement, délais de production délais d'installation, capacité de production ou limites d'inventaire, coût, ressources etc. Lorsque les études sont passées en revue par Aloulou et al. [2014], on constate que, les études ne considèrent pas l'aspect énergétique en tant que paramètre stochastique. Dans notre travail, nous traitons du caractère incertain des sources d'énergie renouvelables en proposant des contraintes probabilistes et des fonctions objectives. A notre connaissance, il s'agit de la première tentative qui intègre de cette manière les sources d'énergie renouvelables au problème de dimensionnement des lots.

A.3 Les modèles déterministes

A.3.1 Définition du problème & objectif

Puisque l'étude de Masmoudi et al. [2017a] constitue la base de notre travail, nous construisons nos modèles mathématiques sur la base de la configuration de production considérée dans leur étude.

Dans le travail de Masmoudi et al. [2017a], le problème de lot-sizing dans un système de production de type flow-shop est étudié. Le système de production est composé de N machines et de N zones de stockage (Figure A.1). L'horizon de planification est divisé en T périodes. Chaque période ($t = 1, ..., T$) est représentée par sa durée L_t (pas nécessairement égale pour toutes les périodes), un prix de l'électricité Co_t, un prix de l'énergie θ_t et une demande extérieure d_t.

L'objectif de l'étude est d'identifier les quantités de production ($x_{m,t}$) pour chaque machine ($m = 1, ..., N$) à chaque période ($t = 1, ..., T$) en minimisant le coût total composé des coût d'électricité, de puissance, de stockage, tout en satisfaisant la demande externe (d_t, $t = 1, ..., T$) et les contraintes liées à la production et à la limitation de la puissance à

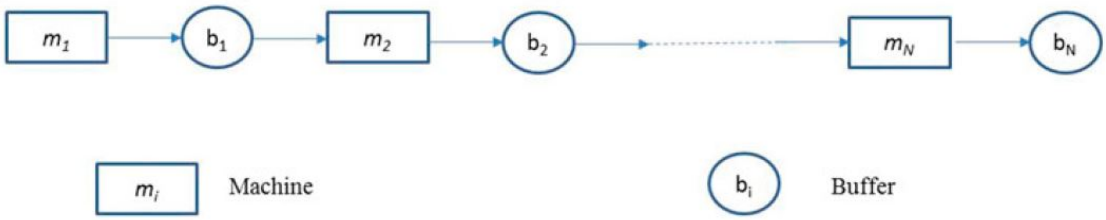

FIGURE A.1: Un système de production de type flow-shop Masmoudi et al. [2017a]

chaque période (α_t).

Le modèle est développé sur les hypothèses suivantes :

— La demande externe est déterministe, connue à l'avance et doit être satisfaite à la fin de chaque période.

— Un seul produit est considéré.

— Le plan de production est élaboré pour un horizon de T périodes ($t = 1, ..., T$).

— La première machine n'est jamais affamée et la dernière n'est jamais bloquée, à chaque période.

— La capacité de chaque machine est limitée par la durée et la puissance disponible maximale.

— Une machine m ne peut démarrer la production que lorsque toute la quantité à produire ($x_{m,t}$) est disponible à la sortie de la machine précédente (contrainte d'interaction verticale).

— Pour chaque machine, un seule lancement (set-up) est autorisée à chaque période.

— La demande d'énergie (E_t^{max}) à chaque période est calculée en tenant compte de la puissance des machines fonctionnant en parallèle et ne doit pas dépasser une puissance maximale définie (α_t)

Les paramètres et les variables de décision du problème sont présentés dans le Tableau 3.1. Chaque machine est caractérisée par sa puissance (ϕ_m) et son temps de traitement (p_m). Dans l'étude de Masmoudi et al. [2017a] le coût de consommation électrique de la machine m à la période t par unité de produit ($\psi_{m,t}$) est calculé en multipliant le temps de traitement de la machine (p_m), la puissance de la machine (ϕ_m) et le prix de l'électricité (Co_t) en période t. La fonction objective du modèle développé par Masmoudi et al. [2017a] est la suivante :

$$Min z = \sum_{t=1}^{T} \sum_{m=1}^{N} (\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) + \sum_{t=1}^{T} (\theta_t.E_t^{max}) \tag{A.1}$$

Le modèle détaillé proposé par Masmoudi et al. [2017a] se trouve dans la section 3.2.4. Lorsque le modèle développé par Masmoudı est testé sur une instance donnée dans la section 3.2.5, la configuration de production est obtenue comme suit :

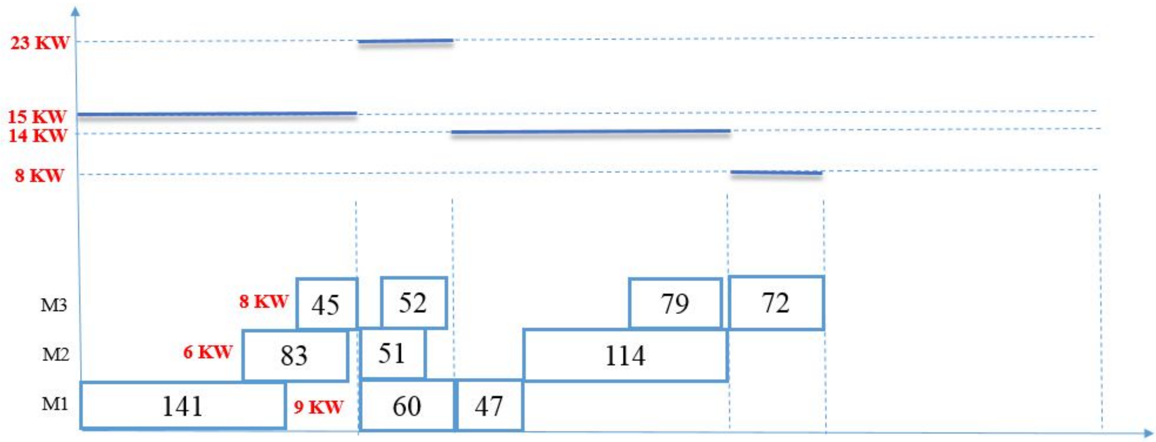

FIGURE A.2: La configuration de fabrication obtenue par le modèle de Masmoudi et al. [2017a]

La configuration de production dans la Figure A.2 représente la solution optimale pour l'instance donnée. Les rectangles représentent les machines et les chiffres à l'intérieur de ceux-ci indiquent la quantité de production optimale. La demande en puissance de chaque machine est affichée à côté des carrés et la demande en puissance maximale pour chaque période est indiquée en haut des intervalles de temps avec des lignes.

Dans la Figure A.2, lorsque on examine la demande de puissance, on observe une tendance de la puissance fluctuante. Il n'y a pas d'équilibre de charge entre les périodes et le système de demande d'énergie existant n'est ni réaliste ni pratique pour le fournisseur d'énergie. Etant donné que les producteurs d'énergie ont du mal à prévoir ce type de conguration oscillante de la demande d'énergie, il est également difficile de planifier la production et la distribution d'énergie. Pour offrir un meilleur service à leurs clients, ils offrent des options d'alimentation à leurs clients. Cette pratique réelle peut être évaluée comme une sorte de relation de type gagnant-gagnant. Tandis que les producteurs d'énergie maintiennent la demande énergétique des clients à certains intervalles et planifient leur production en conséquence, les clients industriels peuvent négocier l'option électrique permettant de couvrir les besoins en énergie de leur système de production.
À ce stade, la question de savoir quelle option de capacité est la meilleure pour mener les activités de production de manière plus sûre et moins coûteuse s'élève.

Notre modèle mathématique associe le problème de dimensionnement de lots pour les systèmes flow-shop au problème de sélection de capacité. Avant de donner les détails du modèle développé dans cette thèse, il est nécessaire de se concentrer sur les faiblesses du modèle développé par Masmoudi et al. [2017a].

A.3.2 Amélioration du calcul de la puissance de pointe

Après avoir testé le modèle développé par Masmoudi et al. [2017a] sur la taille différente des instances, on se rend compte que la méthode proposée, dans leur étude, pour calculer la puissance requise pour chaque période calcule la limite supérieure de la demande de puissance de pointe au lieu de calculer la valeur de puissance de pointe exacte pour certaines des instances. Considérons les configurations de production présentées à la Figure A.3.

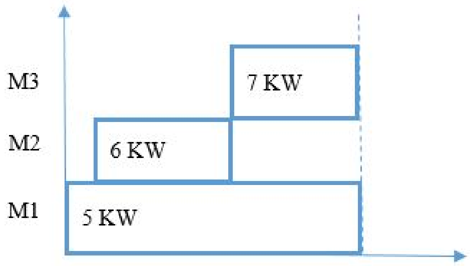

FIGURE A.3: Exemple (1) dans lequel la limite supérieure de la puissance est calculée

TABLEAU A.1: The resolution of the configuration in Figure A.3

	r=1		r=2		r=3		Over.Mac	ϕ_m+ϕ_r
	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$	$f_{m,r,t}$	$g_{m,r,t}$		
m=1	0	0	1	1	1	1	1,2,3	18
m=2	1	0	0	0	1	0		
m=3	1	1	0	1	0	0	1,3	12
							E_t^{max}	18

Pour identifier les valeurs des variables $f_{m,r,t}$ et $g_{m,r,t}$, rappelons les contraintes associées du modèle présenté dans la section 3.2.4.

$$C_{r,t} - C_{m,t} + x_{m,t}.p_m \leq M.f_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{A.2}$$

$$C_{m,t} - C_{r,t} \leq M.g_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N \neq m, t = 1,...,T \tag{A.3}$$

En fonction des contraintes (A.2) et (A.3), les valeurs des variables $f_{m,r,t}$ et $g_{m,r,t}$ sont données dans Tableau A.1. Puisque les valeurs des variables $f_{1,2,t} = g_{1,2,t} = 1$ et $f_{1,3,t} = g_{1,3,t} = 1$, la demande de puissance de pointe est calculée à 18 KW. Tandis que, dans cette configuration, le chevauchement existe qu'entre les première et deuxième machines et les première et troisième machines. La demande de puissance de pointe correcte doit être calculée en comparant les demandes de puissance de pointe de groupes de machines se chevauchant.

Pour faire face à ce problème, premièrement, les valeurs des variables $f_{m,r,t}$ et $f_{m,r,t}$ sont fixées soit à 1 ou à 0 et les contraintes suivantes sont introduites dans le modèle :

$$C_{m,t} - x_{m,t}.p_m - C_{r,t} \leq M.(1 - f_{m,r,t}) - 1 \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, \forall t = 1,...,T \tag{A.4}$$

$$C_{r,t} - C_{m,t} \leq (M.(1 - g_{m,r,t})) + 1 \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \tag{A.5}$$

Dans la deuxième étape, une nouvelle variable $A_{m,r,t}$ est introduite. Elle identifie l'existence d'un chevauchement entre les machines et les contraintes suivantes sont développées en tenant compte des versions symétriques des variables de $f_{m,r,t}$, $g_{m,r,t}$. Ainsi, tant que la condition de chevauchement ($f_{m,r,t} = g_{m,r,t} = 1$) est satisfaite dans au moins une direction, $m \rightarrow r$ ou $r \rightarrow m$, l'existence d'un chevauchement entre les machines m et r est garantie.

$$f_{m,r,t}.g_{m,r,t} + f_{r,m,t}.g_{r,m,t} \leq M.A_{m,r,t} \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \tag{A.6}$$

$$f_{m,r,t}.g_{m,r,t} + f_{r,m,t}.g_{r,m,t} - 1 \geq A_{m,r,t} - 1 \quad \forall m = 1,...,N, r = 1,...,N, r \neq m, t = 1,...,T \tag{A.7}$$

Après avoir assuré l'existence d'un chevauchement avec la variable $A_{m,r,t}$, le calcul de la puissance maximale est amélioré en identifiant les groupes de machines qui se chevauchent. Pour ce faire, la variable $ws_{m,r,t}$ est introduite dans le modèle mathématique défini comme suit :

$$ws_{m,r,t} = \begin{cases} 0, & \text{s'il y a au moins une machine } r' \ (1 \leq r' < r) \text{ qui chevauche la machine } m \\ & \text{mais ne se chevauchent pas avec la machine } r \text{ en période } t \\ 1, & \text{sinon} \end{cases} \tag{A.8}$$

Le point essentiel de $ws_{m,r,t}$ est qu'il permet non seulement d'identifier le chevauchement des machines m et r, mais également de vérifier leur état avec les machines suivantes. Il est donc utile de définir les groupes de machines qui se chevauchent.

Pour traduire la définition et le but donné de la variable $ws_{m,r,t}$ en correspondance mathématique, les contraintes suivantes sont développées :

$$\sum_{r'=1,r'\neq m}^{r-1}(A_{r',r,t}.A_{m,r',t}) \geq (\sum_{r'=1,r'\neq m}^{r-1} A_{m,r',t}).ws_{m,r,t} \quad \forall m=1,...,N, t=1,...,T, r=2,...,N \tag{A.9}$$

$$\sum_{r'=1,r\neq m}^{r-1}(A_{m,r',t}) - \sum_{r'=1,r\neq m}^{r-1}(A_{r',r,t}.A_{m,r',t}) \geq (1-ws_{m,r,t}) \quad \forall m=1,...,N, t=1,...,T, r=2,...,N \tag{A.10}$$

Le défi suivant consiste à calculer la demande de puissance des machines en prenant en compte les groupes de machines qui se chevauchent. Pour ce faire, la contrainte suivante est développée et remplacée par la contrainte (3.11) dans le modèle de Masmoudi et al. [2017a] :

$$E_t^{max} \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N}(A_{m,r,t}.ws_{m,r,t}.\phi_r) \quad \forall m=1,...,N, t=1,...,T \tag{A.11}$$

En conséquence, le besoin en puissance du premier groupe de machines qui se chevauchent est calculé à 11 KW, tandis que le besoin en puissance du second groupe est de 12 KW. Ainsi, par les nouvelles contraintes développées, la demande de puissance de la configuration dans la Figure A.3 est calculée à 12 KW. La lacune du modèle de Masmoudi et al. [2017a] est gérée, au lieu de calculer la limite supérieure de la demande de puissance (18 KW), le besoin de puissance exact des machines est calculé. Après tous ces développements, la version complète du modèle amélioré est présentée in Section 3.3.3.

Le modèle (P_1) présenté dans la Section 3.3.3 inclut des contraintes non linéaires. Pour pouvoir utiliser les solveurs linéaires, le modèle proposé est linéarisé dans la Section 3.3.4. Le modèle linéarisé est testé sur les données générées aléatoirement et les résultats sont présentés dans le Tableau 3.12.

A.3.3 Problème de dimensionnement de lot en prenant en compte le problème de sélection du contrat d'énergie

Dans cette étude, nous étudions le problème de dimensionnement de lots pour une configuration de flow-shop en intégrant le problème de sélection de la capacité énergétique. Un système de production composé de N machines et de N tampons est considéré comme indiqué à la Figure A.1.

Les clients se voient proposer des options de capacité pour trois types de sources d'énergie (éolienne, solaire et traditionnelle) et sont invités à créer le mix énergétique optimal pouvant couvrir les besoins de leur système de production.

Le modèle développé a pour objectif de déterminer les quantités de production optimales à produire sur chaque machine et à chaque période, ainsi que de déterminer la demande de puissance maximale requise en minimisant les coûts de production, de stockage, set-up et d'énergie et de synchroniser la demande de puissance du système avec les options de contrat de capacité offertes par le fournisseur d'énergie.

Les hypothèses liées à la configuration de production sont conservées telles quelles dans le modèle Masmoudi et al. [2017a]. En outre, les hypothèses relatives à l'énergie peuvent être énumérées comme suit :

- Trois types de sources d'énergie (traditionnelle, éolienne et solaire) sont utilisés.
- Toutes les sources d'énergie sont fournies et achetées à un fournisseur d'énergie, c'est-à-dire que le mécanisme de génération sur site est hors contexte.
- Tous les types de sources d'énergie étant fournis par un fournisseur d'énergie, leurs prix sont définis en fonction des tarifs fixés par les fournisseurs d'énergie.
- La stratégie de tarification de l'électricité en fonction de l'heure d'utilisation (TOU) est appliquée. Un jour est composé d'une successive de périodes ON (prix de l'électricité plus élevé) et OFF (coûts de l'électricité moins élevés).
- Les options de capacité peuvent être proposées sous deux formes : On peut demander aux clients de choisir une valeur quelconque dans un intervalle ou une option parmi un certain nombre (R_k) d'options de capacité (qui ne sont pas nécessairement égales pour toutes les sources), proposés par les fournisseurs d'énergie pour chaque type de source d'énergie k. Le client peut choisir celle qui convient le mieux. Dans cette thèse, le modèle mathématique est développé pour ces deux cas. Ces deux versions sont nommées *la capacité continue* et *la capacité discrète*.

Les hypothèses pour la capacité continue

- Les limites inférieure (P_k^{min}) et supérieure (P_k^{max}) de la quantité d'énergie fournie sont définies par le fournisseur d'énergie pour chaque type de sources énergie k.
- Un coût unitaire d'énergie $Vcost_k$ est défini par le fournisseur d'énergie pour chaque type de source d'énergie k.
- Les clients peuvent choisir la valeur de la capacité (P_k^{opt}) dans cet intervalle.

Les hypothèses pour la capacité discrète

- Un certain nombre (R_k) d'options de capacité sont proposées par les fournisseurs pour chaque type de source d'énergie k.

— Les options proposées R_k constituent les vecteurs de contrat d'énergie V_k pour chaque type ou source d'énergie.

— La caractéristique principale de chaque option pour chaque source d'énergie ($l = 1$, ... R_k) est son abonnement ($Vcost_{k,l}$).

— Les clients sont obligés de choisir une option parmi chaque type de source d'énergie.

Les hypothèses pour les deux versions des options de capacité

— Un intervalle de tolérance est défini. Il permet aux clients de s'écarter d'un certain pourcentage (β) de la capacité contractée. Tant que la puissance requise reste dans cet intervalle (valeur du contrat ±β), la capacité fixe facturée est calculée pour les factures d'électricité. En cas de dépassement des niveaux de tolérance, la puissance en dehors de l'intervalle de tolérance est pénalisée du coût de la pénalité (Ʊ) également déterminé par le fournisseur d'énergie.

— Les clients ne sont pas autorisés à passer de l'option convenue à une autre. Il est donc supposé que le système de production est soumis à la même option d'alimentation pour tout l'horizon de planification.

— La capacité totale contractée ($V_{k,l}$) ou (P_k^{opt}) pour chaque source d'énergie k doit couvrir les besoins du système de production et minimiser les coûts d'énergie et de production.

Les paramètres et les variables de décision du problème sont présentés dans Tableau 3.13. Le modèle actuellement présenté, P_2, est développé en intégrant le problème de sélection de la capacité au modèle précédemment amélioré, P_1. En raison de la structure de production, les conditions générales et initiales sont généralement identiques et en raison du nombre limité de pages, seules la fonction objectif modifiée et les nouvelles contraintes développées seront présentées. Pour une explication détaillée, nous renvoyons le lecteur à la Section 3.4.4.

$$\begin{aligned} Min z = & \sum_{t=1}^{T} \sum_{m=1}^{N} (\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) \\ & + \sum_{k=1}^{K} (Vcost_k.P_k^{opt}) \\ & + \sum_{t=1}^{T} \sum_{k=1}^{K} (\mho.(AC_t + BC_t)) \end{aligned} \tag{A.12}$$

La première partie de la fonction objectif (A.12) calcule le coût de production en fonction du coût de la consommation d'électricité. Dans l'étude de Masmoudi et al. [2017a], le coût de la consommation d'électricité ($/ KWh) est normalisé en le multipliant par la puissance requise pour traiter une unité de produit (KWh) et le coût de production est défini comme suit : $\psi_{m,t} = \phi_m.p_m.\mathrm{C}o_t$. Dans ce modèle, la même formule est retenue pour le coût de production afin d'intégrer le coût en électricité dans le coût de production. La première partie de la fonction objectif est complétée par l'addition des coûts de stockage et des coûts de lancement. La deuxième partie calcule le coût total de l'énergie en fonction du montant de la puissance convenue et la dernière partie calcule le coût des pénalités pouvant survenir en cas de dépassement de l'intervalle de tolérance de la somme de la capacité souscrite.

Lorsqu'il s'agit de définir la demande de puissance de pointe, la contrainte (3.72) est remplacée par les contraintes suivantes :

$$\alpha_t \geq \phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (A_{m,r,t}.ws_{m,r,t}.\phi_r) \quad \forall m = 1,...,N, t = 1,...,T \tag{A.13}$$

$$\phi_m.y_{m,t} + \sum_{r=1,r\neq m}^{N} (A_{m,r,t}.ws_{m,r,t}.\phi_r) \geq \alpha_t - (1 - z_{m,t}).M \quad \forall m = 1,...,N, t = 1,...,T \tag{A.14}$$

$$\sum_{m=1}^{N} (z_{m,t}) = 1; \qquad \forall t = 1,...,T \tag{A.15}$$

L'étape suivante consiste à établir un lien entre la demande en énergie du système et les options de capacité offertes sur le marché. Pour ce faire, les contraintes suivantes sont développées en prenant en compte la tolérance de volume (β) :

$$P_k^{min} \leq P_k^{opt} \leq P_k^{max} \quad \forall k = 1,...,K \tag{A.16}$$

$$AC_t + (1+\beta).\sum_{k=1}^{K} (P_k^{opt}) \geq \alpha_t \quad \forall t = 1,...,T \tag{A.17}$$

$$(1-\beta).\sum_{k=1}^{K} (P_k^{opt}) - BC_t \leq \alpha_t \quad \forall t = 1,...,T \tag{A.18}$$

Les contraintes (A.16) garantissent aux clients la possibilité de sélectionner une valeur comprise dans l'intervale spécifié donné par le fournisseur d'énergie. Dans les contraintes (A.17) et (A.18), la somme des capacités souscrites pour chaque type de source d'énergie ($\sum_{k=1}^{K}(P_k^{opt})$) doit couvrir la demande d'alimentation du système (α_t). Lorsque la demande dépasse les limites supérieure ou inférieure (définies par β) de la somme de la puissance souscrite, la quantité excédentaire est pénalisée avec un coût de pénalité défini (℧).

Dans le cas d'options de capacité discrète, la fonction d'objectif est réorganisée comme suit :

$$\begin{aligned} Minz = &\sum_{t=1}^{T}\sum_{m=1}^{N}(\psi_{m,t}.x_{m,t} + h.I_{m,t} + w_{m,t}.y_{m,t}) \\ &+ \sum_{k=1}^{K}\sum_{l=1}^{R_k}(Vcost_{k,l}.P_{k,l}) \\ &+ \sum_{t=1}^{T}\sum_{k=1}^{K}(\mho.(AC_t + BC_t)) \end{aligned} \tag{A.19}$$

Dans la fonction objectif (A.19), la première et la troisième partie de la fonction objectif du modèle P_2 affiché dans A.12 restent les mêmes, seul le la deuxième partie est réorganisée de manière à calculer le coût total de l'énergie en fonction des options de capacité sélectionnées.

Les contraintes (A.16 - A.18) proposées pour définir la puissance requise pour chaque type de source d'énergie k dans le modèle P_2 sont remplacées avec les contraintes suivantes :

$$AC_t + (1+\beta).\sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) \geq \alpha_t \quad \forall t = 1,...,T \tag{A.20}$$

$$(1-\beta).\sum_{k=1}^{K}\sum_{l=1}^{R_k}(V_{k,l}.P_{k,l}) - BC_t \leq \alpha_t \quad \forall t = 1,...,T \tag{A.21}$$

$$\sum_{l=1}^{R_k}(P_{k,l}) = 1 \quad \forall k = 1,...,K \tag{A.22}$$

Les contraintes (A.20) et (A.21) introduisent les vecteurs de contrat ($V_k = V_{k,1},...,V_{k,R_k}$), des options de contrat pour les différentes sources d'énergie du modèle et établissent une relation entre la demande d'énergie maximale pour la période t et les valeurs de contrat $V_{k,l}$. Lorsque la demande dépasse les limites supérieure ou inférieure (définies par β) de la somme de la puissance souscrite, la quantité excédentaire est pénalisée du coût de la pénalité définie (℧). Les contraintes (A.22) obligent les clients à choisir une option d'alimentation parmi chaque type de source d'énergie.

Lorsque le modèle P_3, qui inclut la sélection de la capacité discrète, la configuration de production de l'exemple précédent change comme suit :

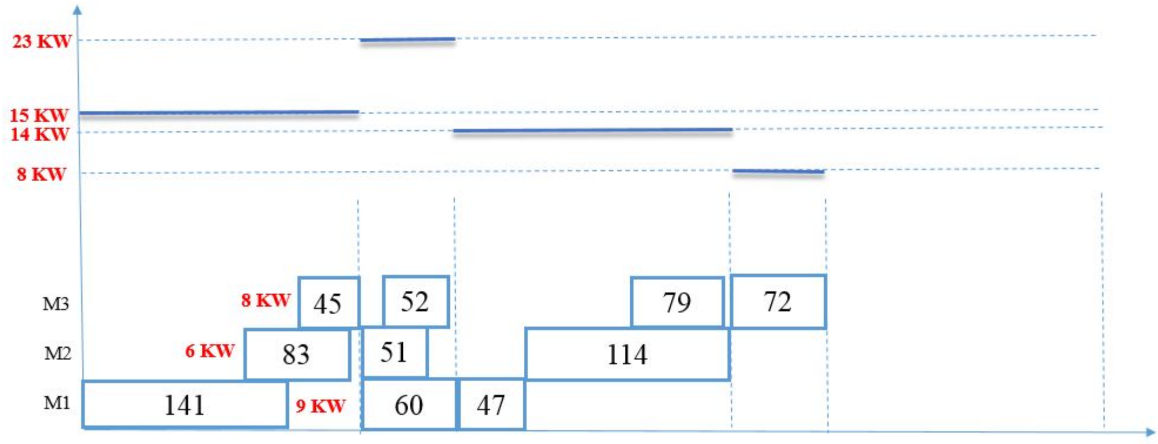

FIGURE A.4: La configuration de fabrication obtenue par le modèle de Masmoudi et al. [2017a]

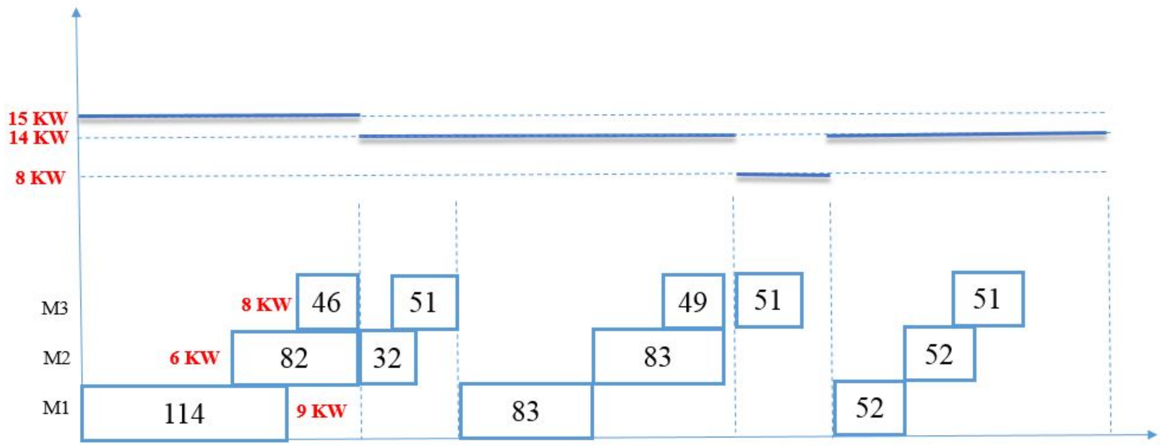

FIGURE A.5: Le plan de production avec des contraintes de sélection de contrat (traditionnelle + source renouvelable)

Lorsque le problème de planification est combiné avec le choix de la capacité avec de multiples sources d'énergie, le modèle mathématique donne un accord sur l'optimisation de 6 KW pour l'énergie traditionnelle, de 3KW pour l'énergie solaire et de 4 KW pour l'énergie éolienne pour réaliser un plan qui réponde à la demande extérieure. Si la configuration d'alimentation dans Figure A.4 est comparée à la configuration d'alimentation dans Figure A.5 où le problème de sélection de capacité est introduit, il est explicitement vu que dans Figure A.5, la configuration est plus équilibrée et réaliste en termes d'alimentation.

Dans la Section 3.4.6 les modèles développés sont résolus en solveur linéaire et les résultats sont présentés et discutés en détail. Les résultats prouvent la nécessité de résoudre le problème avec une méthode d'approximation appropriée.

A.4 Problème de dimensionnement d'un lot sous l'incertitude liée aux énergies renouvelables

Il est un fait que malgré tous les résultats positifs de l'utilisation de sources d'énergie renouvelables, le déploiement de sources d'énergie renouvelables montre un lent progrès. En tant que responsable de cette réalité, le caractère intermittent et aléatoire des sources d'énergie renouvelables peut être évoqué. Étant donné que les sources d'énergie renouvelables ne promettent pas un approvisionnement énergétique fiable et constant, cette caractéristique décourage en particulier les clients industriels qui ont besoin de la continuité de l'approvisionnement en énergie pour soutenir les activités de production.

Dans ce chapitre, l'objectif est de donner un aperçu aux clients industriels tout en prenant une décision concernant la sélection optimale des contrats dans l'incertitude des énergies renouvelables. À cette fin, différents types de contraintes probabilistes sont proposés en tenant compte des ruptures probables de l'approvisionnement en sources d'énergie renouvelables. Les contraintes probabilistes développées sont fusionnées avec le problème de dimensionnement de lot étudié précédemment. Il a donc comme objectif de sélectionner la capacité contractuelle en fonction de la nature stochastique des sources renouvelables dépendantes de la météo.

A.4.1 Définition du problème & objectif

Dans le modèle à contraintes probabilistes, le problème de dimensionnement de lots à capacité unique pour la configuration de flow-shop est étudié en intégrant le problème de sélection de la capacité énergétique dans une incertitude relative aux énergies renouvelables. La même configuration de production composée de N machines et de N buffers est considérée (Figure A.1).

Les modèles proposés ont pour but de déterminer les quantités de production optimales à produire sur chaque machine et à chaque période et d'identifier la demande de puissance maximale requise en minimisant les coûts de production, de stockage, d'installation et d'énergie en synchronisant la demande de puissance du système avec les options de contrat de capacité, y compris les sources d'énergie, dont l'approvisionnement ne peut pas être garanti par le fournisseur d'énergie.

Les hypothèses relatives à la production et à l'énergie présentées dans le modèle déterministe précédemment étudié sont conservées telles quelles. En plus, les hypothèses et modifications suivantes sont considérées :

- Il n'y a pas de procédure pénalisante pour une demande de puissance excessive ou faible.
- La disponibilité des sources d'énergie renouvelables est supposée stochastique et définie pour une distribution donnée.

A.4.2 Contraintes probabilistes

Dans cette section, nous proposons trois types de contraintes probabilistes pour modéliser le caractère stochastique de la disponibilité des sources d'énergie renouvelables.
—Contraintes probabilistes basées sur le niveau de service
—Contraintes probabilistes basées sur la quantité de puissance moyenne
—Contraintes probabilistes basées sur la défaillance en approvisionnement d'énergie.

Dans le premier groupe de contraintes, l'approche de programmation par contraintes aléatoires est utilisée et le risque lié à la fourniture d'énergie renouvelables se transforme en risque de réalisation de l'activité de production prévue en introduisant un *niveau de service* de clients industriels. Par conséquent, les modèles proposés permettent aux clients de combiner des sources renouvelables et traditionnelles en fonction du niveau de service convenu et constituent un puissant outil d'aide à la décision pour faire face aux caractéristiques incertaines et risquées des sources d'énergie renouvelables.

Dans le deuxième groupe de contraintes, le caractère aléatoire de la disponibilité des sources d'énergie renouvelables est reflété dans le modèle en tant que valeur attendue de la disponibilité.

Enfin, dans le troisième groupe de contraintes, la valeur attendue du montant qui pourrait ne pas être atteint selon l'option contractée est calculée et les options de contrat optimales sont sélectionnées en tenant compte de la défaillance attendue.

Les mix énergétiques composés de la source d'énergie traditionnelle et d'un type de source d'énergie renouvelable; une source d'énergie traditionnelle et deux types de sources d'énergie renouvelables sont considérés pour chaque type de contrainte probabiliste.

Contraintes probabilistes basées sur le niveau de service
Cas 1 : Contraintes requises basées sur l'énergie renouvelable
Consommation d'énergie traditionnelle et d'un type de source d'énergie renouvelable

Dans ce premier cas, on suppose que le fabricant consomme une source d'énergie traditionnelle et un type de source d'énergie renouvelable (solaire ou éolienne, par exemple). Le modèle développé prend en compte la disponibilité aléatoire d'une source d'énergie renouvelable et définit le meilleur mix énergétique pouvant couvrir le besoin du système en considérant ce caractère aléatoire. Pour ce faire, le fabricant définit un niveau de service (*SL*) qui est également supposé être une probabilité minimale de disponibilité d'une source d'énergie renouvelable. En d'autres termes, la probabilité que l'énergie renouvelable disponible soit supérieure à la quantité d'énergie requise doit être au moins égale à la valeur *SL* spécifiée pour satisfaire le niveau de service ciblé. Cette idée se traduit par la contrainte de chance suivante :

$$\text{Prob}(X_s \geq \text{la quantité d'énergie renouvelable requise pour satisfaire la production}) \geq SL \tag{A.23}$$

où :
SL : niveau de service minimal défini par le client industriel
X_s : variable aléatoire de la quantité disponible pour la source d'énergie solaire
$\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l}$:la quantité d'énergie renouvelable requise pour la période t.

En conséquence, la version primitive de la contrainte de hasard est reformulée comme suit :

$$\Longleftrightarrow P(X_s \geq \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \geq SL \qquad \forall t = 1, \ldots, T \tag{A.24}$$

$$\Longleftrightarrow P(X_s < \alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l}.P_{tr,l})) \leq 1 - SL \qquad \forall t = 1, \ldots, T \tag{A.25}$$

Ainsi, la première contrainte probabiliste basée sur le niveau de service considère la combinaison de la source d'énergie traditionnelle avec un type de source renouvelable est obtenu.

Consommation d'énergie traditionnelle et deux type de source d'énergie renouvelable

La première contrainte de chance proposée (A.25) peut être améliorée de la même manière pour les clients qui préfèrent mélanger une source d'énergie traditionnelle avec deux types de sources d'énergie renouvelables (solaire et éolienne, par exemple). À partir de ce point de départ, similaire à la contrainte (A.25), la contrainte probabiliste incluant le niveau de service est construite pour la combinaison de sources d'énergie renouvelables et traditionnelles, comme suit :

$$P(X_s + X_w < (\alpha_t - \sum_{l=1}^{R_{tr}} (V_{tr,l} P_{tr,l})) \leq 1 - SL \tag{A.26}$$

ou ;
X_s : Variable aléatoire de source d'énergie solaire.
X_w : Variable aléatoire de la source d'énergie éolienne.

Pour simplifier, dans les formulations suivantes, notons $Q_t = (\alpha_t - \sum_{l=1}^{R_{tr}} V_{tr,l} P_{tr,l})$ la quantité de source d'énergie renouvelable requise. La contrainte peut être reformulée comme suit :

$$\Longleftrightarrow \mathrm{P}(\mathrm{X}_s + \mathrm{X}_w < \mathrm{Q}_t) \leq 1 - \mathrm{SL} \tag{A.27}$$

Comme on peut le voir dans la contrainte (A.27), le côté gauche de l'inégalité inclut la somme des deux variables aléatoires. Dans la théorie des probabilités, la somme des distributions de deux variables aléatoires indépendantes non négatives est la *convolution.*

Le calcul détaillé du produit de convolution est donné dans la Section 4.5 basée sur l'hypothèse d'une distribution exponentielle.

Cas 2 : Contraintes probabilistes basées sur les énergies renouvelables contractées
Dans cette version, au lieu du Cas 1 où le risque est évalué en fonction des besoins réels en énergie renouvelable du système de production, le risque est évalué en fonction du montant de puissance convenu dans le contrat.

Consommation d'énergie traditionnelle et d'un type de source d'énergie renouvelable
Pour développer des contraintes probabilistes basées sur des options contractées, les mêmes étapes que celles suivies pour la construction des contraintes étudiées pour le Cas 1 sont suivies. La version primitive de la contrainte proposée peut être définie comme suit :

$$\mathrm{Prob}(\mathrm{X}_s \geq \text{la quantité souscrite pour une source d'énergie renouvelable}) \geq SL \quad \forall t = 1, ..., \mathrm{T} \tag{A.28}$$

$$\mathrm{P}(\mathrm{X}_s \geq \sum_{l=1}^{\mathrm{R}_s} (\mathrm{V}_{s,l}.\mathrm{P}_{s,l})) \geq \mathrm{SL} \qquad \forall t = 1, ..., \mathrm{T} \tag{A.29}$$

ou;
SL : niveau de service minimal défini par le client industriel
X_s : variable aléatoire de la quantité disponible pour la source d'énergie solaire
$\sum_{l=1}^{\mathrm{R}_s} (\mathrm{V}_{s,l}.\mathrm{P}_{s,l})$: option de capacité contractée pour la source d'énergie solaire

$$\Longleftrightarrow 1 - \mathrm{P}(\mathrm{X}_s < \sum_{l=1}^{\mathrm{R}_s} (\mathrm{V}_{s,l}.\mathrm{P}_{s,l})) \geq \mathrm{SL} \qquad \forall t = 1, ..., \mathrm{T} \tag{A.30}$$

$$\Longleftrightarrow \mathrm{P}(\mathrm{X}_s < \sum_{l=1}^{\mathrm{R}_s} (\mathrm{V}_{s,l}.\mathrm{P}_{s,l})) \leq 1 - \mathrm{SL} \qquad \forall t = 1, ..., \mathrm{T} \tag{A.31}$$

Par conséquent, dans (A.31), la contrainte probabiliste évaluant le risque en fonction de l'option choisie dans les cas où la source d'énergie traditionnelle est mélangée à un type de source d'énergie renouvelable est obtenu.

Consommation d'énergie traditionnelle et de deux types de sources d'énergie renouvelables

En suivant la même logique dans le Cas 1 où l'utilisation des deux types d'énergies renouvelables est envisagée, la contrainte suivante est obtenue :

$$P(X_s + X_w < Q_t) \leq 1 - SL \tag{A.32}$$

ou

$Q_t = \sum_{l=1}^{R_s}(V_{s,l}.P_{s,l}) + \sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})$

Contraintes probabilistes basées sur la quantité de puissance moyenne

Dans cette contrainte, il est envisagé de prendre en compte la valeur moyenne de la production de puissance pour faire face à l'aspect stochastique des sources d'énergie renouvelables. La moyenne des variables aléatoires est définie par l'aide de la formule suivante :

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx \tag{A.33}$$

Même si la disponibilité des sources d'énergie renouvelable est incertaine, il est un fait que lorsque la source d'énergie traditionnelle est mélangée aux sources d'énergie renouvelables, la somme de la puissance traditionnelle connue de manière déterministe et de la production d'énergie attendue doit couvrir le besoin en énergie du système de production. Cette idée peut être traduite comme suit :

$$\alpha_t \leq \sum V_{tr,l} P_{tr,l} + E[X_s] \tag{A.34}$$

ou ;

α_t : le besoin en puissance pendant la période t.

$\sum_{l=1}^{R_{tr}}(V_{tr,l}.P_{tr,l})$: Option de capacité sélectionnée pour la source d'énergie traditionnelle.

$E[X_s]$: Moyenne pour la production d'énergie solaire.

Il est possible de proposer la contrainte probabiliste basée sur la valeur attendue pour les clients qui souhaitent combiner des sources énergie traditionnelle et deux types de sources d'énergie renouvelables, comme dans la contrainte suivante :

$$\alpha_t \leq \sum V_{tr,l} P_{tr,l} + E[X_s] + E[X_w] \tag{A.35}$$

Contraintes probabilistes basées sur la défaillance en approvisionnement d'énergie

Lorsque les clients négocient certaines options de capacité pour les sources d'énergie renouvelables, ils doivent considérer que le montant total de l'option contractuelle pourrait ne pas être fourni en raison de conditions météorologiques aléatoires. En cas d'augmentation de la valeur contractuelle, le risque de ne pas être satisfait de la totalité du montant du contrat augmente et le risque, de ne peut être satisfait, augmente proportionnellement. Dans cette contrainte, l'aspect stochastique des sources d'énergie renouvelables est pris en compte en déterminant le montant de la défaillance attendue en fonction de l'option retenue dans le contrat.

$$\alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - \overline{\nabla_s} \tag{A.36}$$

ou ;

α_t : le besoin en puissance pendant la période t

$\sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l})$: La somme du montant de la puissance contractée.

$\overline{\nabla_s}$: Montant moyen de rupture basé sur la puissance contractée pour l'énergie solaire.

La quantité de rupture ∇_s pour l'énergie solaire peut être défini comme suit :

$$\nabla_s = \begin{cases} \sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) - X_s & X_s \leq \sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}); \\ 0 & X_s > \sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}); \end{cases}$$

ou ;

$\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})$: Montant contractuel pour une source d'énergie renouvelable (énergie solaire dans cette contrainte)

X_s : La variable aléatoire de la source d'énergie solaire.

La moyenne de défaillance attendu peut être calculée comme suit :

$$\overline{\nabla_s} = \int_0^{\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})} (\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) - X_s) f(x) dx \tag{A.37}$$

$$\Longleftrightarrow \overline{\nabla_s} = \sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})} f(x) dx - \int_0^{\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l})} X_s.f(x) dx \tag{A.38}$$

Après avoir obtenu le montant d'échec attendu ($\overline{\nabla_s}$) par la formule entre (A.38), la contrainte

(A.36) peut être transformée en l'expression suivante :

$$\alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - [\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} f(x)dx - \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.f(x)dx] \tag{A.39}$$

$$\forall t = 1, ..., T$$

Par conséquent, les options de contrat peuvent être sélectionnées en prenant en compte la défaillance en approvisionnement qu'il est possible de rencontrer pour les sources d'énergie renouvelables via la contrainte (A.39).

Lorsque la même contrainte est proposée pour les cas dans lesquels une source d'énergie traditionnelle est mélangée avec les deux types de sources renouvelables, similaire à la contrainte (A.39), la contrainte suivante peut être obtenue :

$$\alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - \overline{\nabla_s} - \overline{\nabla_w} \qquad \forall t = 1, ..., T \tag{A.40}$$

où ;
α_t : le besoin en puissance pendant la période t.
$\sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l})$: La somme du montant de la puissance contractée.
$\overline{\nabla_s}$: Montant moyen de rupture basé sur la puissance contractée pour l'énergie solaire.
$\overline{\nabla_w}$: Montant moyen de rupture basé sur la puissance contractée pour l'énergie éolienne.

La contrainte proposée dans (A.40) est étendue en suivant les mêmes étapes que dans le cas susmentionné, dans lequel seuls le type traditionnel et le type de source d'énergie renouvelable sont mélangés la contrainte suivante est obtenue :

$$\alpha_t \leq \sum_{k=1}^{K} \sum_{l=1}^{R_k} (V_{k,l}.P_{k,l}) - [\sum_{l=1}^{R_s} (V_{s,l}.P_{s,l}) \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} f(x)dx - \int_0^{\sum_{l=1}^{R_s}(V_{s,l}.P_{s,l})} X_s.f(x)dx] \tag{A.41}$$

$$-[\sum_{l=1}^{R_w} (V_{w,l}.P_{w,l}) \int_0^{\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})} f(x)dx - \int_0^{\sum_{l=1}^{R_w}(V_{w,l}.P_{w,l})} X_w.f(x)dx] \quad \forall t = 1, ..., T$$

Ainsi, trois types de contraintes probabilistes ont été proposées en considérant les deux types de mix énergétique. Dans la section suivante, le coût des défaillances probables dans l'approvisionnement en sources d'énergie renouvelables est évalué et les deux types de fonctions objectives sont proposés à cet effet.

A.4.3 Fonctions objectives développées

Dans cette section, deux types de fonctions objectifs sont présentés. Dans le premier type, le coût de pénalité moyen en fonction de la probabilité de défaillance est pris en compte et ajouté aux coûts classiques de production et d'achat d'énergie. Dans le second type de fonction objectif, directement le montant de défaillance attendu dans l'approvisionnement en sources d'énergie renouvelables est pénalisé et considéré comme un coût supplémentaire dans la fonction objectif.

Type 1 : Pénaliser la probabilité de rupture

Si la quantité d'énergie renouvelable requise n'est pas entièrement atteinte, les clients industriels peuvent subir une perte de production pouvant entraîner une demande non satisfaite ou satisfaire la quantité manquante de source renouvelable avec les sources d'énergie traditionnelles afin de maintenir les activités de production sans interruption. Toutefois, en cas d'augmentation de l'utilisation de la source d'énergie traditionnelle, le niveau d'émission de carbone augmente en conséquence et les clients peuvent être confrontés à des sanctions pour le réduire. Afin d'éviter de telles situations indésirables, il est considéré de pénaliser la probabilité de défaillance de la source d'énergie renouvelable. Le coût moyen de l'échec est ajouté à la fonction d'objectif actuelle :

$$\begin{aligned} \mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma.\mathrm{P}(\mathrm{X}_s < \alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})) \end{aligned} \quad (A.42)$$

On note,
γ : coût de la pénalité
X_s : Disponibilité aléatoire de la source d'énergie solaire.
$\alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})$:Quantité requise pour une source d'énergie renouvelable.

Il est possible d'appliquer la même idée à la fonction objective des modèles qui prennent en compte la combinaison de sources d'énergie traditionnelles et de deux types de sources d'énergie :

$$\begin{aligned} \mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma.\mathrm{P}(\mathrm{X}_s + \mathrm{X}_w < \alpha_t - \sum_{l=1}^{\mathrm{R}_{tr}} (\mathrm{V}_{tr,l}.\mathrm{P}_{tr,l})) \end{aligned} \quad (A.43)$$

Comme on peut le constater dans la définition ci-dessus, tant que la somme de la disponibilité des sources renouvelables est inférieure au montant d'énergie renouvelable requis, le coût de la pénalité s'ajoute aux autres coûts de la fonction objectif.

Type 2 : Pénaliser la quantité moyenne de rupture en energie renouvelable

L'idée de la fonction objective de Type II consiste à pénaliser directement le montant de l'échec. Il est évident que tant que la valeur de l'option contractée augmente, le montant attendu de l'échec augmente en conséquence. Ainsi, l'ampleur du montant de l'échec est liée à l'option retenue dans le contrat et au potentiel de production d'énergie renouvelable. En liant toutes ces idées, la fonction objectif suivante pour l'utilisation d'un type de source d'énergie renouvelable avec une source traditionnelle est proposée :

$$\begin{aligned} \mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma . \overline{\nabla_s} \end{aligned} \tag{A.44}$$

ou,

γ : Coût de la pénalité par unité.

$\overline{\nabla_s}$: Moyenne de défaillance basée sur l'option contractée pour l'énergie solaire.

L'idée appliquée pour le mélange de sources d'énergie traditionnelles et d'un type de source d'énergie renouvelable peut être mise en œuvre, y compris l'utilisation de la source d'énergie traditionnelle et de deux types de sources d'énergie renouvelables, à savoir :

$$\begin{aligned} \mathrm{M}inz = \sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{N}} (\psi_{m,t} x_{m,t} + h\mathrm{I}_{m,t} + w_{m,t} y_{m,t}) + \sum_{l=1}^{\mathrm{R}_k} \sum_{k=1}^{\mathrm{K}} (\mathrm{V}cost_{k,l} \mathrm{P}_{k,l}) \\ + \sum_{t=1}^{\mathrm{T}} \gamma . \overline{\nabla_s} + \sum_{t=1}^{\mathrm{T}} \gamma . \overline{\nabla_w} \end{aligned} \tag{A.45}$$

Par conséquent, trois types de contraintes probabilistes et deux types de fonctions objectives ont été proposés pour traiter l'incertitude des sources d'énergie renouvelables. Comme le lecteur peut se rendre compte, les contraintes développées et les fonctions objectives sont présentées de manière globale sans spécifier de distribution de probabilité pour les variables aléatoires.

Dans la Section 4.5, les fonctions objectives et les contraintes probabilistes sont développées en prenant en compte une distribution de probabilité spécifique, une distribution exponentielle dans notre cas, et des modèles mathématiques qui prennent en compte la nature stochastique des sources d'énergie renouvelables pour le problème de dimensionnement des lots sont présentés.

Les modèles obtenus sont testés sur une instance de petite taille et les modifications de la production et de la configuration énergétique de chaque modèle sont détaillées. Après avoir testé les modèles stochastiques développés, il a été constaté que les solveurs commerciaux sont capables de résoudre les instances de petite taille, notamment 3 machines et 3 périodes de production (N3_T3). Les instances de taille plus grande qui ne peuvent pas être résolues par les solveurs commerciaux sont résolues par la méthode heuristique Fix-and-Relax. Les résultats sont détaillés dans la section suivante.

A.5 Approches de solutions

Il a été prouvé par Florian et al. [1980] et par Bitran and Yanasse [1982] que le problème de dimensionnement de lot à capacité unique (CLSP) est NP-difficile pour des fonctions objectives générales. Dans cette section, l'un des type d'heuristiques les plus couramment utilisées, les heuristiques Fix-and-Relax, est proposé. L'heuristique F&R étant bien adaptée aux problèmes de dimensionnement de lots et permettant d'atteindre des résultats quasi optimaux dans un délai de calcul raisonnable, elle a été exécutée pour différentes variantes des problèmes de dimensionnement de lots existants (Stadtler [2003],Absi [2005],Akartunali and Miller [2009],Mohammadi and Fatemi [2010],Masmoudi et al. [2016])

F&R est une approche heuristique de type constructive. Le principe fondamental de F&R consiste à décomposer le problème global en sous-problèmes plus petits, gérables et plus faciles que le problème global. La résolution de ces problèmes se fait ultérieurement en utilisant les informations des problèmes précédemment résolus. L'objectif de la décomposition est de réduire la complexité et, par conséquent, la charge de calcul du problème initial.

Dans la procédure F&R, les variables entières sont partitionnées en ensembles disjoints. Ces ensembles sont générés en fonction des intervalles de temps et chacun de ces intervalles est appelé *fenêtre*. Chaque fenêtre comprend un certain nombre de périodes. Lors de la première itération, l'horizon de planification est divisé en deux fenêtres : une fenêtre d'observation (OW) et une fenêtre d'approximation (AW). Les variables relatives à OW sont identiques à celles du modèle d'origine et le problème est relaxé dans AW. À partir de la deuxième itération, l'horizon de planification est décomposé en trois fenêtres : Fenêtre d'observation (OW), Fenêtre gelée (FW) et Fenêtre d'approximation (AW). Une fois que le modèle est résolu dans l'itération k, l'OW glisse dans l'avenir et les variables de décision appartiennent à OW à l'itération k, qui ne sont plus dans l'OW à l'itération $k+1$ sont fixées aux valeurs obtenues à l'itération k. La fenêtre gelée (FW) est donc générée. Il est possible d'appliquer différentes stratégies de fixation pour les variables. Cette procédure de résolution est répétée ultérieurement jusqu'à la fin de l'horizon de planification (Figure A.6). L'algorithme 1 fournit le schéma de l'heuristique F&R.

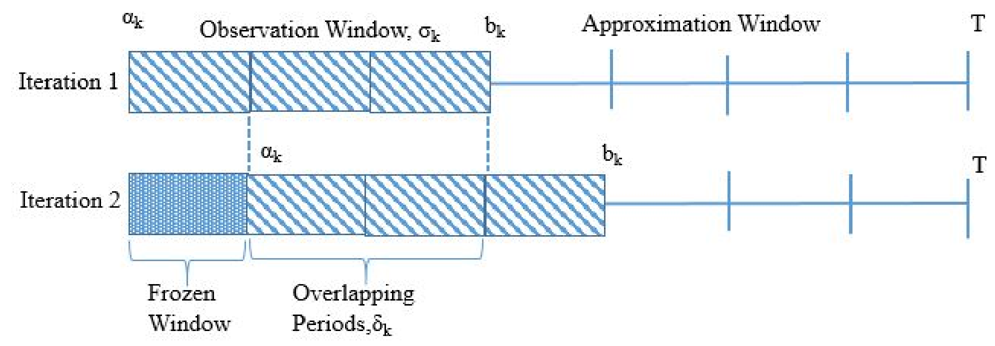

FIGURE A.6: F&R approche heuristique

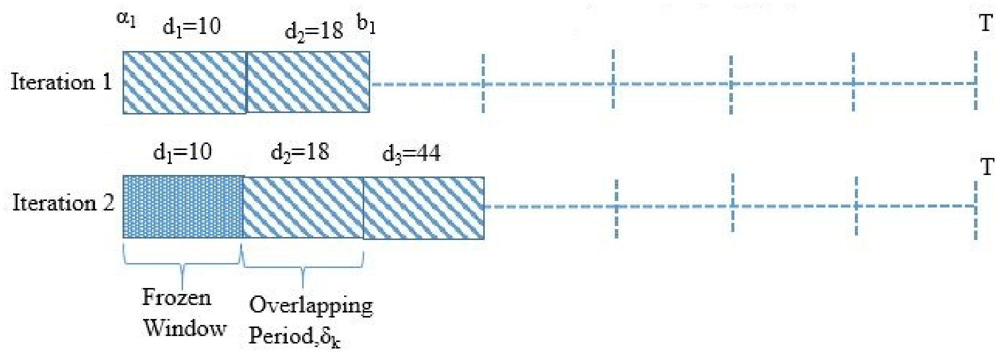

FIGURE A.7: Le principe de F&R sans fenêtre d'approximation

Algorithm A.1: L'algorithme Fix-and Relax Masmoudi et al. [2016]

k=1;
a_k=1;
b_k=σ;
while b_k <T **do**
  Résoudre le sous-problème;
  k=k+1;
  a_k=b_k-δ;
  b_k=b_k+σ-δ;
  if b_k>T **then**
    b_k=T;
  end
end
Résoudre le sous-problème;

Après avoir fourni des informations détaillées sur l'heuristique F&R, les versions proposées de F&R sont maintenant présentées.

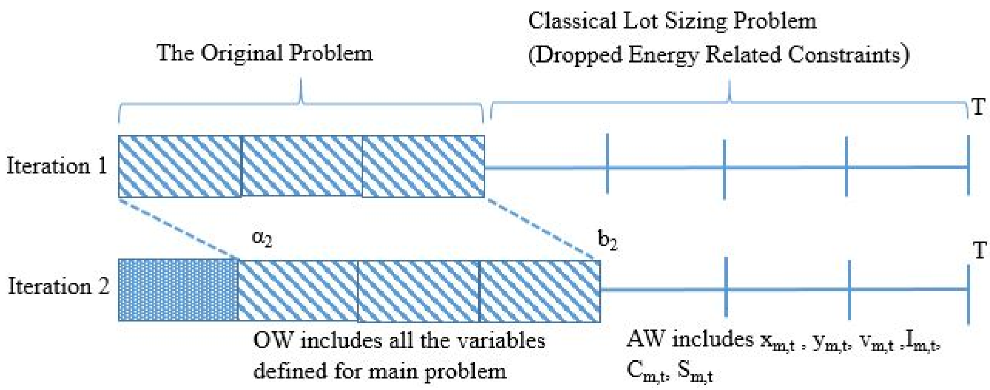

FIGURE A.8: Le principe de F&R avec fenêtre d'approximation

A.5.1 F&R sans fenêtre d'approximation - approche myope

Le principe de cette approche peut être observé dans la Figure A.7. Lors de la première itération, seules les périodes OW comprenant (t = 2) sont prises en compte et le sous-problème est résolu conformément au schéma de demande associé $[d_1 ... d_t]$. Dans la deuxième itération, les variables de décision choisies sont fixées à leurs valeurs actuelles dans la fenêtre gelée. La fenêtre d'observation parcourt l'avenir en conservant les périodes qui se chevauchent (δ_k) entre les fenêtres d'observation consécutives. Le sous-problème est résolu en prenant en compte les variables fixes dans la fenêtre gelée et le schéma de demande nouvelle.

A.5.2 F&R avec fenêtre d'approximation

Dans cette approche, le modèle est résolu en conservant sa structure d'origine et en relaxant une partie pour faire face aux lacunes de l'approche de la version précédente.

Le problème global est pris en compte dans la fenêtre d'observation où les décisions de dimensionnement de lots et de contrats d'énergie sont prises. Les contraintes liées à l'énergie sont éliminées du problème global et celui-ci est transformé en un problème classique de dimensionnement de lot dans la fenêtre d'approximation (Figure A.8). Pour résumer, les variables liées à l'énergie ($\alpha_{k,t}$, $P_{k,l}$, $f_{m,r,t}$, $g_{m,r,t}$, $z_{m,t}$) sont ignorées dans la fenêtre d'approximation pour atténuer le problème.

A.5.3 Stratégies de fixation

Il est tout d'abord proposé de fixer la quantité produite par la machine m dans la période t ($x_{m,t}$). Il est nécessaire de signifier qu'une fois la quantité de production fixée, les variables de configuration associées ($y_{m,t}$) sont également fixées. Par conséquent, le nombre de variables binaires à traiter diminue considérablement et les sous-problèmes traités peuvent être résolus plus facilement. Ce cas nous permet d'atteindre la solution dans un temps de calcul relativement court.

TABLEAU A.2: Stratégies de fixation proposées

Nu.	Stratégie de fixation	Variable
1	Quantité de production	$x_{m,t}$
2	Chevauchements de machines	$f_{m,r,t}, g_{m,r,t}, y_{m,t}, v_{m,t}$
3	Set-up	$y_{m,t}$

La deuxième stratégie proposée consiste à fixer le chevauchement de la machine. Pour ce faire, seules les variables $(y_{m,t}, v_{m,t}, f_{m,r,t}, g_{m,r,t})$ sont fixées à chaque itération.

Enfin, dans la troisième stratégie, les décisions de lancement $(y_{m,t})$ sont fixées. C'est la stratégie de fixation la plus répandue dans la littérature. Différente de la deuxième stratégie, la position des machines $(f_{m,r,r}, g_{m,r,t})$ n'est pas fixée. Lorsque les machines se chevauchent et que les quantités de production $(x_{m,t})$ ne sont pas fixées, le problème a plus de souplesse pour s'adapter au sous-problème changeant à chaque itération.

A.5.4 Computational experiments

L'heuristique F&R est codée sur Python 2.7 et les résultats sont comparés à ceux obtenus avec CPLEX 12.6 sur un processeur Intel Core i7 avec 2,7 GHz et 8 Go de RAM. 5 instances différentes sont générées pour chaque configuration de problème (N,T). Les stratégies de fixation proposées sont appliquées avec différentes tailles de fenêtre d'observation et des chevauchements afin d'identifier la meilleure stratégie de fixation et de partitionnement en termes de qualité de la solution et de temps CPU. Chaque itération de l'algorithme de la solution F&R est définie à 180 secondes pour toutes les instances. Le temps de calcul de la solution globale est limité à 3 600 seconds. Lorsque CPLEX n'est pas en mesure d'atteindre la solution optimale en moins d'une heure, la solution réalisable atteinte au terme de ce délai est prise en compte pour calculer le GAP.

On voit que les résultats obtenus sont assez prometteurs. L'approche heuristique appliquée produit des solutions avec un écart d'optimalité moyen de 0,2 % pour les problèmes de petite taille tels que (N5_T5, N5_T7). Pour les plus grandes instances, cela permet d'obtenir de meilleurs résultats que ceux obtenus par les solveurs commerciaux dans un délai plus court.

Dans ce qui suit, l'approche de Fix-and-Relax est utilisée pour résoudre les modèles stochastiques proposés. Il est précisé que les modèles peuvent être résolus par les solveurs commerciaux pour les instances qui incluent 3 machines et 3 périodes (N3_T3). Les instances composées de 4 machines et de 4 périodes (N4_T4) sont résolues par les méthodes heuristiques Fix-and-Relax. Lorsque certaines des instances basées sur 5 machines et 5 périodes (N5_T5) sont résolues par l'heuristique F&R , les instances plus volumineuses que celles-ci ne peuvent pas être résolues par l'heuristique Fix-and-Relax dans une heure.

A.6 Conclusion et perspectives

L'objectif principal de cette thèse est de proposer des modèles d'optimisation et des solutions permettant de résoudre le problème de dimensionnement de lot pour les systèmes flow shop, en prenant en compte les contraintes de disponibilité de l'énergie. Pour intégrer la disponibilité des sources d'énergie aux modèles de planification de la production, le problème traité est combiné au problème de sélection de la capacité contractuelle en s'inspirant des pratiques réelles.

L'étude de l'état de l'art affirme que le problème traité dans cette thèse n'a jamais été étudié auparavant dans la littérature et que l'on s'aperçoit que l'incertitude de la disponibilité des sources d'énergie renouvelables n'a jamais été intégrée aux problèmes de dimensionnement.

Nous présentons des Mixed Integer Linear Programming Models (MILP) comprenant des contraintes de capacité contractuelle pour le problème traité, qui minimise les coûts de production et d'énergie. Tout d'abord, le modèle de Masmoudi et al. [2017a] qui constitue la base de notre modèle est testé sur une instance représentative et la nécessité de la connexion avec le problème de sélection des capacités est brièvement expliquée. Ensuite, leur modèle est amélioré en termes de calcul de la demande d'énergie à chaque période et est prêt à faire le lien avec les contraintes de capacité contractuelle. Ensuite, les options contractuelles sont intégrées au modèle amélioré de manière continue et discrète. Les modèles proposés sont résolus sur le résolveur CPLEX 12.6 et on constate que le modèle peut atteindre l'optimalité dans le délai défini pour des instances de petite taille.

Ensuite, le modèle développé dans le chapitre précédent est étendu à l'environnement incertain. La nature stochastique des sources d'énergie renouvelables est prise en compte. Pour modéliser l'incertitude des sources d'énergie renouvelables, trois types de contraintes probabilistes prenant en compte la combinaison de l'énergie traditionnelle avec un type de source d'énergie renouvelable et deux types de sources d'énergie renouvelables sont proposés. En cohérence avec les contraintes probabilistes présentées, pour calculer le coût de la défaillance de l'approvisionnement en sources d'énergie renouvelables, deux types de fonctions objectives sont développés. Les modèles construits par différentes combinaisons des contraintes proposées et des fonctions objectives sont testés sur une instance illustrative. Le choix de la capacité contractuelle des fabricants et la configuration de la production changent lorsque l'incertitude des sources d'énergie renouvelables est prise en compte.

Pour la suit, le problème étant NP-Difficile, une heuristique Fix-and-Relax est introduite pour le résoudre. Deux procédures de relaxation différentes sont appliquées et la performance de la solution est testée sur des instances générées aléatoirement. On voit que les résultats obtenus sont assez prometteurs. L'approche heuristique appliquée produit des solutions avec un écart d'optimalité moyen de 0,2 % pour les problèmes de petite taille tels que (N5 _T5, N5 _T7). Pour les grandes instances, cela permet d'obtenir de meilleurs résultats que ceux obtenus par les solveurs commerciaux dans un délai plus court.

Dans l'ensemble, cette thèse contribue au domaine de l'optimisation de la planification de la production soucieuse de l'énergie.

Perspectives à court terme

Dans notre étude, la mise à l'échelle de la vitesse de la machine est laissée en dehors de son contexte et le temps de traitement est supposé être une valeur constante. Lorsque la vitesse de la machine est intégrée au modèle, étant donné que la configuration de la demande de puissance change de manière significative, les résultats obtenus et la comparaison avec notre modèle constituent une étude intéressante.

L'un de nos autres objectifs à court terme est de mettre au point des algorithmes de recherche locaux efficaces capables de résoudre les instances de grande taille en un temps de calcul raisonnable avec des résultats de grande qualité. Pour ce qui est de l'application de notre étude dans des cas réels où des dizaines de machines fonctionnent, cela revêt une importance vitale.

Perspectives à long terme

Dans cette thèse, les modèles visant à respecter l'environnement sont construits sur la base de l'approche de minimisation des coûts. Alternativement, les niveaux d'émission de carbone peuvent être minimisés en modélisant le même problème avec l'approche multi-objectifs. Les conflits existants entre la réduction des coûts et les niveaux d'émission de carbone généreraient différents mélanges d'énergie à souscrire pour les clients.

Bien que la nature stochastique des sources d'énergie renouvelables soit prise en compte, la demande externe reste déterministe. Le caractère aléatoire de la demande peut être considéré parallèlement au caractère aléatoire des sources d'énergie renouvelables. D'une manière générale, les modèles présentés dans cette thèse peuvent être enrichis avec la prise en compte d'autres paramètres incertains.

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Optimisation de la planification de la production avec du contrat énergétique

Cette thèse aborde l'optimisation du problème de planification de la production sous contraintes de disponibilité d'énergie. Le but de cette thèse est de développer des modèles mathématiques appropriés et des méthodes d'optimisation pouvant résoudre le problème traité. Dans la première partie, nous étudions le problème de dimensionnement de lot pour le système *Flow-Shop* en prenant en compte plusieurs sources d'énergie (renouvelables et non renouvelables). L'objectif est de minimiser les coûts de production, de stock et d'énergie en tenant compte à la fois de la consommation et de la combinaison des sources d'énergie dans le contrat énergétique que l'entreprise souscrit auprès du fournisseur d'énergie. Ce problème n'a jamais été abordé dans la littérature. Dans la deuxième partie, le même problème est traité avec la prise en compte de l'aspect stochastique des sources d'énergie renouvelables. La motivation de cette étude est de fournir un outil d'aide à la décision pour les fabricants industriels souhaitant s'engager dans l'utilisation d'énergies renouvelables dont la disponibilité n'est pas garantie. Pour modéliser l'incertitude des sources d'énergie renouvelables, plusieurs contraintes probabilistes sont proposées. Cette étude est la première approche qui utilise les contraintes probabilistes pour modéliser la disponibilité incertaine des sources d'énergie renouvelables.

Mots clés : optimisation mathématique – production, planification – énergies renouvelables – incertitude.

Production Planning and Energy Contract Optimization

This thesis addresses the optimization of the production planning problem under energy availability constraints. The goal of the thesis is to develop appropriate mathematical models and optimization methods that can solve the handled problem. In the first part, Capacitated Single-Item Lot-Sizing Problem for a Flow-Shop System is studied by taking into account several energy sources (renewable and non-renewable). The aim is to minimize production, stock and energy costs by considering both the consumption and the mix of energy sources in the energy contract that the company subscribes from the energy supplier. This problem has never been addressed in the literature. In the second part, the same problem is handled with the consideration of the stochastic aspect of renewable energy sources. The motivation behind this attempt is to provide a decision making system to the manufacturers who wish to use renewable energy whose availability is not guaranteed. To model the uncertainty of the renewable energy sources, several probabilistic constraints are proposed. This study is the first attempt that applies the probabilistic constraints to model the uncertain availability of the renewable energy sources.

Keywords: mathematical optimization – production planning – renewable energy sources – uncertainty.

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