Energy and Uncertainties : Stochastic Modeling and Optimization of Multi-Sources Energy Systems

Abbas Hamze

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Energy and Uncertainties: Stochastic Modeling and Optimization of Multi-sources Energy System

JURY

Mme Nathalie SAUER	PROFESSEURE DES UNIVERSITES	Présidente
M. Hamid ALLAOUI	PROFESSEUR DES UNIVERSITES	Rapporteur
M. Najib ESSOUNBOULI	PROFESSEUR DES UNIVERSITES	Rapporteur
Mme Iman JARKASS	PROFESSEURE	Examinatrice
M. Hassan NOURA	PROFESSEUR	Examinateur
Mme Alice YALAOUI	MAITRE DE CONFERENCES - HDR	Examinatrice
M. Nazir CHEBBO	PROFESSEUR	Directeur de thèse
M. Yassine OUAZENE	MAITRE DE CONFERENCES	Directeur de thèse

Personnalité invitée

Mme Imane MAATOUK	DOCTEURE

This thesis has been prepared at

ROSAS

☎	+33 (0)3 25 71 76 00
🖷	+33 (0)3 25 71 76 75
🖂	secretariat-losi@utt.fr
Web Site	http://losi.utt.fr

This PhD research Thesis is gratefully dedicated to my grand family, specially my parents Ahmad and Dalal who always loved me unconditionally, my brother Mohammad whose good example has always taught me to work hard, my sisters Rana and Mariam who have been a constant source of support and encouragement during the challenges of life, and my future wife and kids whom without everything will be meaningless.

Energy and Uncertainty: Stochastic Modeling and Optimization of Multi-sources Energy Systems

Abstract

World energy demand is still mostly satisfied by traditional sources of fossil energy. Nevertheless, over the last decade, hybrid or multi-sources energy systems have become viable alternatives for energy production because they capitalize on the strengths of conventional energy sources as well as the ecofriendly benefits of renewable energy sources. The need to consider this type of hybrid system can be justified by the fact that renewable energy resources, in addition to being more expensive, are often disturbed by seasonal variations and cannot be considered as a reliable continuous source of energy. As part of this thesis, we carried out a review of the literature of different optimization problems related to systems with multi-sources of energy. At first, we worked on the problem of localization of multi-source energy systems. The objective was to establish an energy profile or potential of a geographical area by considering economic, social and environmental criteria. Then, we are interested in optimizing energy contracts to meet global consumption needs by considering "ecofriendly" aspects of these contracts. We have proposed mathematical models and resolution methods for optimizing the choice of multi-sources energy contracts considering deterministic and random demands.

Keywords: power resources, uncertainty, mathematical optimization, energy consumption, localization theory

Résumé

La demande énergétique mondiale est encore majoritairement satisfaite par les sources traditionnelles d'énergie fossile. Néanmoins, au cours de la dernière décennie, les systèmes énergétiques multi-sources sont devenus des alternatives viables pour la production de l'énergie car ils permettent de capitaliser sur les points forts des sources conventionnelles mais également sur les sources d'énergie renouvelables. L'intérêt de considérer ce type de systèmes hybrides réside dans le fait que les ressources d'énergie renouvelables, en plus de leurs coûts, sont souvent impactées par des variations saisonnières et ne peuvent être considérées comme un apport d'énergie continu et déterministe. Nous avons réalisé, dans le cadre de cette thèse, une revue de la littérature des différents problèmes d'optimisation en relation avec les systèmes énergétiques multi-sources. Dans un premier temps, nous avons travaillé sur la problématique de la localisation des systèmes énergétiques multi-sources. L'objectif est établir un profil ou un potentiel énergétique d'une zone géographique en considérant des critères économiques, sociaux et environnementaux. Ensuite, nous nous sommes intéressés à l'optimisation des contrats d'énergie pour répondre au besoin global de consommation en considérant des aspects «écoresponsables» de ces contrats. Nous avons proposé des modèles mathématiques et des méthodes de résolution pour l'optimisation du choix des contrats d'énergie multi-sources en considérant à la fois des demandes déterministes et des demandes aléatoires.[1]

Mots clés : ressources énergétiques, incertitude, optimisation mathématique, consommation d'énergie, localisation, théorie de la

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Outline

List of Tables

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List of Symbols

EU	**E**uropean **U**nion
Ecofriendly	**Eco**logical **friendly**
HEV	**H**ybrid **E**lectric **V**ehicle's
SPV	**S**olar **P**hoto **V**oltaic
PV	**P**hoto **V**oltaic
NSGA-I	**N**on-dominated **S**orting-based **G**enetic **A**lgorithm I
NSGA-II	Fast **N**on-dominated **S**orting-based **G**enetic **A**lgorithm II
MG	**M**icro**g**rid
AMPL	**A** **M**athematical **P**rogramming **L**anguage
TOU	**T**ime **O**f **U**se
RG	**R**enewable **G**eneration
WHO	**W**orld **H**ealth **O**rganization
DEA	**D**ata **E**nvelopment **A**nalysis
DEA2	Modified **D**ata **E**nvelopment **A**nalysis
DMU	**D**ecision **M**aking **U**nit
MADM	**M**ulti**A**ttribute **D**ecision **M**aking
MODM	**M**ulti**O**bjective **D**ecision **M**aking
MCDM	**M**ulti**C**riteria **D**ecision **M**aking
SAW	**S**imple **A**dditive **W**eighting
ELECTRE	**H**ierarchical **A**dditive **W**eighting **E**limination **A**nd **C**hoice **E**xpressing **R**eality
TOPSIS	**T**echnique **F**or **O**rder **P**reference by **S**imilarity to **I**deal **S**olution
LINMAP	**LI**near programming techniques for **M**ultidimensional **A**nalysis of **P**reference
STEM	**STE**p **M**ethod
GPSTEM	**G**oal **P**rogramming **STEM**
SEMOPS	**SE**quential **M**ulti **O**bjective **P**roblem **S**olving
GP	**G**oal **P**rogramming
DM	**D**ecision **M**aker
AHP	**A**nalytic **H**ierarchical **P**rocess
ANP	**A**nalytic **N**etwork **P**rocess
MPGP	**M**ultiple- **P**hase Simplex Algorithm for **G**oal **P**rogramming
GA	**G**enetic **A**lgorithm
ILP	**I**nteger **L**inear **P**rogram
GIS	**G**eographical **I**nformation **S**ystem
NMD	**N**otified **M**aximum **D**emand
FTOPSIS	**F**uzzy **T**echnique **F**or **O**rder **P**reference by **S**imilarity to **I**deal **S**olution

MOGA	**M**ulti-**O**bjective **G**enetic **A**lgorithm
VEGA	**V**ector **E**valuated **G**enetic **A**lgorithm
MOCO	**M**ulti-**O**bjective **C**ombinarorial **O**ptimization
PESA	**P**areto **E**nvelop based **S**election **A**lgorithm
SPEA2	**S**trength **P**areto **E**volutionary **A**lgorithm version 2
DINAS	**D**ynamic **I**nteractive **N**etwork **A**nalysis **S**ystem
SON	**S**implex special **O**rdered **N**etwork
ILP	**I**nteger **L**inear **P**rogram
INLP	**I**nteger **N**on **L**inear **P**rogram
GIS	**G**eographical **I**nformation **S**ystem
NPV	**N**et **P**resent **V**alue
MF	**M**embership **F**unctions
EP	**E**volutionary **P**rogramming
SOGUs	**S**elf-**O**wned **G**enerating **U**nits
PSO	**P**article **S**warm **O**ptimization
CSO	**C**a **S**warm **O**ptimization
PDF	**P**robability **D**ensity **F**untion
CDF	**C**umulative **D**istributive **F**untion
PP	**P**ower **P**roduced
INV	**INV**estment cost
TCO2/y	**T**ons of **CO2** emissions avoided per **y**ear
JOB	**JOB**s created
OM	**O**peration and **M**aintenance costs
DIS	**DIS**tance between plants
SA	**S**ocial **A**cceptance
ECON	**ECON**omical
ENV	**ENV**ironmental
SOC	**SOC**ial
CC	**C**ontract **C**apacity
TC	**T**otal **C**ost
KKT	**K**arush **K**uhn **T**ucker
TED	**T**otal **E**xcess **T**ucker
R	**R**obust optimization
DR	**D**ualized **R**obust optimization
LDR	**L**inearized and **D**ualized **R**obust optimization

Part I

English Version

Introduction

Outline of the current chapter

Context

Multi-sources of energy are composed of renewable energy and traditional energy sources. Traditional energy resources are composed of crude oil, kerosene, petroleum, diesel, coal, and natural gas. Renewable energy sources are composed of solar, wind, rain, tides, waves, geothermal heat, biofuel, biomass, biogas, and hydropower. Renewable power plants are combined in a network with the nonrenewable energy. The combined model is called multi-sources of energy composed also of energy storage and energy demands such as industries and homes, as illustrated in figure 1.

Nonrenewable energy sources cause global warming due to CO2 emissions through combustion of fossil fuels, they also increase different aspects of pollution in general. Moreover traditional energy sources are limited and will not be able to provide the increase in future energy needs. So, due to these reasons, as well as the price and independence of oil, society and governments are demanding reliance on renewable energy sources instead of traditional energy sources, since the renewable energy sources are ecofriendly and everlasting.

The European Union (EU) defines its energy targets for 2020, 2030 and 2050 to monitor energy consumption of EU countries systematically. The EU's Renewable energy directive sets a

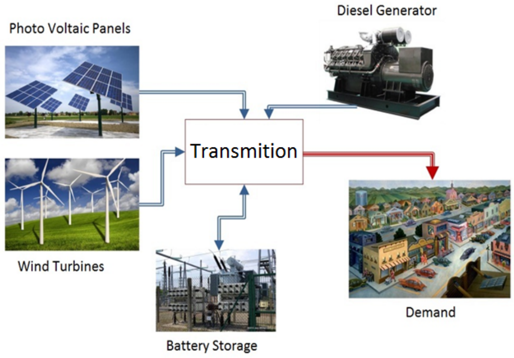
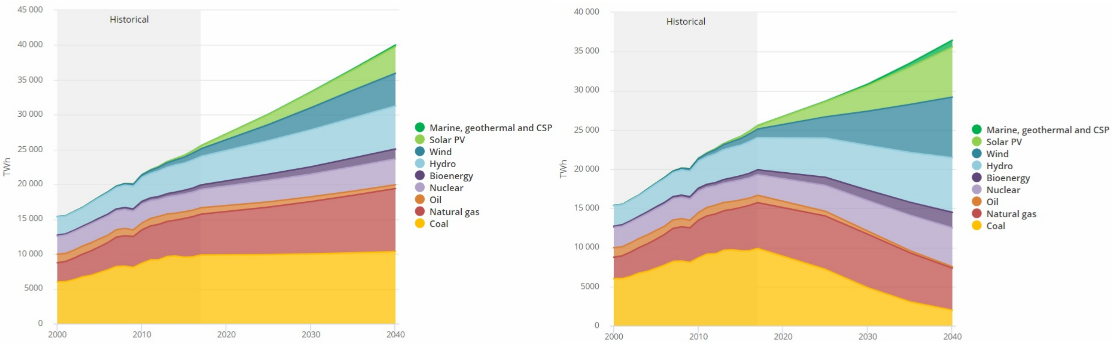


Figure 1 – Multisources of energy illustration [2]

binding target of 20% final energy consumption from renewable sources by 2020. All EU countries have adopted national renewable energy action plans showing what actions they intend to take to meet their renewable targets. These plans include sectorial targets for electricity, heating and cooling, and transport; planned policy measures; the different mix of renewable technologies they expect to employ; and the planned use of cooperation mechanisms. EU countries agreed in 2014 on a new renewable energy target of at least 27% of EU's final energy consumption by 2030, as part of the EU's energy and climate goals for 2030. The EU has set itself a long-term goal of reducing greenhouse gas emissions by 80-95%, when compared to 1990 levels, by 2050. This goal can be achieved by the following steps:

- Decarbonising the energy system.
- Emission reduction target is cheaper than the continuation of current policies.
- Increasing the share of renewable energy and using energy more efficiently.
- Early infrastructure investments cost less.
- Immediate replacement with low-carbon alternatives can avoid more costly changes in the future.

World energy generation according to the new policies scenario and the sustainable development scenario are presented in figures 2a and 2b. To attain a sustainable development scenario and achieve the above mentioned targets, multi-sources of energy should be optimized in a compatible



(a) The new policy scenario (b) The sustainable development scenario

Figure 2 – The electricity generation by technology in TWh for the world with time, based on IEA data in 2018 (https://www.iea.org/weo/)

and efficient manner. Energy optimization faces many problems, as illustrated in figure 3, such as the optimization of location for power plants, energy for machines, dimensioning the implementation of energy sources, energy contract capacities with different pricing, energy buildings optimization and smart grids .

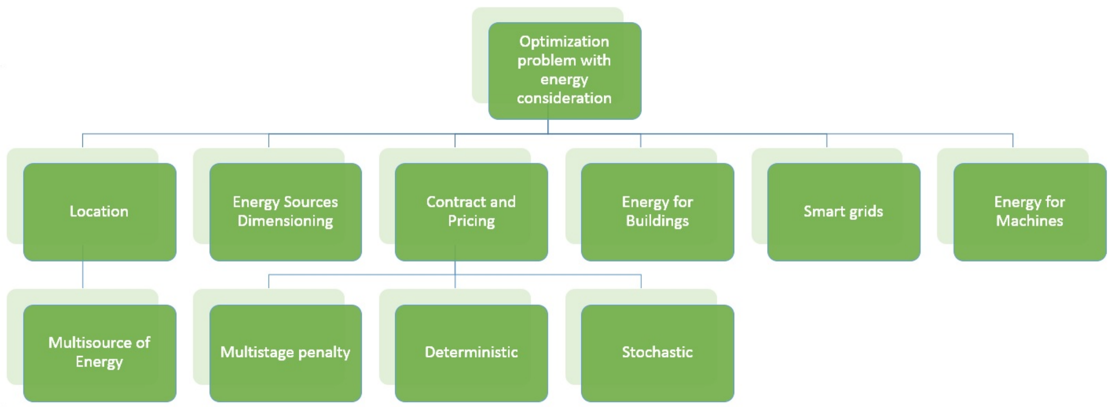


Figure 3 – Problems classification

To reduce the carbon emission for each country in Europe or any country in the world, it is important to invest in renewable energy power plants in the different regions of the country. Each region has its own potential for what type and size of renewable energy power plant to build. Adding an alternative power plant needs to satisfy the demand of energy and other criteria.

The electric contract capacity nowadays is categorized into various types such as traditional and renewable energy contracts, so choosing high values of renewable energy contracts will help meet the European targets, industries are also interested in improving their reputation by using green energy contracts for their production. The uncertainty in demand is also a challenge for choosing the optimal mix of contract capacities.

In the second section how the optimal location distribution of the renewable energy mix in a country is explained, and the way the multi-sources of energy contract capacities are optimized with and without demand uncertainty.

Problems studied in the thesis

Important questions arise for the optimum distribution of renewable energy power plants, which need to be answered. One such question is, "Based on what criteria should the renewable energy power plants be distributed? " which leads to the idea of "multi-criteria decision making". So to distribute the various alternatives in a government economical, environmental and social criteria should be satisfied. Since each region has the potential to hold more than one type of power plant, another question appears is "How can multi power plants be assigned to one place?" which can be formulated as "probability assignment". Therefore, each place can have a profile of the types of energy with a probability of putting the alternative in this location.

To adapt energy production and demand, they need to be balanced by tariffs offered to the customer, in order to achieve this tariffs should have pricing strategies and power demand options. By signing a contract the energy supply agreement is guaranteed, that being the case, energy consumers therefore need to know " What is the capacity option that can satisfy the need of energy?" To utilize renewable energy sources in the market, they are added to the contract capacity choice policy. All countries are concerned about on replacing the traditional energy sources, which have huge greenhouse effect on the planet, by natural, clean and limitless energy sources. Recently, society is becoming more conscious of the need to protect the planet by using technology in an ecological friendly (ecofriendly) way, keeping in mind that the demand of energy is uncertain because it depends on the user and it changes from time to time. Accordingly, "How are multi-sources of energy contract capacities modeled and chosen in an ecofriendly way considering uncertainty?" On the other hand, renewable energy generation such as solar and wind energy depends on the weather condition, so it has a stochastic aspect, i.e. "How can the energy producer decide the maximum contract capacity of multi-sources of energy in case of uncertainty in energy generation and demand?"

In this study we model four optimization problems and find the answers of the questions for increasing the use of renewable energy:

1. Multi-sources energy plants location using goal-programming and flow control analysis approach.
   Based on what criteria should the renewable energy power plants be distributed? How can multi power plants be assigned to one place?

2. Optimization of Energy Demand Contracting Strategy with Ecofriendly Consideration
   What is the capacity option that can satisfy their energy need?

3. Multi-sources of Energy Contracting Strategy with an Ecofriendly Factor and Uncertainties.
   How are multi-sources of energy contract capacities modeled and chosen in an ecofriendly way considering uncertainty?

4. Two stage robust optimization mixed integer linear programming method.
   How can the energy producer decide the maximum contract capacity of multi-sources of energy in case of uncertainty in energy generation and demand?

The primary objective of the thesis is to make a general model to assign optimally different types of power plants to different places satisfying different criteria. We have tried to improve on previous propositions and give the energy profile of each place by finding the probability of allocating this power plant to this place. The second objective is to design a model for energy consumers to optimize the multi-sources of energy contract capacities in an ecofriendly manner to encourage the use of renewable energy. The third objective is to find the optimal mix of multi-sources of energy contracts under uncertainty in energy demand. The final objective is to find the maximum contract capacity of multi-sources of energy considering uncertainty in energy generation and demand.

Thesis contribution

This thesis' objective is to find the optimal distribution of different types of energy power plants with probability assigning, and to find the optimal mix of contract capacities for energy consumers with and without uncertainty.

Firstly, the generalized model developed in this study helps the decision maker to know the energy profile of the various regions of any country in the world. The problem was applied using goal programming to minimize the total deviations around the predefined goals presenting the different criteria to be achieved. The work was inspired from Ramón and Cristóbale [3] who located five renewable energy plants for electric generation in five places found in Cantabria in the north of Spain, and Zogrofidou et al. [4] who assigned the probability distribution of 13 types of alternatives in 51 prefectures of Greece. The model is generalized and improvements are added such as constraint relaxation, place dependant criteria and data envelopment analysis applied on criteria instead of the deviations.

Secondly, multi-sources of energy contract capacity optimization are managed in this thesis including an ecofriendly factor to encourage the use of renewable energy in the mix. In energy contracting the consumer is penalized for a demand of energy exceeding the contract, and if the demand is less than the contract capacity the consumer is charged by the contract itself, to find the optimal contract capacity a linear programming method is used in the deterministic case considering multi-sources of energy. The study of Chen and Liao [5] which finds the optimal contract capacity of one type of energy is generalized to consider multi-sources of energy contract capacity and an ecofriendly factor is introduced to improve the usage of renewable energy, this ecofriendly factor is supported by the government or by the consumer such as the industry supporting the renewable energy to have green products. The model is applied to sets of demand values : low; medium and high. The ecofriendly factor has been changed to test its effect.

Thirdly, since the demand of energy depends on the user and it changes from time to time, a nonlinear model using an interior point algorithm is proposed to find the optimal multi-sources of energy contract capacity considering demand uncertainty, penalty and ecofriendly factor. The model is applied to energy demand in the Grand-Est region of France testing various penalty prices, ecofriendly factors, probability distribution functions and changing the uncertainty by calibrating the parameters of the probability distribution functions.

Finally, to find the set of maximum contract capacities of multi-sources of energy proposed by the producers, and to handle the uncertainty of the demand of energy with the non deterministic nature of the energy produced, a two stage robust optimization mixed integer linear programming method is proposed. The model is inspired by Billionnet et al. [6], the mixed-integer linear robust problem is solved with first-stage variables and continuous second stage variables. Column wise uncertainty is taken into consideration, the left column represents the energy generation and the right column represents the demand of energy, which satisfies a full recourse property. A solution based on a generation constraint algorithm is proposed. The approach for left-hand side uncertainty and for uncertainty sets are called polytope.

Overall, these developed models improve the energy efficiency, raise the use of renewable energy sources and have an environmental-friendly consumers.

The work done in the thesis has been presented in an international workshop, two international conferences and the author is the main contributor of the following presentations and publications:

Journal Article

1. Hamze, A., Ouazene Y., Chebbo N. and Imane Maatouk, "Multisources of Energy Contracting Strategy with an Ecofriendly Factor and Demand Uncertainties", Energies. 2019, 12(20), 3928; https://doi.org/10.3390/en12203928

International Conferences

1. Hamze, A., Ouazene Y., Chebbo N. and Imane Maatouk, "Multi-sources energy plants location using goal-programming and flow control analysis approach" 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT), 1964-1969.

2. Hamze, A., Ouazene Y., Chebbo N. and Imane Maatouk, "Optimization of Energy Demand Contracting Strategy with Ecofriendly Consideration",(Accepted) 7th IEEE (2019) International Conference on Advaced Logistics and Transport (ICALT)

International Workshop

1. Hamze, A., Ouazene Y., Chebbo N. and Imane Maatouk, "Optimal mapping of multi-sources of energy". 9TH INTERNATIONAL WORKSHOP ON OPTIMIZATION IN LOGISTICS AND INDUSTRIAL APPLICATIONS 2018. Karlsruhe, Germany

Structure of the thesis

The remainder of the thesis is organized as follows. Chapter 1 explains briefly the different problems that face multi-sources of energy, it describes the different industrial localization methods, the location distribution of monosource, multi-sources of energy, and explains the data envelopment analysis method. In addition, the general literature review covers the various attempts at contract capacity optimization.

Chapter 2 proposes a general model for multi-sources of energy location optimization, the criteria are categorized into three parts: the location of the different alternatives are optimized using goal programming to achieve the different criteria; the probability of assigning the various power plants to the optimal places is achieved using control flow; the most efficient solution is extracted using data envelopment analysis, the method is applied on the criteria and on the deviations for comparison.

Chapter 3 manages the multi-sources of contract capacity optimization. The model for discrete contract capacity is explained and applied using linear programming, for uncertainty in demand of energy a nonlinear model is proposed for optimization using interior point algorithm.

In Appendix 1 a two stage robust optimization mixed integer linear programming method is described to handle uncertainty in energy generation and demand to find the maximum contract capacity.

Overall, the final chapter summarizes and concludes the research work in this Thesis. Results are shown and the perspectives are presented for future research.

1

Multisource of energy problems: state of the art

Outline of the current chapter

1.1 Introduction

In the first chapter, multisource of energy problems' general review is presented, then energy related to buildings is described with energy optimization for grids , machines and robust optimization of energy, that is to mention the energy pricing, data analysis methods are also classified and explained for data envelopment analysis is going to be used. The location optimization methods for facilities in general are described, more particularly different attempts to optimize the location of one type of renewable energy and multisource of energy, it is shown that there are few contributions for optimization of different energy alternatives. Energy contract capacity optimization is explained, electricity tariffs are classified, second the power demand is described, then the contract capacity is described for different countries and the reasons for their optimization, after that the contract capacity costs are listed and the time of use is described, and finally a comprehensive review of contract capacity optimization methods and applications are presented.

1.2 Energy optimization

1.2.1 Multisources of energy optimization

Hybrid energy automobiles need modeling and control for the flow of energy considering uncertainty in energy demand. A Hybrid Electric Vehicle's (HEV) electrical energy is managed and optimized by Gaoua et al. [7, 8, 9] when running on a known mission profile, that is respecting the different constraints related to the operating system to meet the demand of the electrical motor powertrain. In addition, the consumption of hydrogen by a fuel cell is minimized with an intelligent management of power distribution to meet the demand of the powertrain considering a nonlinear mathematical model. They solved the method using a combinatorial approach with Branch-and-Cut method and quasi Newton offline for known profiles, and fuzzy logic with genetic algorithm for online unknown profiles. The results showed better objective values and computational time when using combinatorial approach. It is more cost effective than normal cars in urban areas but it is the same in country areas. The hybrid electric vehicle energy chain is further mathematically modeled by Caux et al. [10] using an exact method to provide an optimal solution that corresponds to hydrogen consumption. The simulations performed on different realistic mission profiles reveal significant increase in solution quality and computational time.

To solve the problem of green product companies, Tsai et al. [11] studied the feasibility of expanding capacity with regard to the production and maximization of total profits. There are four capacity expansion features in the green product mix decision model: stepwise machine cost, direct material cost, piecewise direct labour cost, CO2 emission cost, and integrated model cost. The method utilized is mixed integer linear programming. The outcome is that companies producing green products can make optimal decisions about further processing and capacity expansion.

To optimize the location to obtain higher sources of energy and better connection with the grid with reduced energy loss Deshmukh et al. [12] modeled multi-sources of renewable energy mathematically. The methods used are linear programming probabilistic approach, iterative technique, dynamic programming, multi objective, Mont Carlo, Simplex, and Genetic Algorithm optimization methods. It is shown that although the cost and technological development of hybrid renewable energy system in several years before 2008 had been encouraging, they remain expensive. Battery storage smooths the mismatch between high load and maximum power generated, and there is a trade off between the size of the storage capacity and the diesel power. The bigger the size of the storage capacity the smaller is the diesel power and vice versa.

The energy storage, generation, transmission, and investment have been optimized by Powell [13] in the presence of uncertainties. The techniques used are stochastic modeling and classification methods for decision making, like policy, myopic cost, and value function approximation. It is noticed that overestimating the failure rate increases the costs by replacing transformers unnecessarily while underestimating it exposes a burst of failure. Batteries can be used for arbitrage which involves drawing energy from the grid when prices are low, and selling them back when prices are high; and for frequency regulation.

For energy cost minimization, polluting emissions, and maximizing renewable energy resources Elsied et al. [14] optimized the multisource of energy taking into account the uncertainty in energy demand and balance between source and load. The method employed is genetic algorithm and linear/quadratic programming. The model optimized the distribution of the power demands on the different energy sources and energy storage with minimum pollution. Effectiveness execution of the proposed methodology and its behavior is formulated in detail for a daily variation of the load.

Hybrid energy system components such as hydro generator, biomass generator, biogas generator, Solar Photo Voltaic (SPV) generator, diesel generator, rectifier, charge controller, inverter, battery bank, dump load, and load demand have been mathematically modeled by Gupta et al. [15]. The aim of this model is to identify the most economic and appropriate power supply for electrification of a selected remote rural area composed of cluster of villages. Gupta et al. formulated the problem as a mixed integer linear programming, assumptions are required for the input data. The approach involves the minimization of an energy cost function subject to a set of equality and inequality constraints. In addition to that, the diesel engine generator is preferred to be operated under constant output with high efficiency in order to reduce the polluting gases from the diesel engine.

Problems in modeling the hybrid energy, such as energy efficiency vs effectiveness, while minimizing the energy loss have been discussed by Prabhu et al. [16], the authors should satisfy the demand in energy, so they optimized energy efficiency considering manufacturing system effectiveness as a constraint, or, they optimized manufacturing system effectiveness for a given profile, using the total available power as a constraint, or they defined a simultaneous optimization of both to get a balanced solution.

The second problem they proposed is the increasing volatility and unpredictability of energy availability, supply and cost, which requires more reactive management systems. To solve this challenge they considered stochastic /probabilistic models, data analysis tools, statistical studies, and data mining, risk management tools, simulation tools or highly reactive algorithms, high-speed heuristics, rule based behaviors or multi-agent techniques, in addition to long-term optimization algorithms, with respect to the previous challenge. It may also require acquiring behavioral models of the energy grid.

The last problem they proposed is modelling energy consumption in varying scales and across different sub-systems, this requires researchers to either develop complex reverse engineering techniques and models to estimate energy profiles or use external energy sensors.

An economic efficiency and energy intensity consumption had been analyzed by Bojnec and Papler [17] as determinants of sustainable economic development for 33 selected European countries. The methods used are multivariate factor analyses, regression, and correlation.

The problem of balancing demand and supply is a challenging task solved by Zhou et al. [18] for a distributed energy system, because it always faces instantaneously varying loads and small quantity of equipment within the system providing limited operation flexibility to cope with the fluctuation in energy demands. If model uncertainties are not adequately identified and handled, the actual economic and feasible operation of the designed distributed energy system diverges from the optimal one. So they used a two-stage decomposition based solution strategy to solve the optimization problem with genetic algorithm performing the search on the first stage variables and a Monte Carlo method dealing with uncertainty in the second stage. Mathematical models have been proposed using different mathematical programming techniques such as mixed-integer programming and multi-objective programming. It can be observed that the total annual cost of different energy generators deterministic programming is smaller than that of the stochastic programming problems, but prohibiting storage leads to a larger difference between energy demand and supply.

The conflict between the cost of renewable energy technologies and the reliability of a multi-sources generation system has been solved by Bilil et al. [19], they presented a multi objective formulation to allow optimizing simultaneously both the annualized renewable energy cost and the system reliability defined as the renewable energy - load disparity. Bilal et al. proposed a fast and elitist multi-objective non-dominated sorting genetic algorithm (NSGA-II) to optimize the use of renewable energy technologies taking into account the annualized cost and the power system reliability in terms of load supplying and including renewable sources in power generation. Following the Pareto dominance, using both solar and wind technologies is better than using wind generators alone, and this is better than generating energy by PV alone. For the same cost, the power system designer can decide in terms of the penalty factor to have lack or excess of produced energy. As a consequence, the total annual cost of different energy generators deterministic programming is smaller than that of the stochastic programming problems, but prohibiting storage leads to a larger difference between both.

For a stand-alone hybrid system composed of wind turbines, solar photovoltaic panels and batteries, and auxiliary fuel generator Billionet et al. [2] found a robust optimal design taking into account the stochastic behavior of the solar and wind energy production, and of the demand. In addition, the robust system generates a minimum total cost when the worst-case scenario occurs. They solved the problem by choosing a two-stage robust approach to take account of the stochastic behavior of the solar, wind energy production, and demand. They used a constraint generation algorithm, each sub-problem can be reformulated by a mixed-integer, linear program and hence solved by a standard solver. They used a polynomial time dynamic programming algorithm for the recourse problem and showed that, in some cases, this algorithm is much more efficient than mixed-integer linear programming. As an influence of the demand uncertainty, the optimal value of the robust problem increases as a function of the bound to the accumulated variations corresponding to an increase of demand but it reaches its maximum value for a certain threshold. This threshold increases as the deviation from the mean demand value maximum variation increase. For intermediate values of uncertainty on demand the dynamic programming approach is much faster than the approach using CPLEX. As mentioned, the optimal value of the robust problem increases as a function of uncertainty on demand, uncertainty budgets, and until a certain threshold. The non efficiency of CPLEX in median cases is due to the large number of nodes explored in the branch and bound because it corresponds to difficult instances, while extreme values correspond to cases where there is little uncertainty because the actual demands are all close either to the mean value or to the largest value. The combined influence of uncertainties in the energy generated by wind turbines and PV-panels induces a larger cost augmentation than the sum of the ones induced by considering separate uncertainties in wind and solar energy generation.

To work on the literature gap regarding the merge of the analytical hierarchy process, solar energy and regional investment attractiveness, Poulos et al. [20] created a rank order of the Greek regions based on their investment attractiveness. The analytic hierarchy process was applied in its group choice approach combined with a purposive sampling of experts from the business, governmental and research fields. The analytical hierarchy process method follows a particular progression of three major stages, namely, the decomposition of the decision problem, the pairwise comparisons and the synthesis of the priorities. The overall inconsistency of this research is 0.01 < 0.1. This combined extracted rank is fully reliable. The group of experts holding positions in the business sector set “solar irradiation” as the first criterion, the group of people related to government chose “available land”, while the third one coming from the research field ranked both “regional electricity consumption and – photovoltaic energy installation” as the most essential criteria. As far as the rank of order of the alternatives is concerned, in all three categories the regions of Sterea Ellada, Attiki and Kentriki Makedonia are ranked in the higher positions. Some contradictions are observed in the criteria. In all groups, solar irradiation, photovoltaic energy installed and available land play significant roles. However, the regional group also raises the significance of regional electricity consumption, and the national group pinpoints the significance of human resources in science and technology.

The complication of achieving better economic and environmental benefits of microgrids (MGs) has been resolved by Wang et al. [21] under multiple uncertainties in renewable energy resources and loads. Uncertainties are covered by symmetric interval sets with budget of uncertainty. Moreover, differences of uncertainty scenarios between operational costs and emissions are distinguished. The proposed approach is energy scheduling based on robust multi-objective (economic and environmental) optimization with minimax criterion. A hierarchical meta-heuristic solution strategy, including multi-objective cross entropy algorithm, is designed to solve the reconstructed problem. Methods-Energy Measurement combined with defined energy reference cycles for manufacturing technologies are used. A Robust Multi Objective optimization-based EPS method is proposed for MGs, which mitigates the disturbances of renewable energy and loads, and optimizes operation costs and emissions simultaneously. A mixed integer minimax multi-objective model is developed, which allows system operators to adjust the robustness of scheduling schemes in a Multi Objective framework based on the scope of the worst-case scenario of uncertainties in MGs. The primal problem is converted into a maximum multi-objective optimization problem and a minimum set-valued optimization problem, which can be effectively solved by a hierarchical meta-heuristic solution strategy and multi-objective cross entropy algorithm. The proposed scheduling method can effectively attenuate the disturbance of uncertainties as well as reduce energy costs and emissions, as compared with single-objective robust optimization and multi-objective optimization scheduling approaches.

A multi-agent system for energy resource scheduling of an islanded power system with distributed resources is presented by Logenthiran et al. [22], it consists of integrated MGs and lumped loads. Multi-agent system deals with modeling of autonomous decision making entities. A Multi-agent system modeling of a microgrid makes more intelligent power system, where each necessary element is represented by an intelligent autonomous agent. It provides a platform to use a combination of artificial intelligence and mathematical tools to decide agents' optimal actions. Each power source and controllable load is modelled as an autonomous agent and a common communication interface is provided for them and all the other agents representing the other components in the network. Distributed intelligent multi-agent technology is applied to make the power system more reliable, efficient and capable of exploiting and integrating alternative sources of energy. The applied algorithm behind the proposed energy resource scheduling has three stages. The first stage is to schedule each microgrid individually to satisfy its internal demand. The next stage involves finding the best possible bids for exporting power to the network and compete in energy market. The final stage is to reschedule each microgrid individually to satisfy the total demand, which is the addition of internal demand and the demand from the results of the energy market simulation. The simulation results of a power system with distributed resources comprising three microgrids and five lumped loads show that the proposed multiagent system allows efficient management of micro-sources with minimum operational cost. The case studies demonstrate that the system is successfully monitored, controlled and operated by means of the developed multi-agent system.

The benefits of increasing the integration of renewable energy resources in this insular power system are shown by Osório et al. [23]. The objectives are minimizing the time for which conventional generation is in operation, maximizing profits, reducing production costs, and reducing greenhouse gas emissions. The proposed approach considers the Unit Commitment and scheduling problem for conventional generation and renewable production, together with random conditions of solar, wind power and load, taking as a real case study an islanded power system in Portugal. Mixed integer quadratic programming is used to model the system, and the CPLEX ensemble on the general algebraic modeling system deficits is used to solve the problem. The outcome gave a decrease of 29% in production costs which represents a significant saving, and a reliable solution is found by the algorithm, which is essential in real applications today.

A modeling for scheduling electrical appliances for an individual household is optimized by Mitra et al. [24]. Taking into consideration a grid connected system with a battery and an in-house renewable energy generator. The customers are offered dynamic prices as a function of the planned consumption and forecasted grid load. This model minimizes the customer's electricity bill subject to different constraints. The different scenarios of the model were implemented in AMPL (A Mathematical Programming Language) with CPLEX solver. The feasibility pump heuristic approach is used in CPLEX to solve these mixed integer linear and non-linear models. The expenditure of the consumer decreases considerably when shifting from flat prices to dynamic prices and individual load flattening is achieved with the use of a battery and an in-house renewable energy generator. Also, the larger the price range the greater is the load flattening and the lower is the expenditure. The proposed pricing policy is beneficial to both consumers and suppliers.

To improve energy sustainability in urban areas Niemi et al. [25] employed different energy carrier networks in connection with distributed renewable energy generation as an attractive approach. An effective option to increase local renewable energy production is to convert surplus electricity into for example thermal energy. They presented a methodology for studying such multi-carrier urban energy systems which enables spatial energy demand and supply, and spatial energy flows to be analyzed. The results indicate that in a northern midsized city, wind power coupled both to an electric grid and a district heating network could raise the allowable wind capacity over the non-heat case by 40-200%. In an Asian megacity dominated by cooling demand, employing dispatched local photovoltaics and tri-generation could even cover more than 30% of all energy demand and lead to major carbon emission reductions.

A multi-criteria optimization analysis for Jordan's energy mix is utilized by Malkawi et al. [26]. Financial, technical, environmental, ecological, social, and risk assessment were included as criteria clusters. To evaluate the electricity generation options for Jordan, a multi-criteria decision-making analysis called the Analytical Hierarchy Process was chosen to evaluate the electricity generation options. Renewable and conventional sources are included in the analysis as an energy options. Natural gas and oil are considered as evaluated conventional sources.

Concentrated solar systems, photovoltaic, biomass, wind are included as renewable sources. Their study also explored generation from nuclear energy and direct combustion of oil shale as well as demand-side savings from energy efficiency measures as a resource. The outcome shows that Jordan's most feasible options are conventional fuels to the date of 02/05/2017 from a technical and financial perspective, taking into consideration that promoting energy security and environmental welfare needs diversification. The results specify that nuclear, oil shale, biomass, and wind energy are Jordan's best diversification.

1.2.2 Energy optimization for buildings

Buildings with multi-sources of energy need optimization to supply their load with lower cost and higher efficiency. The multi-sources for buildings are composed of photovoltaic panels and integrated gasification cogeneration technology, or photovoltaic and solar panels with high efficiency heat pumps [27]. Electricity in buildings is sourced from the grid, while the heat needed is produced by a gas boiler/gas boilers on site [28]. So some buildings have a diesel cogeneration, compression chillers, boiler and grid, or a heat pump, boiler, photovoltaic, gas turbine and fuel cell. Another way of modeling hybrid energy is to consider it in four categories [29], an electrical process, a photovoltaic solar process, a thermal process, and a cogeneration process.

In the European Union the building sector accounts for more than 40% of total primary energy consumption, the remaining 60% is generated for industrial processes. So buildings consume electric energy especially commercial types like hotel buildings [29], shopping malls, offices such as a thirteen-floor tower composed of a two-floor shopping mall at ground level and eleven floors used as offices [27], or any kind of building that does business [28].

To be environmentally friendly a multi-sources systems technologies' proper sizing and energy demands are optimized by Barbieri et al . [27], they used a genetic algorithm for minimum energy consumption and net present value. To reduce the energy demand, cost and emissions Galvão et al. [29] developed an energy model based on a mixed system of renewable energy. It is also an environmentally friendly process aiming to reduce energy demand, costs and emissions. For minimum life-cycle costs of meeting the energy demand (power, heating, cooling) of a commercial building, Safaei et al. [28] integrated cogeneration, solar and conventional energy sources. They

Optimized the investment planning and operating strategies of the energy systems using general algebraic modeling system. The analysis showed varied operating strategies and output levels among cogeneration technologies and the energy systems coupled with them.

1.2.3 Energy optimization for grids

An electrical grid is a network of remote power plants which transmit electrical power through long-distance high-voltage lines to substations via a transmission network, the latter in turn adapt and deliver it to local end users as a distribution network, like the current electrical grid of the United States [30]. A micro grid is a low-voltage or medium-voltage distribution network, consisting of various distribution generators, storage devices, and controllable loads. A micro grid can be a hybrid configuration with multiple energy resources, for example in the model [31] a combined cooling heating and power runs in thermal load tracking mode, and the remaining heating or cooling energy required is imported from a ground source heat pump. Photovoltaic generation and the combined cooling heating and power collectively fulfill electricity demands. The excess electricity is used to charge the battery or sell to the main grid.

Various problems faces multi-sources of energies in microgrids. Achieving better economic and environmental benefits of microgrids under multiple uncertainties in renewable energy resources and loads is difficult. To make the power system more reliable, stable, efficient and capable of exploiting integration with alternative sources of energy are issues to be solved. Distributed energy resources within cooling/heating and power based microgrids need to be optimally designed. Different levels of information sharing in a smart grid are a management challenge to achieve an aggregate load profile suitable for utilities, and to study how close they can get to an ideal flat profile depending on how much information they share.

Distributed intelligent multi-agent technology is applied by Logenthiran et al. [22], the algorithm behind the proposed energy resource scheduling has three stages. The first stage is to schedule each microgrid individually to satisfy its internal demand. The next stage involves finding the best possible bids for exporting power to the network and compete in a whole sale energy market. The final stage is to reschedule each microgrid individually to satisfy the total demand, which is the addition of internal demand and the demand from the results of the whole sale energy market simulation. The simulation of a power system with distributed resources is applied on three microgrids and five lumped loads.

An economic dispatch problem was developed by Nam et al. [32] and the constraints considering reservation for variation in load demand, power outputs of non-dispatchable distributed generators, and stable islanded operation, with flow limits between two different areas.

Environmental and economic sustainability are coupled in a multi-objective optimisation model by Zhang et al. [33] using genetic algorithm which integrates the results of a life cycle assessment.

The energy production scheduling method is based on robust multi-objective optimization with minimax criterion, Wang et al. [31] used A hierarchical meta-heuristic solution strategy, including multi-objective cross entropy algorithm. The proposed scheduling method can effectively attenuate the disturbance of uncertainties as well as reduce energy costs and emissions, as compared with single-objective robust optimization and multi-objective optimization scheduling approaches.

When customers can share all their load profiles, they provide a distributed algorithm, set up as a cooperative game between consumers, which significantly reduces the total cost and peak-to-average ratio of the system, so Caron and Kesidis [30] proposed a dynamic pricing scheme to incentivize consumers.

For future smart grids, Mohsenian-Rad et al. [34] considered autonomous and distributed demand-side energy management system among users that takes advantage of a two-way digital an envisioned communication infrastructure. The procedure utilized is game theory and formulation of energy consumption scheduling game, where the players are the users and their strategies are the daily schedules of their household appliances and loads.

As a result of the different contributions the multiagent system allows efficient management of micro-sources with minimum operational cost. A microgrid could be operated economically during the grid-connected mode, and soundly during the islanded mode. The installation of multiple cooling heating and power technologies has a lower cost with higher environmental saving. These solutions efficiently benefit from information sharing within the grid and reduce both the total cost and peak-to-average ratio. In the absence of full information sharing (for privacy reasons), when users have only access to the instantaneous total load on the grid, a distributed stochastic strategy that successfully exploit this information is provided to improve the overall load profile.

The proposed approach can reduce the peak-to-average ratio of the total energy demand, the total energy costs, as well as each user's individual daily electricity charges.

1.2.4 Energy pricing

When electricity is priced at the marginal cost of supplying the last increment of electricity demand, efficient pricing is achieved as read out by economic theory [35], this can be provided by a perfectly competitive market. Because of the capacity needs for these loads, peak loads and their pricing have been a concern. The high marginal cost of electricity during periods of the peak load is reflected in consumer prices in peak load pricing. Both prices and time period are fixed for some time of use (TOU) pricing.

Different from the TOU constant pricing, in real-time pricing, and prices generally change on an hourly basis and are fixed and known only on a day-ahead or hour-ahead basis. The wholesale prices, weather conditions, generator failures, scarcity of generation, or other contingencies that occur in a wholesale electricity market are reflected in real time pricing.

The problem of peak load pricing is not yet solved, so many experiments have been conducted with time of use pricing. Thanks to the data collected from these experiments econometricians are able to estimate the parameters of electricity demand functions such as cross and own price elasticities, lag elasticities, and elasticities of substitution. Some countries even implemented time of use pricing on a national scale. An experiment for California (statewide pricing pilot) has shown that small to medium industrial, residential and commercial customers cut energy usage in peak periods in response to time of use prices.

The different energy pricing challenges vary, for example, large amounts of electricity can't be stored, and over or under supply causes system collapse or rolling blackouts, so the supply must equal demand instantaneously. Electrical appliances should be scheduled for an individual household, taking into account a grid connected system with a battery and an in-house renewable energy generator. The consumption of electricity in peak periods for industries must be reduced. The speed of response gap between suppliers and consumers needs to be bridged, yet adhere to the principle of marginal cost pricing of electricity. Biomass supply contract pricing and policy making are studied in the biofuel industry. The dissimilarity between the peak and off-peak hours prices are managed, taking into consideration uncertainty in pricing for electricity markets.

One of the ways to manage the balance between supply and demand is contract pricing. So a quantitative analysis on real time pricing and the energy market in New Zealand was studied by Poletti and Wright (2017) [36] introducing different assumptions on the retail market and the shape of the demand function.

Dynamic prices are offered by Mitra and Dutta [24] as function of the planned consumption and forecasted grid load in the optimization model for minimum electricity bills.

A stochastic model for the medium-term decision making problem faced by a distribution company is established by Safdarian et al. [37] considering time varying prices. The model is formulated as a mixed integer linear programming and using a price elasticity matrix the demand response to time of use prices is captured. A typical Finnish 20-kV urban distribution network is used to demonstrate the effectiveness of the developed model.

The complementarity programming models of equilibrium are examined by Çelebi and Fuller [35]. They developed a computable equilibrium model to estimate ex ante time of use prices for retail electricity market.

For biomass supply contract pricing an agent-based simulation model is formulated by Huang and Hu [38] as a mixed integer optimization model. In this model, the agents include a biofuel producer and farmers. Farmers' decision-making is assumed to be profit driven. The case studied was based in Iowa, it has been developed to assist determination of the optimal pricing equation for the biofuel producer and analyze the interactions between the stakeholders.

Demand Side Management is introduced by Sulaima et al. [39] through Demand Response technique for the modification of the demand profile by implementing different strategies of measures. The objective of this study is to optimize the energy profile for the commercial sector, as well as to analyze the significance of electricity cost reduction by using the Evolutionary Algorithm Meta-heuristic optimization technique in Malaysia.

In electricity markets with price uncertainty Luo et al. [40] set up a new self-scheduling model based on robust optimization methodology. By using optimal dual theory, the proposed model is reformulated to an ordinary quadratic and a quadratic cone programming problem in the cases of box and ellipsoidal uncertainty, respectively. The model is tested on IEEE 30-bus system. It does not need a prediction of distribution of random variables and just requires an estimated value and the uncertain set of power price.

The analysis shows that as the customers change from fixed price contracts to real time price contracts the demand profile over the day is flatter, which leads to higher average capacity factors and lower system costs. The overall market revenue falls significantly. The increases in consumer surplus, system efficiency and social welfare are relatively higher. The outcome expenditure of the consumer decreases considerably when shifting from flat prices to dynamic prices and individual load flattening is achieved with the use of a battery and an in-house renewable energy generator. The proposed pricing policy is beneficial to both consumers and suppliers. The proposed models would be useful for jurisdictions where consumers' prices are regulated, but suppliers offer them on a competitive market, for forecasting forward prices in unregulated markets, and in evaluation with welfare analysis of the policies regarding regulated TOU pricing compared to regulated single pricing. For biomass supply, simulation results show that under such a contract pricing strategy, the biofuel producer can achieve higher profitability than using a fixed price.

1.2.5 Energy optimization for machines

For manufacturing products, machines use electricity as the main energy source, so a huge portion of all the energy consumption is associated with industrial activities. Manufacturing was responsible for 31% of primary energy consumption and 36% of CO2 emissions in 2007 [41], about 30% of the energy consumption in the United States was associated with industrial activities in 2016 [42]. Since electricity prices are rising continuously [43], it is important to improve the efficiency of production systems to decrease environmental pollution and the production cost. The total energy cost of a system is related to the variation of electricity prices during the time period. Critical peak pricing, real-time pricing, time-of-use pricing are variable pricing methods used to improve the efficiency and reliability of electrical power grids to balance electricity demand and supply. The quantity of energy consumption for a machine varies depending on different criteria [44] such as the machine's state in each period: Processing, Transition, Idle and OFF, machine type, energy consumption during each phase based on the speed of the machine in process operation and energy costs, and duration of each machine status. Sometimes constraints and assumptions are considered for machine problems, such as production shift is divided into a number of periods, without overlap, each period has its unique energy cost, assuming that the machine is shut down in the first and last periods.

To reduce the total energy consumption cost of a single machine manufacturing system over the planning horizon, the total energy should be reduced and energy costs considering time varied electricity price need to be managed. Single or multiple machines scheduling and preemptive or non-preemptive machine manufacturing needs to be distinguished to reduce the total cost. The capacitated lot-sizing problem in flow-shop system for single-item or multi-item with energy consideration is a problem to be considered.

There are attempts to optimize the total energy costs for machines. For example, two new mathematical models to reduce total energy consumption cost of a single machine manufacturing system are presented by Aghelinejad et al. [44]. The first model improved formulation of Shrouf et al. [45] problem considering a predetermined jobs sequence. Meanwhile, the second model studies production scheduling on job levels and machines, proposing an optimal sequence for them by minimizing the occurrence number of each machines state, the optimal allocation of these states during the periods minimizes energy costs and jobs within the processing state

For a single machine Aghelinejad et al. [46] scheduled n preemptive jobs to minimize the total energy costs considering time varied electricity price. The optimal solution of the problem is provided by calculating the shortest path between the first node and last node representing respectively the first and the last periods. The complexity of the problem is proved to be polynomial of degree 3 based on the Dijkstra algorithm.

Machines consume different amounts of energy in function of their state: processing, idle or off state. So for single machine scheduling problems, Aghelinejad et al. [43] proposed a dynamic programming approach to solve these problems using a finite graph.

A non-preemptive single-machine manufacturing environment was investigated by Aghelinejad et al. [47] to reduce the total costs. They improved the mathematical formulation of scheduling problem in a predetermined order at machine level to process the jobs. Second, the authors generalized the model to deal simultaneously with the production scheduling at machine level as well as job level. A heuristic algorithm and a genetic algorithm were applied to the second model because the problem is NP hard to provide good solutions in reasonable computational time accurately and efficiently. For small size instances, which the mathematical model provides a solution in reasonable computational time, a gap of 2.2% for the heuristic and 1.82% for GA are achieved comparing to the exact method's solution.

To minimize the total energy consumption costs over the planning horizon of several energy-oriented single-machines, Aghelinejad et al. [42] studied two cases: constant energy price and increasing energy prices during all the time-slots. Moreover, two versions are investigated: with and without the fixed sequence for the jobs. The general version of this problem with TOU energy prices and different processing times of the jobs is investigated in two versions: without and with the fixed sequence for the jobs. The results show the version without the fixed sequence (general version) is proved to be NP-hard, and the version with the fixed sequence is proved to be polynomial.

Capacitated lot-sizing problems in flow-shop system with energy consideration was presented by Masmoudi et al. [48]. The planning horizon is split into a set of periods where each one is characterized by a duration, an electricity cost, a maximum peak power and a demand. To minimize the production cost both linear and non-linear mixed integer programming are proposed to solve the problem.

A multi-level capacitated lot-sizing problem was presented by Masmoudi et al. [49] taking into account the energetic aspect. The problem is solved by a linear mixed integer programming model. Also two heuristics are developed to solve NP-hard problems in a reasonable time.

A multi-item capacitated lot-sizing and scheduling problem had been discussed by Masmoudi et al. [50] in a flow-shop system with energy consideration. They formulated a mixed integer linear programming to solve this issue, and because the capacitated lot-sizing problems are NP-hard, a fix-and-relax heuristic is put in place.

A single-item capacitated lot-sizing problem in a flow-shop system taking into account energy aspects is studied by Masmoudi et al. [51]. The objective is to minimize the production cost in terms of electrical, inventory, set-up and power required costs by determining the quantities to be produced by each machine at each period. So two heuristics are formulated to solve the problem in short time since the medium and large problems are hard to solve.

A single-item capacitated lot-sizing problem in a flow-shop system with energy consideration is also addressed by Masmoudi et al. [52]. In addition to the fix-and-relax heuristic method, a genetic algorithm is formed for better quality solutions and to deal with the complexity of the

NP-hard problem. For the problems where the optimal solution is not found, the fix-and-relax heuristic and the genetic algorithm outperforms the heuristic based on movement techniques. The proposed methods have better performances for medium and large problem sizes also.

In a two stage production system, where a product is manufactured on a machine and delivered to the subsequent production stage in batch shipments, Zanoni et al. [53] proposed an analytical model of this system to minimize the total cost of the production, storing, and energy.

To optimally plan energy saving for energy aware scheduling of manufacturing processes, Bruzzone et al. [41] proposed a mixed integer programming model where the reference schedule is modified to account for energy consumption without modifying the jobs' sequencing and assignment provided by the reference schedule. This approach can satisfy hard constraints on the shop floor power requirement while preserving as much as possible the original tardiness and makespan objectives. Furthermore the suggested decoupled approach allows energy-aware scheduling to be promptly integrated into the existing widely used commercial advanced planning and scheduling systems, providing an effective solution to the shop floor power's peak minimization.

For sustainable consideration in manufacturing scheduling, Mansouri et al. [54] incorporated energy consumption as an explicit criterion in shop floor scheduling. They explored the potential for energy saving in manufacturing. They analyzed the trade-off between total energy consumption, minimizing makespan, and a measure of service level.

To find the Pareto frontier comprised of makespan and total energy consumption, they developed a mixed integer linear multi-objective optimization model. For sustainable scheduling Gahm et al. [55] developed a research framework for energy-efficient scheduling.

The results demonstrate the efficiency and accuracy of the proposed algorithms. The results show the complexity of the problems, such as the version without the fixed sequence (general version) is proved to be NP-hard, and the version with the fixed sequence is proved to be polynomial. The total cost is minimized through the production, set-up, inventory, electrical consumption, and power required costs. The proposed methods have better performances for medium and large problem sizes also. The results indicate that energy-related costs can be reduced significantly if energy consumption is considered in planning the production process.

1.2.6 Robust energy optimization

In designing energy supply systems such as local generators, the central grid, renewable energy generations, etc., it is important to estimate the energy demands. This is because designers need to determine what capacities, numbers, and types of equipment should be installed, taking into account equipment operational strategies for hourly and seasonal variations in the estimated energy demands, this greatly affects system energy saving and economic characteristics [56]. At the same time, the limited predictability and intermittent nature of solar and wind power generation, for example, pose significant problems to power system operations. The unit commitment decision, one of the most sensitive decisions for the day-ahead electricity market, is highly subject to power forecast errors [57]. Such solar or wind power uncertainty could endanger the security of power grids and lead to significant economic loss. To solve this, different optimal design methods have been proposed, such as stochastic programming, fuzzy programming, and robust optimization. Stochastic programming uses random variables to describe the uncertainty, and normally probabilistic data determines the probability distributions of these random variables. However, a certain gap usually exists between the probabilistic data and the actual situation. Fuzzy programming uses fuzzy variables to describe the uncertainty. However, the membership function suffers from subjectivity and significant error, since it relies heavily on the experience of decision-makers. Robust optimization uses mathematical sets to describe the uncertainty, and does not require any probabilistic information or prior knowledge [58]. The optimal solution obtained by robust optimization can immunize against any realization of the uncertain parameter within a deterministic uncertainty set. Hence, both the reliability and economy can be easily achieved in robust optimization compared with other approaches.

Researchers and practitioners are involved in the hot subject of robust optimization of energy in case of uncertainty in generation and/or demand. To solve a robust optimization problem the two-stage structure is transformed into dual optimization or by Karush–Kuhn–Tucker conditions then design algorithms and repeat iterations between different layers, for example Bender's algorithm [59] or the two-step relaxation algorithm [60]. For the linear model, according to extreme scenario theory [61] and convex theory [62] , extreme solutions are on the endpoints or bounds.

So robust optimization is used to keep the systems reliable under uncertain circumstances, while ensuring high utilization of intermittent renewable energy and load. Robust optimization takes into account the worst-case scenario for the amount of renewable generation and load. Energy management on a typical micro-grid for operating in islanding mode should be taken into consideration. In addition, different types of uncertainties exist such as uncertainty in prices like fuel tariff and electricity prices, and different stochastic costs like primary energy saving or carbon emission cost which need to be taken into account. Robust optimization includes the problems of intermittency in the combined cooling, heating, and power system operation. Geographically dispersed wind farms need spatio-temporal correlation in wind direction and speed data. Robust optimization must integrate smart grids as well, and minimize the total cost.

To keep the systems reliable under uncertain circumstances, while ensuring high utilization of intermittent wind energy, Jiang et al. [63] made a two-stage robust optimization approach to accommodate ramp events of wind output uncertainty, with the objective of providing a schedule for the thermal generators minimizing the total cost under the worst wind power output scenario, avoiding over protection. The uncertainty set includes the worst-case scenario, and protects this scenario under the minimal increment of costs. The frame work utilized is Bender's decomposition algorithm, for controlling the conservatism of the model, a variable was used to avoid over-protection. The model is applied to a six-bus system as a small power grid, robust optimization and deterministic approaches are applied on a modified IEEE 118-bus system, and the performances are compared under worst case scenario. The experiments are implemented using CPLEX software, the computational results verify the robustness of the solution and the tightness of the bounds under different simulation settings, in considering pumped-storage units, the total cost is reduced significantly.

A scenario-based robust energy management method accounting for the worst-case amount of renewable generation (RG) and load was developed by Xiang et al. [64]. For minimum social benefits cost and maximum total exchange cost, uncertainty of load and renewable energy generation is modeled as an uncertainty set produced by interval estimation. To provide different testing scenarios Taguchi's orthogonal array method is used. By optimizing the worst-case scenario, the energy management solution of the proposed model is robust against most of the possible realizations of the modeled uncertain set by Monte Carlo to verify the effectiveness and feasibility. Numerical cases on the typical microgrid system show the solution strategy.

Optimal energy management on a typical micro-grid with regard to the relevant uncertainties and the capability of operating in islanding mode is proposed by Alavi et al. [65]. Robust optimization technique is utilized to model load demand uncertainty, and the point estimate method is applied for modeling the wind power and solar power uncertainties, that decreased the operational risk. Finally, they make a comparison between deterministic and probabilistic management in different scenarios and their results are analyzed and evaluated. Moreover, the presence of distributed generation and the islanding capability of micro-grid decreased the amount of micro-grid energy not supplied and increased the reliability of the system.

For multiple uncertainties in different prices like fuel tariff and electricity prices, and for different stochastic costs like primary energy saving or carbon emission cost, Akbari et al. [66] focused on designing the energy system for buildings under demand uncertainties concerning insufficient data by means of robust optimization. Various sustainable technologies were considered as alternatives. A real-world problem is studied to know the probable consequence of the proposed robust model. The technology sizes were increased by augmenting the level of conservatism and affected by uncertainty in order to decrease the unmet demands and provide more energy. The most significant increases relate to Heat Buffer Tanks and cooling, heating, and power units. The electric chiller increased to meet the cooling demand, but the absorption chiller was decreased. The photo voltaic unit and boiler were not economical in neither robust nor deterministic solutions.

The intermittency of renewable energy and load uncertainty in the combined cooling, heating, and power system operation is considered by Wang et al. [58]. They proposed a robust optimisation scheduling method to reduce the effect of uncertainty, and derive the day-ahead scheduling. The budget of uncertainty is introduced to decrease the conservatism of robust optimization. A minimax regret non-linear formulation is constructed to describe the performance of the model. They developed a hybrid solution method, which is composed of an improved cross entropy algorithm and a two-stage Lagrangian relaxation iterative algorithm. Simulation results demonstrated that the conservatism of robust optimisation is greatly attenuated by properly setting the level of budget of uncertainty, and the minimum of the maximum regret can be obtained. Therefore, the effectiveness and validity of the proposed robust optimisation model and algorithm are confirmed.

A statistical wind power forecast framework, which leverages the spatio-temporal correlation in wind direction and speed data among geographically dispersed wind farms from west Texas is proposed by Xie et al. [67]. It shows that spatio-temporal wind forecast models are numerically efficient approaches to improving forecast quality. The overall cost benefits on system dispatch can be quantified by reducing uncertainties in near-term wind power forecasts. This economic dispatch framework and integrated forecast was tested on a modified IEEE RTS 24-bus system. The overall generation cost can be reduced by up to 6% using a robust look-ahead dispatch coupled with spatio-temporal wind forecast as compared with persistent wind forecast models as suggested by the Numerical simulation.

A model for the microgrid planning problem with uncertain financial and physical information was presented by Khodaei [68]. This model determines the optimal generation mix of distributed energy resources for installation. A robust optimization approach is adopted for considering market prices, forecast errors in load, and variable renewable generation. The microgrid islanding is further treated as a source of uncertainty. The microgrid planning problem is decomposed into an operation subproblem and an investment master problem. Numerical simulations exhibit the effectiveness of the proposed model and further analyze the sensitivity of microgrid planning results on variety levels of uncertainty.

A data-driven adaptive robust optimization framework for the unit commitment formulated as a four-level optimization problem integrating wind power into smart grids was proposed by Ning and You [57]. Taking advantage of Dirichlet process mixture model, a data-driven uncertainty set for wind power forecast errors is constructed as a union of several basic uncertainty sets. A decomposition-based algorithm was further developed, the proposed approach does not presume independence, single mode or symmetry in uncertainty. Moreover, it not only substantially withstands wind power forecast errors, but also significantly mitigates the conservatism issue by reducing operational costs. The method is compared with state of the art data driven adaptive robust optimization method based on kernel smoothing and principal component analysis to assess its performance. The effectiveness of the proposed approach is demonstrated with the IEEE 118-bus systems and six-bus. Computational results showed that the proposed approach generates solutions that are more cost-effective than the existing data-driven ARO method and scales gracefully with problem size.

A robust optimization based approach for optimal Micro Grid management considering wind power uncertainty was presented by Gupta et al. [69]. To characterize the wind power uncertainty through interval forecasting, a time series based Autoregressive Integrated Moving Average model is used. The proposed approach is illustrated through a case study having both non-dispatchable and dispatchable generators through different modes of operation. Moreover, in both cases on the total cost of operation of the Micro Grid the impact of degree of robustness is analyzed. A comparative analysis between obtained results using the proposed approach and another existing approach gives the best cost minimization.

A robust optimal design method of energy supply systems under uncertain energy demands is revised by Yokoyama et al. [56] so that it can be applied to systems with complex configurations and large numbers of periods for variations in energy demands. Hierarchical relationship among design variables, energy demands, and operation variables is considered. A new solution method was proposed for efficiently evaluating an upper bound for the optimal value of the maximum regret. A method comparing two energy supply systems under uncertain energy demands was proposed by using a part of the revised robust optimal design method. The validity and effectiveness of the revised optimal design method, features of the robust optimal design, and the comparison method are clarified by a case study on a gas turbine cogeneration system for district energy supply.

To intelligently schedule energy generation for microgrids equipped with unstable renewable sources and combined heat and power generators, a cost minimization problem is formulated by Wang et al. [70] under indeterminate electricity market prices. They introduced reference distributions according to field measurements and predictions, then they defined uncertainty sets to enclose net and heat demands. The proposed model allows the heat demand and net demand distributions to fluctuate around their reference distributions. They developed chance constraint approximations and robust optimization approaches first to transform and second to solve the prime problem. Based on real-world data numerical results value the influences of the different parameters. The integration of combined heat and power generators greatly reduces the system expenditure and the energy generation scheduling strategy performs well.

For solving a linear robust problem with mixed-integer first-stage variables and continuous second stage variables, Billionnet et al. [6] considered column wise uncertainty. First, a problem with right hand-side uncertainty satisfying full recourse property and a specific definition of the uncertainty are focused on. The solution proposed is based on a generation constraint algorithm. Then the model is generalized by adding a left-hand side uncertainty and defined uncertainty sets defined as polytope. To compensate for a possible lack of energy from renewable sources and batteries, an auxiliary fuel generator guarantees to meet the demand in every case. However, its use induces important costs, so Billionnet et al. [2] applied the two-stage robust method to take account of the stochastic behavior of the solar and wind energy production and also of the demand. The system generates a minimum total cost when the worst case scenario relating to this system occurs. A constraint generation algorithm was proposed, where each recourse problem can be reformulated by a mixed-integer linear program and hence solved by a standard solver. Also a polynomial time dynamic programming algorithm was used for the recourse problem and showed that, in some cases, this algorithm is much more efficient than mixed-integer linear programming.

The computational results and simulations verify the robustness of solution, the tightness of the bounds, the effectiveness and feasibility. The total cost is reduced significantly and energy demands are satisfied in worst case scenarios. Robust optimization in micro-grid increased the reliability of the system and the amount of micro-grids energy not supplied. Numerical simulations exhibit the effectiveness of the proposed model and further analyze the sensitivity of microgrid planning results on a variety of levels of uncertainty. The energy generation scheduling strategy performs well for the combined heat and power generators.

1.3 Data analysis

When analyzing the data of different optimal solutions, they are tested as decision making units to distinguish efficient units from inefficient ones. Unit inefficiency can result from technical deficiencies or nonoptimal allocation of resources into production as mentioned by Furkova [71]. Both technical and allocative inefficiencies are included in cost inefficiency.

Generally, there are two families of methods based on efficient frontiers:

- Non-parametric methods, like Data Envelopment Analysis or Free Disposal Hull. These methods originate from operations research and use linear programming to calculate an efficient deterministic frontier against which units are compared.

- Parametric methods, like Stochastic Frontier Analysis, Thick Frontier Approach and Distribution Free Approach. Econometric theory is used to estimate pre-specified functional form and inefficiency is modeled as an additional stochastic term.

Stochastic frontier analysis is a parametric method that can test hypotheses, it uses maximum likelihood econometric estimation, it separates noises from efficiency scores. It can typically test one output with many inputs, and finally its functional form should be specified. Meanwhile, data envelopment analysis is a non parametric method that cannot test hypotheses, it uses mathematical programming, noise is part of its efficiency scores so it cannot accommodate noise, but it can accommodate multiple inputs with multiple outputs, and finally its functional form is not necessarily specified.

Stochastic frontier analysis produces efficiency estimates or efficiency scores of individual units. Thus one can identify those which need intervention and corrective measures. Since efficiency scores vary across units, they can be related to unit characteristics like size, ownership, location, etc. Thus one can identify the source of inefficiency.

There are different applications for data envelopment analysis and stochastic frontier analysis. An empirical application stochastic frontier analysis is obtained using up to ten years of data on paddy farmers from an Indian village by Batteseand and Coelli [72]. They defined a stochastic frontier production function for panel data on firms, in which the non-negative technical inefficiency effects are assumed to be a function of firm-specific variables and time. With means which are a linear function of observable variables, they assumed the inefficiency effects are independently distributed as truncations of normal distributions with constant variance.

The numbers of banks in Croatia increased significantly since 1990, so for the data of the banks in 1994 and 1995, Kraft et al. [73] used stochastic-cost frontier methodology to estimate X-efficiency and scale-efficiencies for both old and new, state and private banks. New banks are shown to be more X-inefficient and more scale-inefficient than either old state banks or old privatized banks. However, private, new banks are highly profitable. Consequently, a negative, but only weakly statistically significant relationship between X-efficiency and profitability emerges in Croatia. This abnormality appears as a result of free-riding opportunities created by start-up difficulties, distressed borrowers, and limited competition at the new banks.

To rank efficient hospitals over their inefficient counterparts Jacobs [74] studied the UK Department of Health using three cost indices to benchmark NHS hospitals (Trusts). This study uses the same dataset and compares the efficiency rankings from the cost indices with those obtained using Data Envelopment Analysis and Stochastic Frontier Analysis. Using Data Envelopment Analysis and Stochastic Frontier Analysis, they compared the efficiency rankings of the data from the cost indices. The results indicate that there are not big efficiency differences between Trusts, and savings from improving poorer performers would in fact be quite modest.

The blending of heterogeneity and inefficiency effects is particularly problematic in the World Health Organization's (WHO) panel data set on health care delivery, which is a 191 country, five year panel. This problem is studied by Greene [75], where a large number of developed alternative approaches to stochastic frontier analysis with panel data are studied. Some of these were applied to the WHO data. Results suggest that in this data, there is considerable evidence of heterogeneity that has masqueraded as inefficiency in other studies.

Both approaches (data envelopment analysis and stochastic frontier analysis) are applied to the same set of container port data for the world's largest container ports and compared by Cullinane [76]. Between the efficiency estimates derived from all the models applied a high degree of correlation is obtained. High levels of technical efficiency are associated with transhipment, as opposed to gateway ports, scale and with greater private-sector participation. In analysing the implications of the results for management and policy makers, a number of shortcomings of applying a cross-sectional approach to an industry characterised by risky, significant, and lumpy investments are identified, and the potential benefits of a dynamic analysis are enumerated.

Data envelopment analysis (DEA) is used to study the relative efficiency of decision making units (DMU). The efficiency increases with decision making units having large outputs and less input, data envelopment analysis is a balanced benchmarking tool where inputs and outputs simply represent performance metrics, so data envelopment analysis minimizes inputs and maximizes outputs. In some cases, higher levels of outputs indicate worse performance like pollution, so in certain circumstances, a factor can play a dual role of input and output simultaneously. There is input oriented data envelopment analysis which finds the minimum input decision making unit and the output oriented data envelopment analysis which finds the decision making unit with maximum output. Data envelopment analysis can be applied bank branches, cities, hospitals, and universities.

Data envelopment analysis is used to compare the efficiency between the different solutions of renewable energy power plant location distribution by Zografidou et al. [4], the inputs and outputs are the deviations obtained. The data envelopment analysis used is output oriented and desirable and undesirable outputs are considered, at the same time a super efficiency method is applied for comparison. The disposability Data Envelopment Analysis model identifies the discrimination between the efficiency of solutions. On the contrary, the classical Data Envelopment Analysis model provides higher efficiency scores to the solutions. From the analysis it can be identified that a fully efficient score can be achieved with many combinations of weights. Results of the disposability data envelopment analysis model suggested that the most efficient solutions are the ones with higher weights in social acceptance criterion where as the Super-Efficiency data envelopment analysis model confirmed the above finding.

For the purpose of calculating efficiencies in production Coelli [77] described a computer program which had been written to conduct data envelopment analyses. In the computer program three principle options are available. Standard CRS and VRS data envelopment analysis models are involved first. The extension of these models to account for cost and allocative efficiencies is considered as a second option. To calculate indices of scale efficiency change, technical efficiency change, technological change, and total factor productivity change the application of Malmaquist data envelopment analysis methods to panel data is considered as third option. Most methods are available in either an input or an output orientation.

A user data envelopment command in Stata was introduced by Ji and Lee [78] to allow users to conduct the standard optimization procedure and extended managerial analysis. The data envelopment analysis command developed in this article selects the chosen variables from a Stata data file and constructs a linear programming model based on the selected data envelopment analysis options. Examples are given to illustrate how one could use the code to measure the efficiency of decision-making units.

To choose the most efficient alternative courses of action en route, Banker et al. [79] used data envelopment analysis to employs mathematical programming to obtain ex post facto evaluations of the relative efficiency of management accomplishments, however they may have been planned or executed. A new separate variable is introduced which makes it possible to determine whether operations were conducted in regions of increasing, constant or decreasing returns of scale. The results are discussed and related not only to classical (single output) economics but also to more modern versions of economics which are identified with "contestable market theories."

1.4 Location optimization problem

1.4.1 Facility location optimization

There are different methods for solving multiple criteria facility location problems. Multi-criteria location problems have three categories they include bi-objective, multi-attribute and multi-objective problems and their solution methods. The multi-attribute decision making (MADM) problem or a multi-objective decision making (MODM) problem come together in one category, named multi-criteria decision making (MCDM) problems [80]. Facility location is a part of operations research related to positioning or locating at least one new facility among several existing facilities in order to optimize (minimize or maximize) at least one objective function (like profit, revenue, travel distance, service, waiting time, coverage, market shares, and cost).

From an application point of view there are no limitations on the science of location. Many application areas including national level, international scopes, business, military environment, public and private facilities can be seen. Multi-criteria decision making has been implemented in location problems. As previously explained the multi-criteria decision making technique is a combination of the Multi-objective decision making and the multi-attribute decision making techniques. A limited number of predetermined alternatives exist in multi-attribute decision making. These alternatives meet each objective in a specified level and the decision maker chooses the best solution (or solutions) among all alternatives, according to the interaction between each objective and the priority between them. There are many methods which are used to solve the multi-attribute decision making problems. The most popular ones are: simple additive weighting (SAW), hierarchical additive weighting, elimination and choice expressing reality (ELECTRE), technique for order preference by similarity to ideal solution (TOPSIS), hierarchical tradeoffs, linear programming techniques for multidimensional analysis of preference (LINMAP), interactive SAW method, MDS with the ideal point, maximin, maximax, conjunctive method, disjunctive method, lexicographic method, elimination by aspects, permutation method, linear assignment method, and dominant. The Multi-objective decision making techniques try to achieve the best alternative by taking into account the various relations within the design constraints that best fulfil the decision maker's wishes by attaining some acceptable levels of a set of objectives. The Multi-objective decision making problems have different components, but the common characteristics of them are a process of obtaining some trade-off information, a set of quantifiable objectives, and a set of well defined constraints.

There are many ways used to attack Multi-objective decision making difficulties. The most popular ones are as follows: adaptive search methods, metric L-P methods, C-constraint methods, lexicographic methods, parametric methods, method of displaced ideal, goal programming STEM (GPSTEM), method of Geoffrion, interactive goal programming, surrogate worth trade-off, method of satisfactory goals, method of Zionts–Wallenius, the methods as step method (STEM) and related methods, sequential multi-objective problem solving (SEMOPS) and sequential information generator for multi-objective problems (SIGMOP) methods, goal attainment methods, goal programming (GP), method of Steuer, bounded objective methods, utility function, and global criterion methods.

Regardless of the technique employed, the following steps are necessary to solve the MODM problems without considering the used technique:

- Efficient solution: An ideal solution to a multi-objective decision making problem is one that gives the optimum value of each of the objective functions simultaneously. An efficient solution is one in which no one objective function can be advanced without a disadvantage to the other objectives at the same time.
- A preferred solution: A preferred solution is an efficient solution, which is chosen by the decision maker (DM) as the final decision.
- Conflicting objectives: It is normal for multi-objective decision making problems to have conflicting objectives.

There are different approaches divided into three categories to solve multi-objective optimization problems:

- "Classical approaches" convert the multi-objective problem into a single objective problem and optimize it.
- In "Pareto optimal approaches" when solving the problem a set of solutions will be resulted.
- If the problems in the first and the second category are complex then those can be solved using evolutionary algorithms. Some of these approaches are multi-objective genetic algorithm

(MOGA), (non-dominate sorting genetic algorithm) (NSGA I1) [81] and fast non-dominate sorting genetic algorithm (NSGA II2). There are other special purpose attempts for solving complex multi-objective decision making difficulties such as: distance method, weight min-max method, lexicographic ordering, and vector evaluated genetic algorithm (VEGA). Multi-objective combinatorial optimization (MOCO) e.g. [82, 83] provides an adequate framework to tackle various multi-criteria problems.

The location objectives are summarized as follows:

- Maximizing responsiveness.
- Minimizing the number of located facilities.
- Minimizing maximum time/ distance traveled.
- Minimizing average time/ distance traveled.
- Maximizing service.
- Minimizing total annual operating cost.
- Minimizing fixed cost.
- Minimizing the longest distance from the existing facilities.
- Minimizing the total setup cost.

Environmental and social objectives based on tourism, fossil fuel crisis congestion, pollution, quality of life, noise, land use, construction cost, and energy cost are becoming customary. Consequently, one of the most important difficulties in tackling these problems is to find a way to measure these criteria.

The classification:

Location optimization problems can be divided into ‘multi-objective’ and ‘multi-attribute’ location problems. ‘Bi-objective’ location problems have become of particular consideration, they are investigated separately from other k-objective one ($k \geq 3$). Multi-criteria decision making techniques can be utilized for all types of facility location models including location in supply chain, location-reliability, location-inventory, location-routing, quadratic assignment problems, warehouse location problems, competitive facility location, hub location problems, hierarchical facility location problem, center problems, median problems, dynamic facility location problems, covering problems, location–allocation, multiple facility location and single facility location.

Bi-objective location problems:

In order to formulate and find optimal and efficient facility location/allocation patterns Klimberg and Ratick [84] have utilized a different concept. This concept is Data Envelopment Analysis as defined before.

A weighted anti-median and median facility location models have been set up by Hamacher et al. [85] on a network with the maxisum and minisum objectives. The issue of the multi-criteria Weber problem was mentioned by Puerto and Fernández [86] with strict norms in a convex set with Euclidean distances.

With reference to capacity in location problems, Melachrinoudis et al. [87] modeled their multi-period, capacitated discrete location problem of siting landfills into a dynamic multi-objective mix integer program. On the contrary, Fernández and Puerto [88] talked about the discrete multi-objective uncapacitated plant location issue.

For location problems, Analytic Hierarchical Process (AHP), which is a special case of the Analytical Network Process (ANP), has been widely used, including in Aras et al. [89], in which a large number of criteria were taken into consideration for a wind observation station location problem.

Goal programming has been used to improve the problems solved by AHP. For example, Badri [90] gave a combination of goal program and AHP modeling approach for international facility location/allocation problem; the role of AHP was to prioritize the set of location alternatives at first. Another paper, in which these combined approaches were shown, is Guo and He [91]. They introduced an attempt at the location/allocation problem of a grain post-harvest system, which was cleared up by Multiple-Phase Simplex Algorithm for GP (MPGP). Chan and Chung [91] made a combination of Genetic Algorithm (GA) and AHP model for solving distribution network problems in supply chain management. The optimization results showed them that this model was robust and reliable.

Multi-attribute methods other than AHP have been utilized by Barda et al. [92] to choose the best sites for each region. They modeled their thermal plant location problem in a hierarchical decision process in which they have used ELECTRE III.

TOPSIS approach can apply fuzzy numbers to solve muddles in which criteria or their weights are not accurate like AHP. The example can be Yong [93] in which a new fuzzy TOPSIS was presented for selecting a plant location under linguistic terms for membership functions as triangular fuzzy numbers.

The instances in the literature which used heuristics and meta-heuristics in multi-attribute location problems are limited. An example is Guimarães Pereira et al. [94] who applied a Genetic Algorithm (GA) for locating a retail facility in their multi-criteria location problem, by defining degrees of membership to a group of solutions called suitable sites for each solution.

Sometimes in location problems, we are not dealing with numbers and mathematical findings but the decision is based on human judgment. For these reasons, multi-attribute decision making is an important part of location science and based on the data type which is sometimes vague, fuzzy multi-attribute models are used more and more.

Solution methods:

For their trans-shipment location problem, Ogryczak et al. [21] developed a Dynamic Interactive Network Analysis System (DINAS) which is an extension of the classic reference point method and has a Simplex Special Ordered Network (SOP) algorithm and a branch-and-bound, to solve their integer programming problem. In Ogryczak et al. [95] they applied this DINAS approach to health service districts reorganization.

Klimberg and Ratick [84] proposed an interactive model named Modified Data Envelope Analysis model (DEA2) using the concept of Data Envelope Analysis (DEA) as another objective function.

A greedy algorithm is implemented by Raisanen and Whitaker [96] whose performance was dependent on the order in which the candidate sites were considered. In order to find an optimal ordering of potential base stations, Non-dominated Sorting Genetic Algorithm II (NSGA-II), Pareto Envelop based Selection Algorithm (PESA), Strength Pareto Evolutionary Algorithm version 2 (SPEA2), Simple Evolutionary Algorithm for Multi-Objective Optimization (SEAMO) and four multiple objective genetic algorithms, were compared from many different angles, such as time, simplicity, quality of solution, etc.

A genetic algorithm for its combinatorial goal programming model was proposed by Leung [97]. The author finds this method more effective and flexible than common models such as entropy-maximization model or the standard gravity model.

The number of criteria for location optimization problems are many and varied, but they can be summarized in general categories as follows:

- The presence of competitors and competition environment are gathered in competition criteria.
- Regulations and political matters including government regulations, country measures, and community consideration.
- Having access to public facilities like accommodation, resting, motor or railways or recreation, airports, etc. is important in some problems.
- The use of the facility to be located and resource accessibility is detailed enough.
- Environmental risks concern health effects, waste collection, air or water pollution, smells, sound and optical pollution, etc.
- Value and benefits can be revenue, product value, or land or asset value.
- Costs include maintenance, installation, transportation, land cost, etc.

A general problem for location optimization to serve a set of demands of whatever type, considering the coverage probability, investment cost, and capacity was considered by Karatas [98]. The facilities are characterized by gradual covering decay, cooperative demand coverage and variable coverage performance. The objectives include minimizing deviations from demand coverage level requirements, allocated budget, and facility capacities. The gradual coverage performance, variable facility costs and facility capacities are considered as non-linear functions. The location problem is first modeled as a multi-objective integer non-linear program (INLP). Next, after mapping the problem to a network-like structure, an equivalent multi-objective integer linear program (ILP) is developed. With the objective of attaining high-quality solutions within reasonable computing times, we propose a combined INLP–ILP solution procedure. As a consequence, the INLP model is practical with tight time constraints. Using the combined

INLP-ILP approach guarantees high-quality solutions within plausible computing times, even for large-scale problems.

A fuzzy multi-criteria decision-making approach to evaluate the alternative options with respect to the user's preference orders was found by Torfi et al. [99]. They applied Fuzzy Analytic Hierarchy Process to determine the relative weights of the evaluation criteria. They also applied extension of the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) to rank the alternatives. The outcome of Fuzzy systematic evaluation of the multi-criteria decision-making problem reduces the risk of poor management decisions. When precise performance ratings are available, the TOPSIS method is considered a viable approach in solving a decision problem. The Data Envelopment Analysis method is a viable approach. However, it has the constraints in the number of decision-making units and in the limitation to the discrepancy between performance frontiers. For the instance of imprecise or vague performance rating, the fuzzy TOPSIS is a preferred choice.

The problem of Development and implementation of the Dynamic Interactive Network Analysis System which solves various multi-objective trans-shipment problems with facility location was solved by Ogryczak et al. [21]. The Decision maker forms his aspiration and reservation levels. And a method of TRANSLOC solver based on branch-and-bound scheme with a pioneering implementation of the simplex special ordered network (SON) algorithm with implicit representation of the variable and simple upper bound constraints. The used methodology is appropriate for solving multi-objective trans-shipment problems with facility location.

The facility location problem in the presence of alternative processing routes using a genetic algorithm is solved by Solimanpur et al. [100]. Machines and departments are examples of manufacturing facilities. The performance of the manufacturing system is mostly effected by this problem. Multiple products to be produced on several machines are considered. The objective is to determine the optimal location of each machine and the optimal processing route of each product out of the different alternative processing routes to minimize the total distance traveled by the materials on the shop floor. They applied mixed-integer non-linear mathematical programming formulation to find the optimal solution of the problem. The conventional mathematical programming methods cannot solve the linearized model within a reasonable time due to the NP-hardness of this problem. So, a genetic algorithm is proposed to solve the linearized model. It is showed that the proposed genetic algorithm is both effective and efficient in solving the attempted problem.

1.4.2 Location optimization of mono-source renewable energy

Several research works were devoted to the optimization of locations of renewable energy sources. For example, Bojić et al. [101] optimized the locations of solid biomass power plants in Vojvodina, a province of Serbia, the authors used a linear optimization model for determining the capacity, type and locations of solid biomass power plants in order to minimize the electricity generation costs. A geographical information system (GIS) had been implemented by Villacreses et al. [102] to select the most feasible locations for installing wind power plants in continental Ecuador. They used multi-criteria decision making methods, the Pearson correlation coefficient is used to analyse mutual correspondence between these methods. Accurate energy predictions had been made by Sabo et al. [103] for large-scale photovoltaic systems connected to a smart grid. The authors used Multi-criteria evaluation techniques for different site selection studies. Optimal site definition model and GIS were used to select sites for the installation.

The locations of grids and wind turbines are optimized by Bjørnebye et al. [104] in Norway using TIMES model. They used Karush Kuhn Tucker to minimize the grid investment and production cost. Results show that uniform feed-in premiums leads to capacity increase in areas with better wind conditions. To maximize the amount of energy taking into account wake effects that are produced by the different turbines on the wind farm, Wagner et al. [105] resolved the confusion over placement of wind turbines on a given area by employing the strategy of Turbine Distribution Algorithm, which modifies only a single turbine of the layout by updating the velocity deficits. The method is applied on Woolnorth wind farm in Tasmania, Australia. This method allows the optimization of large real-world scenarios within a single night on a standard computer with better objective values. To determine the most suitable sites for locating biogas in Portugal, Silva et al. [106] used multicriteria spatial decision support sytem. They combined a Geographic Information System to manage and process spatial information with the flexibility of Multicriteria Decision Aid using ELECTRE TRI. This method is suitable for addressing real-world problems of land suitability, leading towards a flexible and integrated assessment. To evaluate the electricity generation options for Jordan Malkawi et al. [26] used multi-criteria decision-making analysis called the Analytical Hierarchy Process to evaluate the electricity generation options for Jordan. Renewable and conventional sources are included in the analysis as energy options. The outcome shows that, from a technical and financial perspective, Jordan's most feasible options are conventional fuels up to 02/05/2017.

A goal-programming model under target and structural constraints to optimize the location of solar energy power plants in Greece had been developed by Zografidou et al. [107] with the examination of all possible weight combinations. They subjected the solutions derived from each iteration to a financial meta-analysis, considering different tax and return scenarios aligned to the Greek taxation and banking system. The analysis considers Greece and each region separately, taking net present value (NPV) as an objective measure to assess the solutions. There are 13 large regions in Greece, with special land morphology and extreme socio-economic differences, the criteria taken into consideration are social, financial, and power production. An average solar power plant units for the different regions of the map of Greece was calculated.

1.4.3 Location optimization of multi-sources of energy

Regarding the multi-sources of energy location problem, the literature is less rich. So we based our study explained in chapter 2 on the problems [3, 4, 108]. The question of finding the optimal location and sizing of distributed generation which has significant impact on the system losses was described by Ali et al. [109]. The most suitable candidates buses for installing distributed generation are identified using Loss Sensitivity Factors. Then the proposed ant lion optimization algorithm is used to deduce the locations and sizing of distributed generation from the selected buses. The proposed algorithm outperforms Backtracking Search Optimization Algorithm in minimizing losses and enhancing voltage profiles. In addition, the designed WT type gives better results than Photo Voltaic type in terms of voltage profiles and Voltage Stability Index.

A goal programming model, based on a multi-source multi-sink network, was developed by Ramon and Cristobal [3], in order to locate five different types of renewable energy plants for electric generation in five places located in the autonomous region of Cantabria, in the north of Spain. The goal is to locate one plant in each place, maximizing the number of plants that are matched with suitable locations, in a way that they minimized the total deviations from the goals. The goals represent different criteria such as the power generated, investment cost, quantity of CO_2 emissions avoided, social acceptance, number of jobs offered, distance between power plants, and operation with maintenance cost.

The model was improved further by expansion of the feasible region as Chang [108] mentioned, where it can avoid underestimation of aspiration level and achieve findings more closely approaching actual conditions, and Chang introduced normalization to avoid the unintentional bias towards objectives. Notably, the goal of social acceptance rate is the highest social acceptance rate in this case, while the highest achievements of other goals are slightly lower. Compared with the Ramón and Cristóbal model, the power generated is higher, investment cost is lower, emissions avoided are higher, and operation and maintenance costs are lower in the Multi Choice Goal Programming– multi-source multi-sink normalized model. It is seen that by adding weights to the objective function, the proposed method can easily be used as a decision aid to determine the best or most appropriate solution to multiple objective problems. Each goal of the multiple objective problem can be divided into multiple aspiration levels to better suit management requirements, such as “the more the better ” or “the less the better”. These constraints can also be easily added in the Multi Choice Goal Programming multi-source multi-sink-normalized model to mirror real-world situations. This model provides a feasible and robust way to choose an optimal location for renewable energy plants. A linear utility function is given as the following two membership functions (MF), to represent social acceptance rate for the wind turbines installation. The aim is to find a balance between the requirements of residents and construction considerations. This shows that the proposed model provides feasible features for a decision maker to deal with multiple decision making problems.

The Greek renewable energy production network in 52 prefecture was optimally designed by Zografidou et al. [4], they apply a 0-1 Weighted Goal Programming model, considering, environmental, social, and economic criteria. They used the Data Envelopment Analysis (DEA) approach, using pareto front, in order to filter the best of the possible network structures, seeking for the maximum technical efficiency, they assigned different scales of importance and incremental steps of the range of each weight for the economic, social, and environmental criteria. A probability of assignment of each power plant to each place is formulated to the map of Greece. Different permutations of the weights of the environmental, social, and economic criteria of the deviations of the objective function are made. To calculate the different probabilities the average of the different solutions of these weight combinations are calculated.

To optimize multi-sources of energy in any country in the world we made a general model in [110] goal programming method and introducing control flow analysis. The method calculates probabilities of assigning different power plants to different places for decision making and average distribution.

1.5 Energy contract capacity optimization

1.5.1 Classification of electricity tariffs

Optimizing the power capacity contracts is important for the energy producer and the consumers such as industries. There are several challenges in this domain.

There are different electricity tariffs for residential, commercial and industrial customers. The service types applicable to industrial customers are further classified into low-tension and high-tension. The rate schedules available for high-tension service are based on TOU and maximum demand. This thesis focuses on the electricity contract decisions of high-tension industrial customers [111, 112].

1.5.2 Description of demand power

Depending on how industries use electricity, they pay for different electric services, like connection, energy, demand, and reactive power consumption. Most industrial and commercial customers are required to pay for their peak demand, besides the energy they consume. Electric utilities charge them for the highest average demand measured in any 15 or 30 min during their billing period. Billing demand is based on consumers' measured maximal demand and their contract demand with utility companies as per the supply agreement.

1.5.3 Contract capacity in different countries

In mainland China, utilities allow large customers to adjust their contract demand monthly [113], if the peak demand does not exceed the contract demand, a fixed demand charge is levied; on the other hand, if the peak demand exceeds the contract demand, a penalty charge twice of the basic rate is levied.

In Southern Africa, the contract demand is determined by the notified maximum demand (NMD) [114]. Customers can temporarily or permanently increase/decrease their NMD, and their demand charge is based on the maximum of the measured demand and NMD. Jemena Electricity Networks Ltd., of Victoria, Australia, also has a similar contract demand reset policy, which allows their customers to permanently/temporarily increase and permanently decrease their contract demand through request.

In Shanghai, the timely adjustment and notification of the contract demand is a valuable information source for utilities' load forecast and maintenance planning [115]. Along with the development of advanced metering infrastructures and data analysis platform, it is expected that a wider range of customers can adjust the contract demand more frequently and conveniently, to provide more accurate and complete information for smart grid operation and smart city functionalities.

1.5.4 Reasons for contract capacity optimization

Energy suppliers need to know the capacity demand to plan the generation and the transmission of the energy for better service to the customers. It is necessary to protect the energy generation facilities and to manage the energy availability in a more efficient way. To deal with this issue, energy producers propose different energy tariffs and contract options to their customers. This strategy ensures that fluctuations in energy demand are controlled, gives a useful insight into the quantity of energy needed to be generated and allows efficient transmission to customers.

When it comes to industrial customers, matching system requirements with the offers in the energy market is one of the important decisions that must be made [116]. Many industrial customers opt to sign a maximum contracted demand. Such an electricity bill consists of an energy charge and a capacity charge. The energy charge is based on kilowatt-hours, while the capacity charge is based on maximum demand consumed during each TOU period. If the peak demand does not exceed the contract capacity, a fixed capacity charge is levied. On the other hand, if the peak demand exceeds the contract capacity, a penalty charge from two to three times the basic rate is levied [5]. Hence, choosing an excessively low contract capacity will impose high capacity charges, while choosing an excessively high contract capacity may result in an unnecessary basic capacity charge. Therefore, optimal contract capacity decisions have received significant attention from customers with high electricity usage.

1.5.5 Contract capacity costs

In some countries, electricity bills are composed of five primary components: capacity cost, demand of energy cost, power factor adjustment, penalty cost, and expanding construction cost. The energy costs include the active and reactive energy charges, but energy demand is not included here since it does not affect the optimization problem. Improper contract capacity scheduling would also cause high expanding construction cost when users modify their contract capacities. If customers modify their contract capacities, electricity suppliers would adopt expanding line construction cost schedules. Capacity cost is based on kilowatt hours, with the unit price varying by peak, medium and off-peak and capacity charge is determined by kilowatts per month based on maximum demand (in 15 minutes average) during the TOU period [117]. In our case, for simplicity, we consider only peak contract capacity.

In some countries, when the demand exceeds the upper or lower limits of the contract option, excess quantity is penalized with the double power price [116]. In Taiwan, an excess within 10 % of the contract demand is charged at twice the rate of the contract demand, whereas the excess over 10 % of the contract demand is charged at three times the rate, and high-tension industrial customers can change their contract demand each month [5].

1.5.6 Time of use description

The TOU rate is a load management policy designed to shift electricity use from peak load periods to off peak load periods. The TOU rate for electrical power implements different prices for different TOU. Power companies confirm power peak and power off-peak times, and then adopt higher prices during the peak time and lower prices during the off-peak time in order to motivate consumers to adjust their policy on using electricity. So the TOU rate strategy can shave peak power consumption and increase off-peak consumption, reducing the requirements for new construction projects and raising the efficiency of the power system. For a 3-section TOU rate user, the twenty four hours in a day are divided into three time periods, for a TOU rates industrial customer, the total electricity cost is the sum of the demand contract capacity cost, the total energy cost and the penalty bill that is caused by exceeding contracts. The total energy cost depends on the total energy consumption during each time period. For a 3-section TOU user, this means the power consumption is in peak load, medium load and off-peak load periods. Depending on the electricity demand, customers taking TOU rate service need to determine a peak period contract capacity, a medium peak period contract capacity, and an off-peak contract capacity [117].

1.5.7 Contract capacity optimization methods

The problems facing the consumer when choosing between the different energy contracts are the difference in the cost, the penalty cost when the maximum demand exceeds the contract capacity, and the available capacity of power in each contract. Therefore, the challenge is to optimize the choice of the contract minimizing the cost and adjusting the contract capacity of energy to fit with the amount of demand of energy with time in an ecofriendly way during the day, the month, and the year. There are different approaches to optimizing the contract capacities of energy demands in industries.

To determine the electricity contract capacity for industrial customers in Taiwan, Chen et al. [5] used a linear programming approach. They formulated the problem as a linear program using LINDO software. Since no previous literature proved that the problem is NP hard they considered that the problem can probably be solved in polynomial time. So they made the necessary variable replacements so that the problem became linear. The authors considered capacity charge, power factor adjustment, expanding construction fee, and disallowed decrease in contract capacities in the optimization problem. A fixed capacity charge will be levied if the peak demand does not exceed the contract capacity. In addition, there is a surcharge for excess demand: the excess portion within 10% of the contract capacity is charged at twice the rate of the contract capacity, while the portion over 10% of the contract capacity is charged at three times the rate. The authors proposed two models, the first model determines the peak contract capacity and the second determines both the peak and the off-peak period capacity. The method is applied to two real-world cases, a university and a paper mill, which are used to demonstrate that the model can minimize the electricity bill for industrial customers with computational time less than 0.001 min.

A meta-heuristic evolutionary programming (EP) method was used by Tsay et al. [118] to calculate the optimal capacity for peak, semi-peak, and off-peak capacities respectively. They introduced the demand charge and the penalty charge in the objective function. The method initializes random values of penalty charges, and a mutation occurs in each iteration following a normal law, the standard deviation decreases exponentially for convergence, the 30 individuals with the highest fitness score are selected out of 100 in each iteration until stopping criteria are met. The method is applied on Drow-Ing refinery contract, Ho-Jin region contract, Ling-Jan refinery contract, and Da-Liau station contract. As a result, the electricity bill can be considerably reduced using this method.

Another meta heuristic method called iteration particle swarm optimization for selection of optimal capacities, for peak, semi-peak, and off-peak capacities respectively was utilized by Tsay et al. [117]. They considered the expanding line construction cost, contract recovery cost, demand contract capacity cost, and penalty bill in the optimization problem. A new index, called iteration best is incorporated into particle swarm optimization to improve solution quality and computation efficiency. In addition to the best value of the fitness function of every particle that has been achieved and the best value of the fitness function that has been achieved so far by any particle, the authors introduced the best value of the fitness function that has been achieved by any particle in each iteration. Demand Cost and the rate of the expanding line construction cost exert a great influence on the peak load period contract, medium load contract and contract recovery cost, but their impact on other parameters is not large. Demand cost increases will lead to increases in the peak load period contract, expanding line construction cost, contract recovery cost and total demand contract capacity cost. An increase in construction cost will cause an incremental increase in the medium load contract, while the other parameters all drop. Load increases lead to an increase in the peak load period contract, expanding line construction cost, contract recovery cost and total demand contract capacity cost, but the influence on medium load period and light load period contracts is indeterminate. The calculation time is proportional to particle number. This means that a large number of particles would improve the solution quality. However, it would also increase the computation time. The proposed method can quickly converge on optimal contract capacities while achieving minimum total demand contract capacity cost. In addition, the performance of the proposed iteration particle swarm optimization method is better than those of real-valued genetic algorithm and evolutionary programming in both solution quality and computation time.

For industrial machines the optimal production planning and energy contract was determined by Rodoplu et al. [116] which minimizes production and energy costs with respect to constraints of production systems and energy supplier contract conditions. The penalty tolerance level is assumed to be 10% above and below the contracted power value. Within this interval, the customer is charged with the fixed capacity charge. The optimization problem minimizes production and energy costs with respect to constraints of production systems and energy supplier contract conditions. The authors considered production cost including the electricity consumption cost, holding and set-up costs, contract capacity cost, and over or under contract capacity cost in the objective function. Traditional and renewable energy peak contract capacities are considered. As a particular case, they applied it to three machines to choose the different capacity contracts of multi-sources of energy for optimal production planning and minimum cost. Three types of energy sources (traditional, solar, wind) are used. All the energies (traditional and renewable) are provided by and purchased from the supplier. In the proposed model, optimum contract value is described as a decision variable. The objective is to choose the best contract value for each energy source by minimizing costs and satisfying external demand. Linear programming is used to solve the problem using CPLEX software, and the problem is tested on different instances, it is found that CPLEX can solve small and medium size problems optimally within an acceptable time. For large size problems, no optimal solution has been obtained after 1 hour.

The problem of optimization of contract capacity setting for industrial consumers with self-owned generating units (SOGUs) which is a highly discrete and nonlinear was solved by Chung et al. [119]. They consider the peak, semi-peak, and off-peak contract capacities in their problem. The authors used an improved method of Taguchi by combining it with a particle swarm optimization (PSO) algorithm to solve this problem. An orthogonal matrix corresponds to a generation of PSO in searching the optimal solution. Quality analysis on the particles of a population is performed with the costs and contribution values derived from the matrix for each iteration. The element of the orthogonal matrix of the experiment with the best cost function is then the solution obtained for the contract capacities. The approach uses data obtained from the SCADA system of a large optoelectronics factory with SOGUs in September 2004 to March 2005. In comparison with other optimization methods such as genetic algorithm, mixed integer linear programming, existing Taguchi method; the proposed improved Taguchi method has superior performance as revealed in the numerical results in terms of the convergence process and the quality of solution obtained. It leads to significant savings of the electricity costs and effective management of the SOGUs. In addition, it has a higher probability of achieving a near optimal solution. The proposed approach takes more time than the existing Taguchi method, due to more time consumed by the integrated PSO algorithm for each iteration. The sensitivity of the solution time needed by the proposed approach to the initialization of the capacities in the first iteration of the method were randomly varied within a wide range of zero to a large contract capacity. It was found that only the first five iterations were different. After that, the process converges the solutions towards the common narrower range of solutions.

A very fast method for contracted optimization by a new algorithm with three methods was performed by Ferdavani et al. [120] in (2016). They consider peak contract capacity in their optimization problem. The algorithm sorts the maximum demand of each forecasted month and finds the index of the optimal solution. The methods start by either incrementing the index, decrementing the index, or starting the index from a very close point from the optimal solution. The different methods are applied on real data and the obtained results of the proposed methods have been compared. The third method of the proposed algorithm is simpler and quicker while the objective value and the solution remains the same optimal one.

The new proposed method to solve the contracting capacity optimization problem was further explained by Ferdavani et al. [1] in (2018) where several rates are available in the market. They consider peak contract capacity in their optimization problem. The proposed method is faster than the linear programming and gave a better concept for optimizing contract capacity considering errors in the forecasted maximum demand or forecasted prices. They have proved that there is one global optimal solution without any local optimal solutions, which is one of the monthly maximum demands. To find the optimal solution they sort the monthly maximum demands by descending order, then they calculate the index of the optimal solution depending on the capacity contract price and uncontracted demand price. The solution is found within a maximum of two iterations using Newton-Raphson method. The proposed method is performed on the data of various scenarios of a large real electrical user in Singapore to highlight the effectiveness of this method.

The issue of optimal demand contracting strategy under uncertainty was solved by Feng et al.

[121]. They consider peak contract capacities in their problem. The demand of energy follows a probability density function (PDF) and cumulative distributive function (CDF). The function can be drawn in two ways: for an old consumer with sufficient historical data of its own monthly peak demand data, the most direct way is distribution fitting, i.e., the fitting of a probability distribution. For a new consumer without enough historical data of its own consumption, the PDF/CDF of those consumers of a similar type can be very helpful to form the PDF/CDF of its own future peak demand. They proved that there is one global optimal solution even under uncertainty. They adopted Newton–Rapson-based numerical method in this section to calculate the optimal contract value. Simulation results support the convexity of the proposed model and the effectiveness of the proposed solution method compared with Monte Carlo simulation-based methods, the computation burden is significantly lower. In the perspective, they propose dynamic optimization for real-time pricing mechanism for excessive demand consumption.

The demand contract decision for the Taiwanese industries was optimized by Hwang et al. [122]. This research aims at exploring the benefit on load management options and providing decision-makers and leaders with useful operation and management strategies as reference. The technique employed is cat swarm optimization (CSO) and PSO. Results indicated that the CSO algorithm is highly helpful to Taiwanese industries on the optimal demand contract decision. Also the CSO is superior to PSO in fast convergence and better performance to find the global best solution.

Energy suppliers have different types of energy contracts: traditional and renewable energy contracts. Each type of contract has a capacity of energy in KW and a price. Industries need to determine the optimal combination of contracts to satisfy their peak demand with minimum cost on the one hand, and to increase the percentage of green energy used for marketing purposes on the other. The objective is to combine the traditional non-renewable energy and the renewable energy sources. The more renewable energy sources are used, the greener the contract is, and that is good for the reputation of industrial consumers and also good for nature as pollution is minimized.

1.6 Summary and Conclusion

Using energy efficiently and the use of renewable energy resources are very important targets for the world. Distributing renewable energy in a country has a major impact on achieving these targets. The lack of literature on optimization of the location of multi-sources of energy shows the urgent need for more research.

The studies of Ramon and Cristobal [3] and Zografidou et al. [4] have set the direction for multi-sources of energy power plants location optimization considering different criteria. However, their studies do not provide a general model to optimize the power plants applicable to any country of the world. In their application they consider that the criteria of the alternatives are independent of the place, but in reality the criteria of the alternative power plants change from one place to another. This gap needs to be filled by providing a generalized model with better constraints to be applicable worldwide to have a green planet.

There are different attempts to optimize the contract capacities, in the mean time, multi-sources of energy contract capacity optimization have not been mentioned accept by Rodoplu et al. [116] for machines. In the next few years, renewable energy will become so common that it will be omnipresent in the contracts, which creates the need to solve multi-sources of energy contract capacity optimization under various conditions such as deterministic and stochastic aspects of generation and demand. So a linear model is proposed to solve the deterministic problem, nonlinear model and robust model for the stochastic problem to manage contract capacities of multi-sources of energy.

The work presented in this thesis fill all these gaps and gives insight for future improvements and modeling for multi-sources of energy.

2

Location Optimization of Multi-Sources Energy

Outline of the current chapter

2.1 Introduction

To improve the use of alternative energy, it is important that governments distribute different sources of energy in an organized manner, this chapter proposes a general model for location optimization of multi-sources of energy plants in a country. The proposed method is a multi objective goal programming method to optimize the location of variable number of power plants in a variable number of places. The objective function is to minimize the total deviations of the criteria around the desired goals. We give different combinations of weights assigned to different types of criteria to generate different solutions. Then the frequency of distribution of different power plants in different places is calculated. In this approach, it is proven that using DEA directly on criteria gives more efficient results than using it on the deviations. The most efficient solutions having maximum outputs and minimum inputs are extracted, and the results between the two methods are compared. Previously researchers considered that the parameters of the power plants are constant with respect to the places. In fact that is not true, the parameters of the alternative power plants, in reality, vary from one place to another as considered in this approach. In this approach it is shown that relaxing the constraints gives more feasible solutions with better objective functions.

The remainder of the chapter is structured as follows: In Section 2.2 the problem and the optimization techniques are presented; in Section 2.3 the numerical applications for the contribution are shown in tables and graphs. First, the Mono-Criterion Optimization is used. Second, a constraint relaxation is made. Third, the CPLEX capacity is measured to handle large optimization problems. Fourth, the frequency of distributing different power plants in different places is calculated. Lastly, the efficient solutions through deviations and criteria are extracted. The chapter ends with sections 2.4 and 2.5 a discussion and conclusion respectively.

2.2 Problem Formulation and Model

2.2.1 Notation

The indices, parameters and variables of the proposed model are shown in Tables 2.1, 2.2, and 2.3.

Index	
$i(i = 1, ..., n)$	Power Plant
$j(j = 1, ..., m)$	Location
$w(w = 1, ..., Max\_iter)$	weight combination
Binary variables	
X_{ij}	1 if power plant i is placed in location j, 0 otherwise
net_{ij}^{w}	optimal solution if power plant i is placed in location j with weight combination w
Non-negative variables	
d_{PP}^{-}	Slack variable for under-achieving power production aspiration level y^{PP}
d_{PP}^{+}	Slack variable for over-achieving power production aspiration level y^{PP}
d_{INV}^{-}	Slack variable for under-achieving investment cost aspiration level y^{INV}
d_{INV}^{+}	Slack variable for over-achieving investment cost aspiration level y^{INV}
$d_{CO_2}^{-}$	Slack variable for under-achieving quantity of CO2 emission avoided aspiration level y^{CO_2}
$d_{CO_2}^{+}$	Slack variable for over-achieving quantity of CO2 emission avoided aspiration level y^{CO_2}
d_{JOB}^{-}	Slack variable for under-achieving jobs created aspiration level y^{JOB}
d_{JOB}^{+}	Slack variable for over-achieving jobs created aspiration level y^{JOB}
d_{OM}^{-}	Slack variable for under-achieving operation and maintenance cost aspiration level y^{OM}
d_{OM}^{+}	Slack variable for over-achieving operation and maintenance cost aspiration level y^{OM}
d_{DIS}^{-}	Slack variable for under-achieving distance between power plants aspiration level y^{DIS}
d_{DIS}^{+}	Slack variable for over-achieving distance between power plants aspiration level y^{DIS}

Table 2.1 – Indices, parameters, and variables of the proposed model.

Non-negative variables	
d_{SA}^{-}	Slack variable for under-achieving social acceptance aspiration level y^{SA}
d_{SA}^{+}	Slack variable for over-achieving social acceptance aspiration level y^{SA}
e_{PP}^{-}	negative deviation for under-achieving power production G^{PP}
e_{PP}^{+}	positive deviation for over-achieving power production G^{PP}
e_{INV}^{-}	negative deviation for under-achieving investment cost G^{INV}
e_{INV}^{+}	positive deviation for over-achieving investment cost G^{INV}
$e_{CO_2}^{-}$	negative deviation for under-achieving quantity of CO2 emission avoided G^{CO_2}
$e_{CO_2}^{+}$	positive deviation for over-achieving quantity of CO2 emission avoided G^{CO_2}
e_{JOB}^{-}	negative deviation for under-achieving jobs created G^{JOB}
e_{JOB}^{+}	positive deviation for over-achieving jobs created G^{JOB}
e_{OM}^{-}	negative deviation for under-achieving Operation and maintenance cost G^{OM}
e_{OM}^{+}	positive deviation for over-achieving Operation and maintenance cost G^{OM}
e_{DIS}^{-}	negative deviation for under-achieving distance between power plants G^{DIS}
e_{DIS}^{+}	positive deviation for over-achieving distance between power plants G^{DIS}
e_{SA}^{-}	negative deviation for under-achieving social acceptance G^{SA}
e_{SA}^{+}	positive deviation for over-achieving social acceptance G^{SA}
y^{PP}	vector aspiration level for power production created
y^{INV}	vector aspiration level for investment cost created
y^{CO_2}	vector aspiration level for quantity of CO_2 emission avoided
y^{JOB}	vector aspiration level for jobs created
y^{OM}	vector aspiration level for operation and maintenance cost
y^{DIS}	vector aspiration level for total distance between power plants
y^{SA}	vector aspiration level for social acceptance

Table 2.2 – Indices, parameters, and variables of the proposed model cont'd.

Non-negative variables	
fr_{ij}	frequency of assigning power plant i in location j
$f(X)$	achievement function of a criterion
Parameters	
n	Number of power plants
m	Number of locations
c	Number of connections
Max_iter	Total number of weight combinations
w_{ECON}	economical weight
w_{ENV}	environmental weight
w_{SOC}	social weight
$G^{PP}_{min,max}$	minimum, maximal goal for power production
$G^{INV}_{min,max}$	minimum, maximal goal for investment cost
$G^{CO_2}_{min,max}$	minimum, maximal goal for quantity of CO_2 emission avoided
$G^{JOB}_{min,max}$	minimum, maximal goal for jobs created
$G^{OM}_{min,max}$	minimum, maximal goal for operation and maintenance cost
$G^{DIS}_{min,max}$	minimum, maximal goal for total distance between power plants
$G^{SA}_{min,max}$	minimum, maximal goal for social acceptance
PP_{ij}	power generated by power plant i in location j
INV_{ij}	investment cost of power plant i in location j
CO_{2ij}	quantity of CO_2 emission avoided by power plant i in location j
JOB_{ij}	jobs created by power plant i in location j
OM_{ij}	operation and maintenance cost of power plant i in location j
$DIS_{j\acute{j}}$	distance between place j and place $\acute{j}$
SA_{ij}	social acceptance of power plant i in location j
a_{ij}	value of a criterion of power plant i in location j

Table 2.3 – Indices, parameters, and variables of the proposed model cont'd.

2.2.2 Generalized Goal Programming Model

While researchers apply goal programming on particular cases of multi-sources of energy location optimization with limited number of power plants and places, a generalized GP model is proposed to locate a variable number of different types of power plants (alternatives) n in a variable number of different locations m with a total number of connections c. The attributes considered for evaluating these renewable energy systems in this model are: power produced (PP); investment cost (INV); tons of CO2 emissions avoided per year (TCO2/y); jobs created (JOB); operation and maintenance costs (OM); distance between plants (DIS) and social acceptance (SA). The social acceptability is expressed using a scale of 1 (low acceptance) to 10 (high acceptance). The objective is to ensure the minimum total deviation from the goals. X_{ij} is a binary variable equal to 1 if power plant i is assigned to place j and zero otherwise. d^+ and d^- are positive and negative deviations from the goals and S is the set of all power plants and places [3]. These goals are given as:

$$\sum_{i,j \in S} PP_i * X_{ij} + d^-_{PP} - d^+_{PP} = G^{PP} \tag{2.1}$$

$$\sum_{i,j \in S} INV_i * X_{ij} + d^-_{INV} - d^+_{INV} = G^{INV} \tag{2.2}$$

$$\sum_{i,j \in S} CO_{2i} * X_{ij} + d^-_{CO_2} - d^+_{CO_2} = G^{CO_2} \tag{2.3}$$

$$\sum_{i,j \in S} JOB_i * X_{ij} + d^-_{JOB} - d^+_{JOB} = G^{JOB} \tag{2.4}$$

$$\sum_{i,j \in S} OM_i * X_{ij} + d^-_{OM} - d^+_{OM} = G^{OM} \tag{2.5}$$

$$\sum_{i,j \in S} DIS_i * X_{ij} * \acute{X}_{ij} + d^-_{DIS} - d^+_{DIS} = G^{DIS} \tag{2.6}$$

$$\sum_{i,j \in S} SA_i * X_{ij} + d^-_{SA} - d^+_{SA} = G^{SA} \tag{2.7}$$

These goals are the constraints which represent the following criteria:

- The power generated must be higher than G^{PP} W.

- The investment cost must be limited to G^{INV}€/year.
- The emissions avoided must be higher than G^{CO_2}.
- The jobs created must be higher than G^{JOB}.
- The operation and maintenance costs must be limited to G^{OM} €/year.
- The distance between plants must be maximized to G^{DIS} (Km).
- The social acceptance must be as close as possible to the highest level of G^{SA}.

The goal programming flexibility allows users to take into account several conflicting objectives, multiple criteria, and incomplete information at the same time in order to choose the most satisfactory solution within a feasible region. In practice, the GP model minimizes $\sum_i d_i^+ + d_i^-$, where d_i^+ and d_i^- are positive and negative deviations from the scalar aspiration level g_i. In other words, the purpose of GP is to minimize the deviations between the achievement of goals and the scalar aspiration levels.

2.2.3 Linearization Of The Model

CPLEX software is applied instead of Lingo software which researchers generally use. Lingo is good at solving nonlinear problems, but it takes much more time than CPLEX, on the other than CPLEX solves only linear problems although it is much faster. So to make the optimization possible using CPLEX, the multiplication of binary variables is linearized, in the case of the distance between the power plants, by the following technique:

$$X * \acute{X} \Leftrightarrow Z \begin{cases} Z \leq X \\ Z \leq \acute{X} \\ Z \geq X + \acute{X} - 1. \end{cases} \tag{2.8}$$

The technique in (2.8) linearizes the multiplication of binary variables using the necessary constraints and replacement of variables. This technique (2.8) is utilized for each pair of multiplied binary variables in the equation of distance between power plants in equation (2.9) as illustrated in equation (2.6):

$$\begin{cases} \sum_{i,j\in S} DIS_{j\acute{j}} * (X_{ij} * \acute{X}_{ij}) + d^-_{DIS} - d^+_{DIS} = G^{DIS} \\ \sum_{i,j\in S} DIS_{j\acute{j}} * Z_{j\acute{j}} + d^-_{DIS} - d^+_{DIS} = G^{DIS}. \end{cases} \tag{2.9}$$

This technique conserves the results, which are obtained faster and makes the operation feasible by CPLEX.

2.2.4 Constraint Relaxation

Relaxing the constraints gives more feasible solutions for the algorithm to choose among and find better objective functions, let g be the goal for a criteria what is obtained is:

$$\begin{cases} \sum_{i,j\in S} a_{ij} * X_{ij} - d^+ + d^- = g \\ \Longrightarrow \sum_{i,j\in S} a_{ij} * X_{ij} - d^+ + d^- = g1, \end{cases} \tag{2.10}$$

such that $g > g1$ in case the less the better or $g < g1$ in case the greater the better.

2.2.5 Expansion of the Feasible Region

The expansion of the original feasible region, can be obtained by GP, to find more and better solutions. The objective function becomes $\sum_{criteria}(d^+ + d^- + e^+ + e^-)$, and the constraints are formulated as following:

$f(x) - d^+ + d^- = y$, $y - e^+ + e^- = g_{max}$ or g_{min} where $x \in X \subset R^n, d^+$ and d^- are positive and negative deviations of the achievement function $f(x)$ from the vector aspiration level y, e^+ and e^- are positive and negative deviations of the vector achievement level y from the scalar aspiration level g_{max} or g_{min}.

2.2.6 Place Dependent Criteria

Researchers considered that the parameters of the power plants are constant for any place to be located, except for social acceptance and distance between power plants. But in reality the parameters' values vary from one place to another, for example, the solar energy produced by solar energy power plants varies depending on the intensity of the sun in the area, and it varies from one position to another. The wind energy produced by the wind turbines depends on the intensity of the wind in the area and it varies from one place to another. For the investment cost it is well known that the cost of a unit area depends on the location, and the installation cost differs from one site to another due to geological reasons. The same thing for the rest of criteria CO2, JOB, and OM varies depending on the area. So the coefficient criteria a_{ij} of each power plant i is different in each location j. The goal programming expansion of feasible region technique, the place dependent criteria, and linearization of multiplication of binary variables are adapted to the present problem so the constraints become as following:

$$\begin{cases} \sum_{i,j\in S} PP_{ij} * X_{ij} + d^-_{PP} - d^+_{PP} = y^{PP} \\ y^{PP} + e^-_{PP} - e^+_{PP} = G^{PP}_{max} \\ G^{PP}_{min} \leq y^{PP} \leq G^{PP}_{max} \end{cases} \tag{2.11}$$

$$\begin{cases} \sum_{i,j\in S} INV_{ij} * X_{ij} + d^-_{INV} - d^+_{INV} = y^{INV} \\ y^{INV} + e^-_{INV} - e^+_{INV} = G^{INV}_{min} \\ G^{INV}_{min} \leq y^{INV} \leq G^{INV}_{max} \end{cases} \tag{2.12}$$

$$\begin{cases} \sum_{i,j\in S} CO_{2ij} * X_{ij} + d^-_{CO_2} - d^+_{CO_2} = y^{CO_2} \\ y^{CO_2} + e^-_{CO_2} - e^+_{CO_2} = G^{CO_2}_{max} \\ G^{CO_2}_{min} \leq y^{CO_2} \leq G^{CO_2}_{max} \end{cases} \tag{2.13}$$

$$\begin{cases} \sum_{i,j\in S} JOB_{ij} * X_{ij} + d^-_{JOB} - d^+_{JOB} = y^{JOB} \\ y^{JOB} + e^-_{JOB} - e^+_{JOB} = G^{JOB}_{max} \\ G^{JOB}_{min} \leq y^{JOB} \leq G^{JOB}_{max} \end{cases} \tag{2.14}$$

$$\begin{cases} \sum_{i,j\in S} OM_{ij} * X_{ij} + d^-_{OM} - d^+_{OM} = y^{OM} \\ y^{OM} + e^-_{OM} - e^+_{OM} = G^{OM}_{min} \\ G^{OM}_{min} \leq y^{OM} \leq G^{OM}_{max} \end{cases} \tag{2.15}$$

$$\begin{cases} \sum_{i,j\in S} DIS_{j\acute{j}} * Z_{j\acute{j}} + d^-_{DIS} - d^+_{DIS} = y^{DIS} \\ y^{DIS} + e^-_{DIS} - e^+_{DIS} = G^{DIS}_{min} \\ G^{DIS}_{min} \leq y^{DIS} \leq G^{DIS}_{max} \end{cases} \tag{2.16}$$

$$\sum_{i,j\in S} SA_{ij} * X_{ij} + d^-_{SA} - d^+_{SA} = G^{SA} \tag{2.17}$$

Normalization technique is introduced to avoid unintentional bias toward the objective function. The deviations are divided by the maximum goal value, in other words, weights are assigned to the deviations:

$$\sum_i w_i(d^+_i + d^-_i + e^+_i + e^-_i)$$

So this technique is used in the objective function, the variables that correspond to the over and under achievement of each goal are normalized, and the deviations are divided by their respective maximum goal. To each term of the objective function, a weight is assigned to the different kinds of criteria. The criteria are classified into three types: economical (ECON) criteria; Environmental (ENV) criteria; and social (SOC) criteria. In this problem, the ECON criteria consider the PP, INV, OMC, and DIS. The ENV criterion stands for (TCO2/y), and the SOC criteria represents the SA and JOB. So the objective function becomes:

$$\begin{cases} w_{ECON}(\sum_{ECON} \frac{1}{G^{Max}_{ECON}} * (d^+_{ECON} + d^-_{ECON} \\ +e^+_{ECON} + e^-_{ECON})) + w_{ENV}(\sum_{ENV} \frac{1}{G^{Max}_{ENV}} * \\ (d^+_{ENV} + d^-_{ENV} + e^+_{ENV} + e^-_{ENV})) + w_{SOC} \\ (\sum_{SOC} \frac{1}{G^{Max}_{SOC}} * (d^+_{SOC} + d^-_{SOC} + e^+_{SOC} + e^-_{ENV})) \end{cases} \tag{2.18}$$

The weight restriction must be always sum to unity as the weights are determined in advance.

$$w_{ECON} + w_{ENV} + w_{SOC} = 1 \tag{2.19}$$

Also the different networks created by each set of weights are the following:

$$net_{ij}^{w} = X_{ij}^{*}, \forall i, j \in S \tag{2.20}$$

2.2.7 Assigning Frequencies

The next step of the proposed analysis is the renewable energy map for all representations of weight importance in the objective function. The representations of all networks have been stored in a matrix for all the iterations, namely net_{ij}^{w}. Summing over all the representations of networks and dividing by the total to calculate the frequency.

$$fr_{ij} = \sum_{w=1}^{Max\_iter} \frac{net_{ij}^{w}}{|Max\_iter|} \tag{2.21}$$

This method gives the user the opportunity to place an average number of each type of power plant in different places, multiplying the total number of power plants of each type by the different frequencies as following.

$$N_{ij} = N_i * fr_{ij} \tag{2.22}$$

2.2.8 Data Envelopment Analysis

Changing the weights assigned to the criteria of the objective function will eventually lead to different representations of the renewable energy network and variations in the over and under achievement of each goal. This will eventually construct the Pareto front, which is the space of all possible solutions. In order to filter the solutions provided by the previous 0-1 Weighted Goal Programming model, we employed different DEA techniques.

We consider $x_{w,in}$ the matrix of inputs and $y_{w,out}$ the matrix containing the outputs that will be used in DEA. Slack variables that correspond to goals that will be minimized serve as inputs, while those that correspond to goals that will be maximized serve as outputs.

In our case $x_{w,in}$ is a $300 * 4$ matrix of inputs and $y_{w,out}$ is a $300 * 9$ in the following form:

$$x_{w,in} = [d^{+}_{INV} \;\; e^{+}_{INV} \;\; d^{+}_{OM} \;\; e^{+}_{OM}] \tag{2.23}$$

$$y_{w,out} = [d^{-}_{PP}\, e^{-}_{PP}\, d^{-}_{JOB}\, e^{-}_{JOB}\, d^{-}_{CO_2}\, e^{-}_{CO_2}\, d^{-}_{DIS}\, e^{-}_{DIS}\, d^{-}_{SA}] \tag{2.24}$$

By experiment we realize that replacing the deviations by the criteria directly leads to more efficient solutions as follows:

$$x_{w,in} = [INV \;\; OM] \tag{2.25}$$

$$y_{w,out} = [PP \;\; JOB \;\; CO_2 \;\; DIS \;\; SA] \tag{2.26}$$

Then we choose the maximum of the subtraction between the normalized outputs and inputs to extract the most efficient solution as follows:

$$max \sum w_{out} * y_{w,out} - \sum w_{in} * x_{in} \tag{2.27}$$

This method gives a deterministic solution with high efficiency, it is good when assigning one power plant of each type in one place, but if we have more power plants of the same type, we lose the opportunity to distribute this type in different places instead of one place, so it is preferable to use the frequency method.

The steps are shown in the algorithm of figure 2.1.

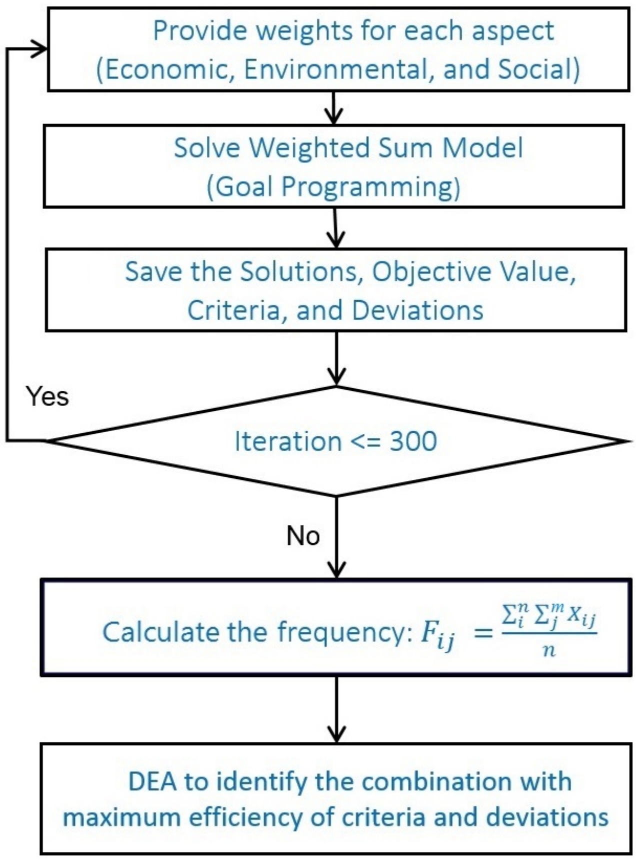


Figure 2.1 – Algorithm for Goal Programming, Frequency Calculation, and Data Envelopment Analysis

2.3 Numerical Application

2.3.1 Mono-Criterion Optimization Problem

We tried using different mono objective optimization methods other than the multi objective goal programming method. As examples of mono criterion optimization we maximize the power generated, minimize the investment cost and quantity of CO_2 emission avoided, maximize jobs offered, minimize the operation and maintenance cost, maximize the social acceptance rate, or maximize the total distance. We simulated the different optimization methods and the results for the different connections obtained are similar as shown in figure 2.2 but there is a slight difference in social acceptance and distance optimization as shown in figure 2.3. We were expecting to obtain different solutions with better values for the criterion we are optimizing, so we suggested to relax the constrains.

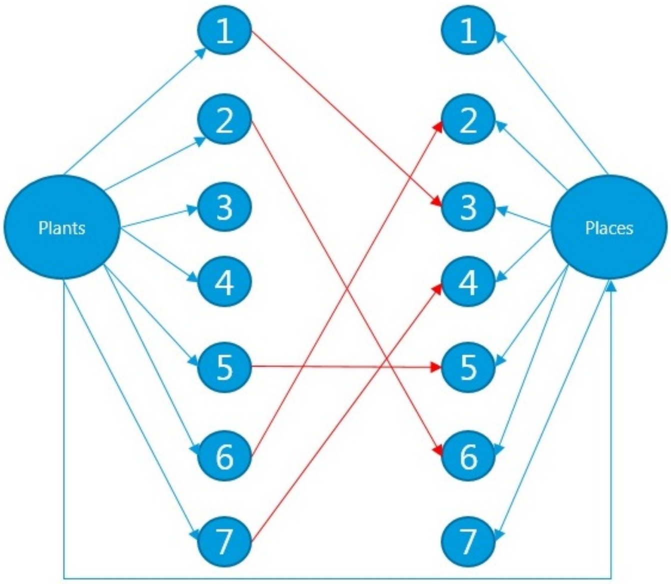


Figure 2.2 – Similar Solutions For Mono-Criterion Optimization before Constraint Relaxation

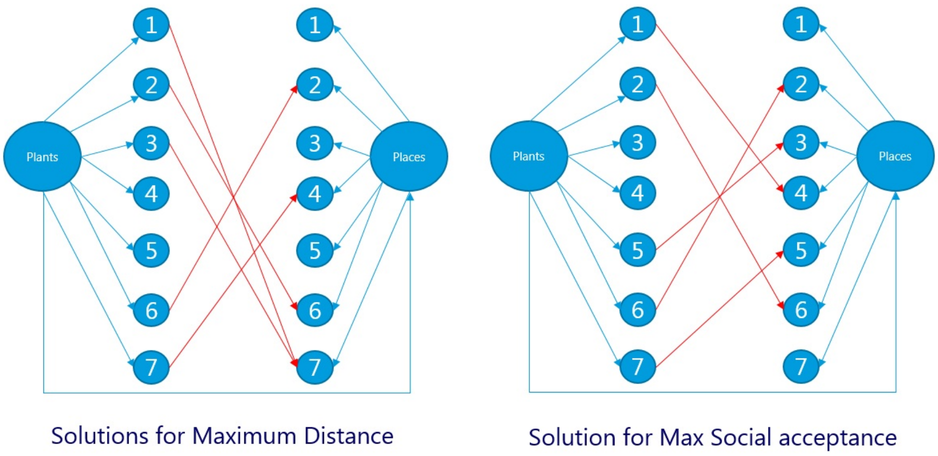


Figure 2.3 – Slightly Different Solutions For Mono-Criterion Optimization after Constraint Relaxation

2.3.2 Constraint Relaxation

As shown in figures 2.2 and 2.3, the results are approximately the same since the constraints are too strict. There were not enough feasible solutions, where the program gradually goes to these limited solutions. Therefore, the constraints were relaxed by applying equation (2.10), for the goal of the power generated is decreased from 110 MW to 11 MW, because it is the case of the greater the better. The goal of investment cost is also increased from 350000€/year to 3500000€/year, because it is the case of the less the better, and the same thing is done with the rest of criteria. Instead of having 5 connections out of 7, 4 connections are made out of 7 so that we have larger number of feasible solutions.

Simulations using different mono criterion optimization methods were made, after relaxing the different constraints, and the results for the different connections obtained are shown in figures 2.4 and 2.5, totally different solutions are successfully obtained in mono optimum criterion with better objective functions.

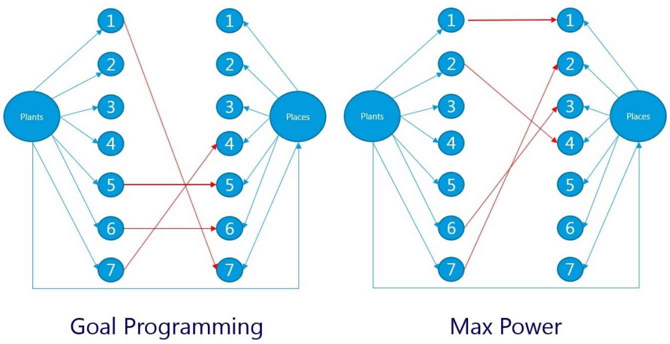


Figure 2.4 – Solutions For Goal Programming and Maximum Power after Constraint Relaxation

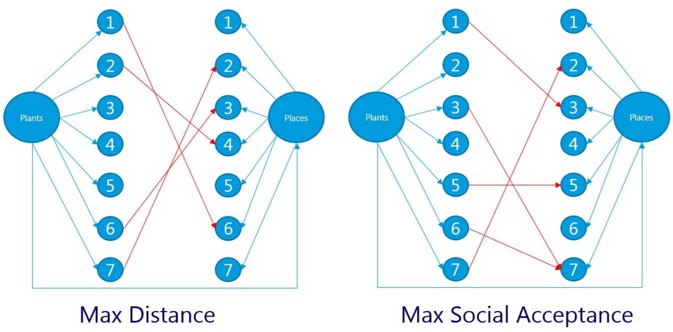


Figure 2.5 – Solutions For Maximum Distance and Social Acceptance after Constraint Relaxation

2.3.3 Time of simulation

A general model is proposed to optimize the location of variable number of power plants, places, and connections. The time of simulation of CPLEX is measured which uses simplex algorithm for different location optimization problems of renewable energy plants. New virtual alternatives and places are introduced, and their parameters are randomly generated around the average using MATLAB. The average is calculated by the sum of the parameters of the alternatives in [4] and dividing them by the total number as shown in table 2.4, then this average is multiplied by a uniform random value between 0 and 2 to fabricate different alternative power plants. The places' parameters are generated randomly as integers between the minimum and the maximum values of those given in [4].

PP (W)	INV (€/y)	CO2 (ton)	OM (€/y)
16852000	18322000	2640100	2627000

Table 2.4 – Average Parameters of the Alternative Power Plants

The goal programming model is applied to the objective function (2.18) and constraints (2.11) to (2.17). The total number of power plants n equal to the total number of places m are varied from 25 to 300 and so that of the total number of connections c from 10 to 300, with limitation of the time of execution to 1 hour and stops, after that it gives us a feasible solution instead of optimal one. So, as the number of alternatives and the number of connections done between them increases, the time of execution increases from few seconds to few minutes until it reaches one hour as shown in the graph of figure 2.6.

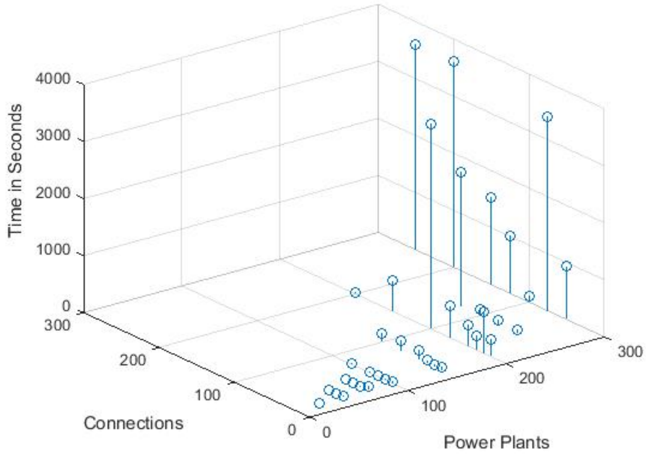


Figure 2.6 – The Variation of Time of Execution of Cplex as function of the number of Alternatives and Connections.

2.3.4 Assigning frequencies

For assigning frequencies of different alternatives to different places, a virtual country is considered with m virtual places of parameters generated randomly between the minimum and maximum values given in [4], and n virtual power plants with random parameters around the average, and in the OPL CPLEX program c connections are chosen out of $\min m, n$.

Cplex control flow is used to assign weights to the three categories of economic, environmental, and social criteria change by an incremental step of $\frac{3}{Max\_iter}$ for Max_iter iterations, in this case $Max\_iter = 300$ with incremental step 0.01 and the weights are changed as following:

$$\begin{cases} w_{ECON} \; increase \; from \; 0 \; to \; 1, \\ w_{SOC} \; decrease \; from \; 1 \; to \; 0, \; and \; w_{ENV} = 0 \\ w_{ECON} \; increase \; from \; 0 \; to \; 1, \\ w_{ENV} \; decrease \; from \; 1 \; to \; 0, \; and \; w_{SOC} = 0 \\ w_{SOC} \; increase \; from \; 0 \; to \; 1, \\ w_{ENV} \; decrease \; from \; 1 \; to \; 0, \; and \; w_{ECON} = 0 \\ w_{ECON} + w_{ENV} + w_{SOC} = 1 \end{cases} \tag{2.28}$$

In each iteration a set of solutions for X_{ij} are generated, they are accumulated in another variable, and after the total iterations are finished, they are divided by a total number of weight combinations $Max\_iter = 300$ as mentioned in (2.21) to obtain the frequency of each plant to be assigned to each place.

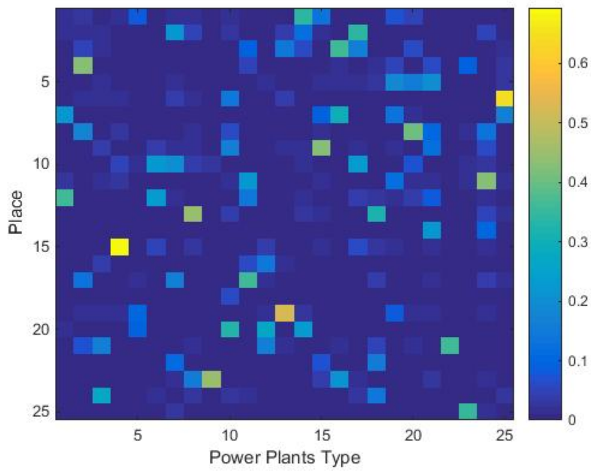


Figure 2.7 – The Frequency Distribution Of Different Types Of Power Plants In Different Places

This method is tested on different instances of different numbers of power plant types, places, and connections. Figure 2.7 is an illustration example of frequency distribution of 20 connections out of 25 power plants and 25 places, the horizontal axis is the index of the power plant and the vertical axis is the index of the place. As the color intensity changes from dark blue through green to yellow the probability increases from 0 to 0.7. As shown in the figure the probability of assigning power plant 4 in place 15 is approximately 0.7, the probability of assigning power plant 25 in place 6 is approximately 0.7 as well. There are probabilities approximately 0.35 for different power plants in different areas and the rest of the probabilities are 0. This indicates that there are certain types of power plants that are strongly suitable to be assigned in certain places.

2.3.5 Difference Between DEA on Criteria and on Deviations

The most efficient solutions are extracted out of the 300 weight combinations mentioned in (2.28), we use the DEA by the two methods of criteria and deviations mentioned in (2.27).

Table 2.5 shows the values of the different criteria of the most efficient solutions obtained after simulating different problems of different dimensions. The dimensions' column is composed of two numbers, the left number is the same for available power plants n equal to the number of places m, and the right number represents the connections c to be made. Table 2.5 represents the values of the criteria of the most efficient solutions with respect to the criteria in the first line of each row and most efficient solutions with respect to the deviations in the second line of each row. As shown in table 2.5 the numbers with red marks have better values, their outputs are higher and their inputs are lower. So the efficient solutions obtained from the DEA of Criteria are better from the solutions obtained by the DEA of the deviations.

dimension	PP(MW)	INV(M€/y)	CO2(M)	JOB	OM(M€/y)	SA	DIS(Km)	Efficiency
25; 5	89047673,11	85419833,81	10859424,93	80	249243	39	633	110,9665289
25; 5	117309477,1	71244627,14	18170659,75	75	218744	33	518	90,25211503
25; 15	258381511,9	221688658,1	46272963,78	194	1667389,575	96,99999999	8163	187,2014887
25; 15	262528087,1	241206626	46664525,19	194	1654041,792	93	8196	106,2600723
25; 20	462976028,4	328212044,7	51512448,04	279	40872830,12	175	16124	-5143,062237
25; 20	462976028,4	328212044,7	51512448,04	279	40872830,12	122	16068	-5467,540136
25; 25	449958245,7	466409843,6	80759353,05	340	8576017,74	166	23085	-384,9688697
25; 25	400609616,2	468691178,6	66808593,25	340	8194549,76	174	23085	-696,3308189
50; 20	439921695,2	313687621,2	77282930,32	305	1205746,916	132	15660	554,7760106
50; 20	457024915,2	314319910,4	52323120,4	300	1206601,53	132	15926	173,1955947
50; 30	557022119	474361116,8	113688062,4	457	2094058,619	196	35165	884,387361
50; 30	567231102,1	472748285,3	104008559,1	463	1878800,867	190	34406	-7382,680427
50; 50	811395913,8	808710203,9	147827968,4	720	6916480,671	322	96709	1265,531758
50; 50	808936661,4	815469786,1	147895255	720	6876630,456	320	96709	18,52143879
75; 30	684372106,2	431368105,1	108367775,5	384	1757194,5	196	35493	956,6133438
75; 30	660785623,2	469855835	112262192,8	401	1780241,472	187	35055	-63984,31784
75; 45	684372105,9	431368105,1	108367775,5	384	1757194,5	196	35493	956,6133438
75; 45	781751724,1	721188444	108351604,6	631	2696492,768	333	78341	504,9839371
75; 60	1067357166	976509647,3	180008598,8	794	4580929,169	400	139872	2365,262387
75; 60	967854077,9	959984297,3	162308405,4	793	4250027,566	398	140094	638,1826096
75; 75	1333282075	1257816336	234013506,3	978	9282847,874	505,0000001	217890	2988,266423
75; 75	1258318366	1262868537	214734110,1	978	8800960,577	498	217890	262,8936667
100; 80	1597898607	1282735088	253208376,5	1095	4810035,734	530	249810	4264,545785
100; 80	1714157942	1282579430	198370013,3	1097	4789782,57	519	248746	834,006097
100; 100	1909324106	1574075658	322228423,6	1370	10058941,43	672	390182	5729,838232
100; 100	1743045859	1590660952	260069850,2	1370	8881026,616	670	390182	746,6492589

Table 2.5 – The Efficient Normalized Values Of The Different Dimensions Of Simulation With Respect To The Criteria

2.4 Discussion

Figures 2.2 and 2.3 show that the constraints were too strict where there is only limited number of solutions, so it is necessary to find the appropriate values of the goals carefully. This helps to find the appropriate solution for mono objective optimization. Constraint relaxation gives a variety of solutions with better objective values as shown in figures 2.4 and 2.5.

In figure 2.6 which represents the time of simulation as function of the number of power plants and connections, the number of connections c is always less than the number of power plants n and places m, so we have a semi-space which is empty, and for the rest the time of execution increases by few seconds and few minutes as the number of power plants and connections increases. However, when the number of connections reaches 100 or above, and the number of power plants reaches 200 or above the time of executions reaches 1 hour. So the simplex algorithm handles limited instances to find the optimal solution within an hour.

Regarding the frequency distribution method, for any country or region the different frequency distributions can be obtained as shown in figure 2.7, where for each place shown by each row there is a certain frequency color for a certain type of power plant. This helps to decide to put a power plant with higher frequency, or to assign average power plants by multiplying the total number of powerplants of certain type with the frequency of distribution in a certain place.

The DEA method is chosen for finding a deterministic solution for the location distribution of the power plant, it is used to extract the solutions with maximum outputs and minimum inputs out of the different solutions obtained. As shown in 2.5 applying the DEA methods directly on the criteria gives more efficient solutions than applying it on the deviations.

2.5 Conclusion

This chapter proposes a general goal programming model for dealing with the capacity expansion planning problem of the renewable energy industry. So for any country with a given statistical data about the different criteria, it decides the optimal mix for variable numbers of different plant types in variable number of locations. Different types of plants should be located in appropriate places to minimize the total deviations from predefined goals concerning the criteria such as: power generated, investment cost, emission CO_2 avoided, jobs created, operation and maintenance costs, distance security, and social acceptance. The proposed method can solve variable instances close to actual conditions since it considers variable parameters with respect to the place. The constraints are relaxed to find more feasible solutions with better objective functions. The method can find the frequency distribution of the different types of power plants to the different places, and better method of DEA is proposed to extract more efficient solutions.

For the future we are planning to distribute renewable energy power plants in the different prefectures taking into account the weather forecast for uncertainty in energy generation. We are also planning to introduce factors such as the demand to decide the location of the power plant with minimum energy transmission loss satisfying different criteria. We want to find an optimization method to solve large instances of our problem in reasonable times.

3

Contract Capacity Optimization of Multi-Sources Energy

Outline of the current chapter

3.1 Introduction

The investment of renewable energy in different regions in a country increases energy production and has several consequences, first, instead of having one contract for energy, the increase in renewable energy production gives rise of multi-sources of energy contracts for energy consumers, traditional and renewable energy contracts to cover the energy demand. Second, the investment in renewable energy needs support such as the discount given by the government to encourage the use of renewable energy, and the consumers support for renewable energy such as industries that are interested to have green products. Third, Consumers should decide the optimal choice of multi-sources of energy contracts to satisfy their demand under uncertainty conditions, taking into account the penalty price if the demand exceeds the total contract capacities and the price of the contracts themselves. Finally, energy producer need to know the maximum contract capacity of the different types of energy to be assigned, considering stochastic features in energy generation and demand at the same time.

This chapter introduces a new concept in modelling contract capacity (CC) in multi-sources of energy for deterministic and stochastic problems. In the deterministic case, the model of Ferdavani et al. [1] has been improved to be applicable to multi-stage penalties, and a second model has been proposed considering discrete contract capacities of multi-sources of energy for industrial demand of energy over a certain range of periods. The objective is to find the optimal combination of multi-sources of energy contract capacities taking into account the penalty price of the excess demand, the price of the contracts, and the ecofriendly cost for encouraging renewable energy use. The model is linear and is solved using linear programming in CPLEX software. For the uncertainty in the demand of energy in different periods, a nonlinear problem is modeled to test the influence of uncertainty on the choice of the optimal combination of the different types of energy contract capacities. The objective function is nonlinear, so the model is proved to be convex and an interior point algorithm is used to find the optimal solution. The influence of the penalty price and the uncertainty on the optimal solution are studied with the change of the ecofriendly price. For uncertainty in energy generation and demand at the same time, a two-stage mixed-integer linear robust program with recourse model is suggested for the producer to decide the maximum contract capacity of each type of energy.

3.2 Multi-stage penalty

3.2.1 Problem presentation

For a single type contract capacity and one value of contract for all periods, Ferdavani et al. (2018) [1] found a simple formula for the optimal solution, and in case of variable contract prices and penalty prices they made an algorithm to obtain the optimal solution within two iterations maximum. In our approach this formula and algorithm are tested to find out if they are applicable in case of a multi-stage penalty. The multistage penalty and demand sorting are illustrated in figure 3.1.

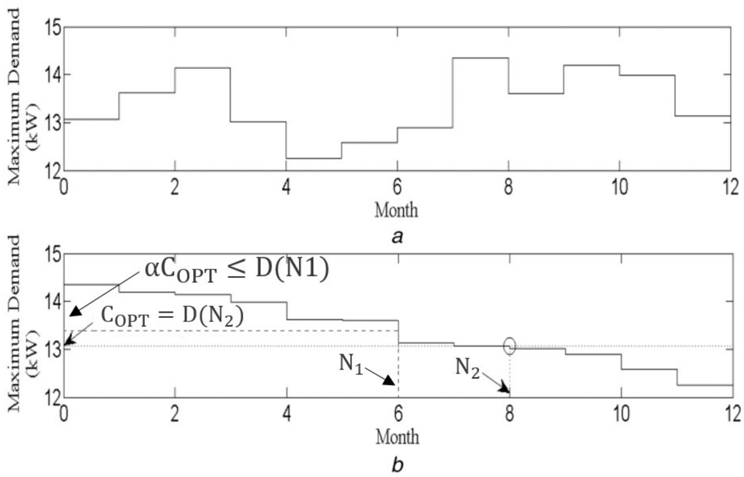


Figure 3.1 – The data and optimal values (a) The maximum demands, (b) The sorted data with the key points

Consider the following notations in table 3.1, the total cost in case of the one stage penalty is shown in equation 3.1:

$$min \ \ TC(C) = \sum_{m=1}^{N_M} P^{CC}(m).C + \sum_{m=1}^{N_E} P^{UC}(m).[D(m) - C] \tag{3.1}$$

In the case where $P^{CC}(m)$ and $P^{UC}(m)$ are constant the objective function becomes:

$$TC(C) = P^{UC} * \sum_{m=1}^{N_E} D(m) + (N_M * P^{CC} - N_E * P^{UC}) * C \tag{3.2}$$

Indexes	
$m(m = 1, ..., N_M)$	Period
Variables	
C	Power contract capacity in KW
Parameters	
$TC(C)$	Total cost
$P^{CC}(m)$	Contract capacity price in period m
$P^{UC}(m)$	Upper contract capacity price in period m
N_M	Total number of periods
N_E	Total number of periods that their maximum demands surpass the contracted demand
N_1	Total number of periods that their maximum demands surpass α times the contracted demand for two stage penalty
N_2	Total number of periods that their maximum demands surpass the contracted demand for two stage penalty
$D(m)$	Peak power demand at period m
α	Ratio of contract capacity over which a high penalty is charged
β	Ratio of the penalty price to the contract capacity price
γ	Ratio of the high penalty price to the contract capacity price

Table 3.1 – Indices, parameters, and variables of the multi-stage penalty model

To solve the problem first the data is sorted in descending order, so the formula of the optimal solution in the case of constant prices is obtained is as follows:

$$N_E = Round\_Up(N_m * \frac{P^{CC}}{P^{UC}}) \tag{3.3}$$

In the case of variable prices the optimal solution is found according to the algorithm shown in figure 3.2:

The optimization problem in case of a multistage penalty is as following:

$$\sum_{m=1}^{N_M} P^{CC}(m) * C + \sum_{m=1}^{N_1} (\gamma - \beta) * P^{CC}(m) * (D(m) - \alpha * C) + \sum_{m=1}^{N_2} \beta * P^{CC}(m) * (D(m) - C) \tag{3.4}$$

Estimating that the P^{CC} is constant for all periods the problem is reformulated as follows:

$$(\gamma - \beta) * P^{CC} * \sum_{m=1}^{N_1} D(m) + \beta * P^{CC} * \sum_{m=1}^{N_2} D(m) + (N_m - \alpha * (\gamma - \beta) * N_1 - \beta * N_2) * P^{CC} * C \tag{3.5}$$

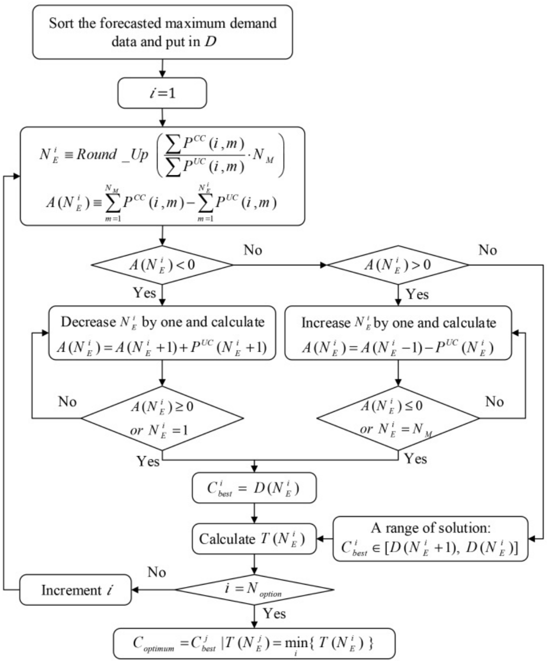


Figure 3.2 – Flowchart of the method to solve the contract capacity optimization problem with several sets of prices [1]

Now the unknown variables to find in the optimal solution of the objective function 3.5 are C, N_1, and N_2. When N_2 is found C and N_1 are automatically found. For the sorted data consider the following procedure:

1. Set $C_1 = D(m_1)$ and $C_2 = D(m_1 + 1)$.

2. Calculate $TC_1 = TC(C_1)$ and $TC_2 = TC(C_2)$.

3. If $TC_2 \leq TC_1$, increment m_1 and go to step 2; stop otherwise.

Now, set $N_2 = m_1$. Suppose that $N_2 > 1$ and N_2 is the period that we have reached the following status:

$C_0 = D(N_2 - 1)$ and $TC_0 = TC(C_0)$

$C_1 = D(N_2)$ and $TC_1 = TC(C_1)$

$C_2 = D(N_2 + 1)$ and $TC_2 = TC(C_2)$

$$TC_0 = (\gamma - \beta) * P^{CC} * \sum_{m=1}^{N_{10}} D(m) + \beta * P^{CC} * \sum_{m=1}^{N_2-1} D(m) + \\ (N_m - \alpha * (\gamma - \beta) * N_{10} - \beta * (N_2 - 1)) * P^{CC} * D(N_2 - 1) \tag{3.6}$$

$$TC_1 = (\gamma - \beta) * P^{CC} * \sum_{m=1}^{N_{11}} D(m) + \beta * P_{CC} * \sum_{m=1}^{N_2} D(m) \\ +(N_m - \alpha * (\gamma - \beta) * N_{11} - \beta * N_2) * P^{CC} * D(N_2) \tag{3.7}$$

$$TC_2 = (\gamma - \beta) * P^{CC} * \sum_{m=1}^{N_{12}} D(m) + \beta * P^{CC} * \sum_{m=1}^{N_2+1} D(m) + \\ (N_m - \alpha * (\gamma - \beta) * N_{12} - \beta * (N_2 + 1)) * P^{CC} * D(N_2 + 1) \tag{3.8}$$

$$TC_0 - TC_1 \geq 0 \tag{3.9}$$

$$TC_2 - TC_1 \geq 0 \tag{3.10}$$

This means that the cost decreases with increasing m_1 until reaching N_2, and then it increases as N_2 increases. To see if it is possible to obtain the optimal capacity in one formula the equations 3.9 and 3.10 are investigated as following:

$$TC_2 - TC_1 = (\gamma - \beta) * P^{CC} * \sum_{N_{11}}^{N_{12}} D(m) + P^{CC} * (N_m - \beta * N_2) * (D(N_2 + 1) \\ -D(N_2)) - \alpha * (\gamma - \beta) * P_{CC} * (N_{12} * D(N_2 + 1) - N_{E11} * D(N_2)) \tag{3.11}$$

$(\gamma - \beta) * P^{CC} * \sum_{N_{11}}^{N_{12}} D(m) > 0$ since $\gamma > \beta$.

The sign of $P^{CC} * (N_m - \beta * N_2) * (D(N_2 + 1) - D(N_2))$ is unknown since it depends on the value of N_2.

$N_{12} > N_{11}$ and $D(N_2 + 1) < D(N_2)$ then the sign of $N_{12} * D(N_2 + 1) - N_{E11} * D(N_2)$ is unknown. So the sign of $TC_2 - TC_1$ is unknown.

$$TC_0 - TC_1 = -(\gamma - \beta) * P^{CC} * \sum_{N_{10}}^{N_{11}} D(m) + P^{CC} * (N_m + (1-\beta) * N_2) * \\ (D(N_2 - 1) - D(N_2)) - \alpha * (\gamma - \beta) * P^{CC} * (N_{10} * D(N_2 - 1) - N_{11} * D(N_2)) \tag{3.12}$$

$-(\gamma - \beta) * P^{CC} * \sum_{N_{10}}^{N_{11}} D(m) < 0$ since $\gamma > \beta$.

The sign of $P^{CC} * (N_m + (1-\beta) * N_2) * (D(N_2 - 1) - D(N_2))$ is unknown since it depends on the value of N_2.

$N_{12} > N_{11}$ and $D(N_2 + 1) < D(N_2)$ so the sign of $-\alpha * (\gamma - \beta) * P^{CC} * (N_{10} * D(N_2 - 1) - N_{11} * D(N_2))$ is unknown.

For $N_2 = \frac{N_m}{\beta}$:

$$TC_2 - TC_1 = (\gamma - \beta) * P^{CC} * \sum_{N_{11}}^{N_{12}} D(m) + \alpha * (\gamma - \beta) * P^{CC} * (N_{11} * D(\frac{N_m}{\beta}) - N_{12} * D(\frac{N_m}{\beta} + 1)) \tag{3.13}$$

Since $N_{11} \leq N_{12}$ and $D(\frac{N_m}{\beta}) \geq D(\frac{N_m}{\beta} + 1)$ then $TC_2 - TC_1$ is not necessarily greater than or equal zero.

Similarly:

$$TC_0 - TC_1 = -(\gamma - \beta) * P^{CC} * \sum_{N_{10}}^{N_{11}} D(m) - \beta * P^{CC} * (D(\frac{N_m}{\beta}) - D(\frac{N_m}{\beta} - 1)) \\ -\alpha * (\gamma - \beta) * P^{CC} * (N_{10} * D(\frac{N_m}{\beta} - 1) - N_{11} * D(\frac{N_m}{\beta})) \tag{3.14}$$

$-(\gamma - \beta) * P^{CC} * \sum_{N_{10}}^{N_{11}} D(m) < 0$, $-\beta * P^{CC} * (D(\frac{N_m}{\beta}) - D(\frac{N_m}{\beta} - 1)) > 0$ because of the sorting of the demand, and $-\alpha * (\gamma - \beta) * P^{CC} * (N_{10} * D(\frac{N_m}{\beta} - 1) - N_{11} * D(\frac{N_m}{\beta}))$ is unknown since N_{10} and N_{11} depend on $\frac{N_m}{\beta}$.

In conclusion $N_2 = \frac{N_m}{\beta}$ is not necessarily the optimal solution. To know if the optimal solution is $C_{optimal} = D(N_2)$ or $D(N_2+1) \leq C_{optimal} \leq D(N_2-1)$, the following test is carried out, suppose that C_1 satisfies the inequalities $D(N_2+1) \leq C_1 \leq D(N_2)$.

$$TC(C_1) - TC(D(N_2)) = (N_m - \beta * N_2 - \alpha * (\gamma - \beta) * N_1) * (C_1 - D(N_2)) * P^{CC}$$

$C_1 - D(N_2) \leq 0$ but the sign of the term $(N_m - \beta * N_2 - \alpha * (\gamma - \beta) * N_1)$ depends on N_2 and N_1 so C_1 is possibly between $D(N_2)$ and $D(N_2+1)$.

Similarly, to know if the optimal solution lies between $D(N_2)$ and $D(N_2-1)$, suppose that C_2 satisfies the inequalities $D(N_2) \leq C_2 \leq D(N_2-1)$.

$$TC(C_2) - TC(D(N_2)) = (N_m - \beta * N_2 - \alpha * (\gamma - \beta) * N_1) * (C_2 - D(N_2)) * P^{CC}$$

The same term is obtained so C_2 is in the range $[D(N_2); D(N_2-1)]$. In general the optimal solution in case a multi-stage penalty is $D(N_2+1) \leq C_{optimal} \leq D(N_2-1)$.

3.2.2 Proposed algorithm

The algorithm of several sets of prices proposed in [1] can be applied in the case that the prices are known for each period. In case of a multi-stage penalty, the prices depend on the demand, the optimal solution, and the value of α. So a new algorithm should be applied taking into consideration the multistage-stage penalty. $A(N_E)$ can be calculated in a different manner, and because the solution is not necessarily equal to $D(N_2)$ in the case of discrete contracts to choose an optimal contract capacity within the range of $[D(N_2+1); D(N_2-1)]$. That is because periods of high penalty are unknown. So in each iteration the value of N_1 should be calculated to obtain the total penalty price in each period. After that the value of $A(N_E)$ is calculated as shown in the equation.

$$A(N_E) = \sum_{m=1}^{N_M} P^{CC}(m) - \sum_{m=1}^{N_1} \gamma * P^{CC}(m) - \sum_{m=N_1+1}^{N_2} \beta * P^{CC}(m) \tag{3.15}$$

Algorithm 1
initialization:
Choose the starting point $N_{E2} = Round\_Up(\frac{N_M}{\beta})$
Find N_{E1} such that:
$D(N_{E1}) > \alpha * D(N_{E2})$
Calculate $A(N_E)$
$= \sum_{m=1}^{N_M} P^{CC}(m) - \sum_{m=1}^{N_{E1}} \gamma * P^{CC}(m) - \sum_{N_{E1}+1}^{N_{E2}} \beta * P^{CC}(m)$
While $(A(N_E) < 0$ And $N_{E2} \geq Round\_Up(\frac{N_m}{\gamma}))$
{
Decrease N_{E2} by one
Find N_{E1} such that
$D(N_{E1}) > \alpha * D(N_{E2})$
Calculate $A(N_E)$
$= \sum_{m=1}^{N_M} P^{CC}(m) - \sum_{m=1}^{N_{E1}} \gamma * P^{CC}(m) - \sum_{N_{E1}+1}^{N_{E2}} \beta * P^{CC}(m)$
}
Choose $C_{optimal} \in [D(N_{E2}+1); D(N_{E2}-1)]$
Calculate $TC(C_{optimal})$

Table 3.2 – Algorithm to solve the contract capacity optimization with two stage penalties

Based on equation 3.3 the optimal solution in case of constant penalty price depends on the ratio of P^{CC} to the P^{UC}, if this ratio increases N_E will be reduced and then the optimal contract capacity will increase. So, since this ratio is either γ for $D(m) > \alpha * C$ or β for $D(m) > C$ the optimal solution N_E ranges between $Round\_Up(\frac{N_M}{\gamma})$ and $Round\_Up(\frac{N_M}{\beta})$.

Therefore, the algorithm needs to be modified to apply it to the case of multistage penalty. The initial point estimated is $N_2 = Round\_Up(\frac{N_M}{\beta})$, after that the index N_1 is found such that $D(N_1) > \alpha * D(N_2)$. Then $A(N_E)$ is calculated as given in equation 3.15. When $A(N_E)$ is less than 0 the value of N_2 is decremented by one and the same process is repeated. The stopping criteria are either when $A(N_E)$ becomes positive or when $N_2 = Round\_Up(\frac{N_M}{\gamma})$ since $N_2 \in [\frac{N_M}{\gamma}; \frac{N_M}{\beta}]$. So the algorithm is expressed in Table 3.2.

3.2.3 Data Experiments

To demonstrate the method contributed, the algorithm is applied to university data inspired from [5], a big electric user's data inspired from [1], Grand-Est and France data inspired from [123]. Since linear programming is an exact method, it is applied to the same data for comparison. The values of α, β, and γ are changed to study their effect on the optimal solution and at the same time see the accuracy of the proposed method.

The mathematical model for the linear programming is formulated as follows:

$$Minimize \qquad \sum_{t=1}^{T}(P^{CC} * C + \beta * P^{CC} * X_t + \gamma * P^{CC} * Y_t) \tag{3.16}$$

Subject to:

$$X_t + C \geq D_t \qquad \forall\, t = 1, ..., T \tag{3.17}$$

$$Y_t + \alpha * C \geq D_t \qquad \forall\, t = 1, ..., T \tag{3.18}$$

$$X_t \geq 0 \qquad \forall\, t = 1, ..., T \tag{3.19}$$

$$Y_t \geq 0 \qquad \forall\, t = 1, ..., T \tag{3.20}$$

The objective function 3.16 is to minimize the total cost of the contract capacity price and the penalty price. X_t is the excess demand charged by a penalty price $\beta * P^{CC}$. X_t is defined by equations 3.17 and 3.19, it is the maximum between 0 and the difference between the demand and the chosen contract. Y_t is the demand exceeding a threshold equal to α ratio of the contract. The problem is solved using CPLEX.

Tests	Linear programming for continuous contracts				Algorithm for discrete contracts		
(α, β, γ)	C_{opt}	TC	Time	% Gap in objective	C_{opt}	TC	Time
$(1.1, 2, 3)$	4616	9908000	1.575 s	0	4616	9908000	0.0013 s
$(1.1, 2, 2.5)$	4616	9896900	1.623 s	0	4616	9896900	0.00097 s
$(1.1, 1.5, 3)$	4616	9758800	1.638 s	0	4616	9758800	0.0023 s
$(1.1, 1.5, 2.5)$	4589.09	9744200	1.622 s	0.037	4616	9747800	0.0007 s
$(1.05, 2, 3)$	4807	10046000	1.591 s	0.06	4616	10052000	0.002 s
$(1.05, 2, 2.5)$	4616	9969000	1.638 s	0	4616	9969000	0.0002 s
$(1.05, 1.5, 3)$	4807.62	9965551	1.529 s	0.096	4616	9975100	0.0001 s
$(1.05, 1.5, 2.5)$	4616	9891962	1.685 s	0.0004	4616	9892000	0.0001 s

Table 3.3 – Results of data inspired from university in [5]

Tests	Linear programming for continuous contracts				Algorithm for discrete contracts		
(α, β, γ)	C_{opt}	TC	Time	% Gap in objective	C_{opt}	TC	Time
$(1.05, 1.5, 2)$	30586	5306712	1.67 s	0	30586	5306712	0.0028 s
$(1.05, 1.5, 2.5)$	31067	5318277	1.965 s	0.002	31129	5318400	0.002 s
$(1.05, 1.8, 2)$	31129	5339298	1.762 s	0	31129	5339298	0.0003 s
$(1.05, 1.8, 2.5)$	31351	5344370	1.747 s	0.0006	31354	5344400	0.0003 s
$(1.1, 1.5, 2)$	30245	5285303	1.747 s	0.00006	30250	5285300	0.0021 s
$(1.1, 1.5, 2.5)$	30250	5285632	1.7 s	0	30250	5285632	0.00002 s
$(1.1, 1.8, 2)$	30586	5334692	1.762 s	0	30586	5334692	0.001 s
$(1.1, 1.8, 2.5)$	30586	5334692	1.701 s	0	30586	5334692	0.0001 s

Table 3.4 – Results of data inspired from a large electric user in [1]

3.2.4 Data Analysis

The data of the energy demand of the university [5] are of 12 periods, out of 8 tests, 5 gave an optimal solution $C_{Optimal} = D(N_{E2})$, one test gave $D(N_{E2} + 1) \leq C_{Optimal} \leq D(N_{E2})$, and 2 tests gave $D(N_{E2}) \leq C_{Optimal} \leq D(N_{E2} - 1)$. In the university case [5] the value of $D(N_{E2})$ remains equal to 4616 KW though the values of α, β, and γ change. That is due to the small number of periods and the lack of variation between the demand in each period.

The energy demand of the large electric user in Singapore [1] comprises number of 24 periods and there is variation between the demand of each period. Out of 8 tests, 5 gave an an optimal solution $C_{Optimal} = D(N_{E2})$ and 3 tests gave $D(N_{E2} + 1) \leq C_{Optimal} \leq D(N_{E2})$.

For 12 periods of energy demand in the Grand-Est region in France [123], from the 8 different

Tests	**Linear programming for continuous contracts**				**Algorithm for discrete contracts**		
(α, β, γ)	C_{opt}	TC	Time	% Gap in objective	C_{opt}	TC	Time
(1.05, 2, 4)	4352.38	482575714	1.623 s	0.062	4370	482877000	0.0017 s
(1.05, 2, 5)	4352.38	482854714	1.623 s	0.028	4370	482989500	0.0012 s
(1.05, 3, 4)	4370	488110500	1.716 s	0	4370	488110500	0.0007 s
(1.05, 3, 5)	4370	488223000	1.654 s	0	4370	488223000	0.0004 s
(1.1, 2, 4)	4182.73	477175090	1.701 s	0.265	4253	478440000	0.0031 s
(1.1, 2, 5)	4182.73	477175090	1.747 s	0.265	4253	478440000	0.00006 s
(1.1, 3, 4)	4253	487998000	1.762 s	0	4370	487998000	0.00007 s
(1.1, 3, 5)	4253	487998000	1.716 s	0	4370	487998000	0.00006 s

Table 3.5 – Results of data inspired from Grand-Est 2018 in [123]

Tests	**Linear programming for continuous contracts**				**Algorithm for discrete contracts**		
(α, β, γ)	C_{opt}	TC	Time	% Gap in objective	C_{opt}	TC	Time
(1.05, 2, 4)	46482.9	5210706857	1.669 s	0.355	47562	5229200000	0.0018 s
(1.05, 2, 5)	46482.9	5223567857	1.67 s	0.158	47562	5231800000	0.0012 s
(1.05, 3, 4)	47562	5270066100	1.653 s	0	47562	5270066100	0.0006 s
(1.05, 3, 5)	47562	5272729200	1.654 s	0	47562	5272729200	0.0005 s
(1.1, 2, 4)	44370	5134644000	1.825 s	1.736	47562	5223800000	0.0023 s
(1.1, 2, 5)	44370	5147505000	1.7 s	1.482	47562	5223800000	0.00009 s
(1.1, 3, 4)	45669.1	5267403000	1.685 s	0.000038	47562	5267405000	0.00009 s
(1.1, 3, 5)	45669.1	5267403000	1.654 s	0.000133	47562	5267410000	0.00006 s

Table 3.6 – Results of data inspired from France 2018 in [123]

tests, 2 tests gave an optimal solution $C_{Optimal} = D(N_{E2})$ six tests gave $D(N_{E2}+1) \leq C_{Optimal} \leq D(N_{E2})$. For all of France 2 tests gave optimal solution $C_{Optimal} = D(N_{E2})$ and six tests gave $D(N_{E2}+1) \leq C_{Optimal} \leq D(N_{E2})$.

So the different tests on the data from various consumers show that the optimal solution lies between $D(N_{E2}+1)$ and $D(N_{E2}-1)$. Using **Algorithm 1** N_{E2} can be found. So in discrete contract capacity optimization the optimal solution is the contract having a value between $D(N_{E2}+1)$ and $D(N_{E2}-1)$. The time of simulation for the algorithm 3.2 is smaller than that of linear programming in all cases, this shows the effectiveness of the method. For future improvements, multi-sources of energy can be integrated in discrete contract capacity optimization using the proposed algorithm. Linear programming can start from an initial point of $D(N_{E2})$ obtained from **Algorithm 1** to obtain a fast solution and exact solution, this is helpful for contract capacity optimization with a large number of periods.

3.3 Energy Demand Contracting with Ecofriendly Consideration

3.3.1 Problem Statement

In this approach, the penalty for excess peak power demand over the total contract capacity values is studied. This excess is multiplied by the penalty price P_p and customers can change their contract demand each period. Based on reference [5] we take the same assumption of disallowed decrease in contract capacities. The type of costs considered are fixed capacity costs, penalty cost, and ecofriendly cost. The ecofriendly cost gives a discount when using more renewable energy, and pays more when using more traditional energy. Discrete values of capacity contracts are considered and three types are included: traditional, solar, and wind. A linear programming model is proposed for this problem.

The indexes, parameters and variables of the proposed model are as follows:

Indexes	
$t(t = 1, ..., T)$	Period
$l(l = 1, ..., L)$	Contract
$k(l = 1, ..., K)$	Type of Energy
Variables	
X_t	The excess of the power demand over the total contract capacities at period t
$Wtr_{t,l}$	Binary variable = 1 if contract l of traditional power is taken at period t 0 otherwise
$Wren_{k,t,l}$	Binary variable = 1 if contract l of renewable energy k is taken at period t 0 otherwise
Parameters	
T	Total number of periods
L	Total number of contracts
K	Total number of renewable power contract capacity types
P_p	Penalty price in \$/KW
P_{eco}	Ecofriendly price in \$/KW
$Trad_l$	Power capacity of Traditional contract l in KW
$Ren_{k,l}$	Power capacity of Renewable contract l of type k in KW
$Ptrad_l$	Price of traditional contract l in \$
$Pren_{k,l}$	Price of contract l of renewable energy type k in \$
D_t	Power demand at period t in KW

3.3.2 Mathematical Model

The objective is to find a model that encourages the use of renewable energy sources. The objective function represents the TC, the total cost is composed of three parts. The first part is the total contract capacity cost, the penalty cost, and the ecofriendly factor. In this optimization model the optimal solution of the contract capacities of the traditional, solar, and wind energies, with a maximum percentage of renewable energy and a minimum cost to satisfy the power demand of the industry should be found.

The optimization model chooses between a set of discrete contract capacities of traditional, solar, and wind energies.

$$\sum_{t=1}^{T}\sum_{l=1}^{L}(Wtr_{t,l} * Ptrad_l + \sum_{k=1}^{K} Wren_{t,l,k} * Pren_{k,l}) \tag{3.21}$$

Part 3.21 of the objective function represents the sum of the prices of the different contracts chosen. The binary variables $Wtr_{t,l}$ and $Wren_{t,l,k}$ will take the value of 1 for choosing the optimal combination of traditional renewable energy contract capacities l respectively for each period t.

$$\sum_{t=1}^{T}\sum_{l=1}^{L} P_{eco} * (Wtr_{t,l} * Trad_l - \sum_{k=1}^{K} Wren_{k,t,l} * Ren_{k,l}) \tag{3.22}$$

Part 3.22 of the objective function represents the ecofriendly encouragement factor, the more the traditional energy used, the more the consumer pays. On the other hand, the more the consumer uses renewable energy sources, the greater the consumer's discount is.

$$P_p * X_t \tag{3.23}$$

Each contract has its own price, the objective is to find the optimal combination of the different types of contract capacities of the multisources of energy at a minimum cost to satisfy the given demand. The mathematical model is described as follows:

$$
\begin{aligned}
Minimize \quad & \sum_{t=1}^{T}\sum_{l=1}^{L}(Wtr_{t,l} * Ptrad_l) + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{k=1}^{K}(Wren_{t,l,k} * Pren_{l,k}) + \\
& P_{eco} * (\sum_{t=1}^{T}\sum_{l=1}^{L}(Wtr_{t,l} * Trad_l - \sum_{k=1}^{K} Wren_{t,l,k} * Ren_{l,k})) + \sum_{t=1}^{T} P_p * X_t
\end{aligned}
\tag{3.24}
$$

Subject to:

$$
Wtr_{t+1,l} \geq Wtr_{t,l} \qquad \forall\, t = 1,...,T-1, l = 1,...,L \tag{3.25}
$$

$$
\begin{gathered}
Wren_{t+1,l,k} \geq Wren_{t,l,k} \qquad \forall\, t = 1,...,T-1, l = 1,...,L, \\
k = 1,...,K
\end{gathered}
\tag{3.26}
$$

$$
\sum_{l=1}^{L} Wtr_{t,l} = 1 \qquad \forall\, t = 1,...,T \tag{3.27}
$$

$$
\sum_{l=1}^{L} Wren_{t,l,k} = 1 \qquad \forall\, t = 1,...,T, k = 1,...,K \tag{3.28}
$$

$$
\begin{gathered}
X_t + \sum_{l=1}^{L}(Wtr_{t,l} * Trad_l + \sum_{k=1}^{K} Wren_{t,l,k} * Ren_{k,l}) \geq D_t \\
\forall\, t = 1,...,T
\end{gathered}
\tag{3.29}
$$

$$
X_t \geq 0 \qquad \forall\, t = 1,...,T \tag{3.30}
$$

Part 3.23 of the objective function represents the penalty price charged on the excess demand X_t over the chosen contracts, when the difference is less than zero no penalty is charged. Regarding the penalty price P_p, in this case it is debatable whether to put random penalty price, the same price of the traditional energy, or the average price of the different types of energy contracts. X_t is illustrated in figure 3.3.

Constraints 3.25 and 3.26 are for choosing either the same contract capacity or a higher value

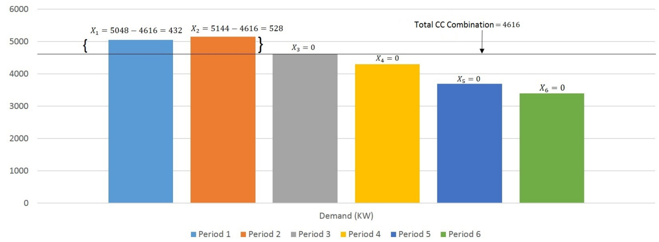


Figure 3.3 – Illustration of excess demand

in the next period, since decreases in contract capacities rarely happen. Customers may request a decrease in the contract capacity at no cost. However, if customers subsequently request an increase in contract capacity within two years, they have to pay a maintenance fee that will cost them more than staying with the original contract capacity. For simplicity, the situation of requesting a decrease in contract capacity is ignored, since such a situation almost never occurs for the majority of customers. Constraints 3.27 and 3.28 are for choosing one contract capacity of each type in each period t. The program chooses optimally one contract of each type.

There are different types of renewable energy sources such as solar, thermal, wind, hydroelectric, biomass, bio-fuels, etc. K is the total number of these renewable contract capacity types.

3.3.3 Numerical Experiments

There are discrete contract capacities and discrete prices, three different data demand scenarios are generated to test the model. For these scenarios random demands for 24 periods are generated. The probability of distribution follows a continuous uniform density function, and for each scenario different lower and upper bounds are assumed. The first set of data has a small lower bound and a small upper bound of $a = 0$ KW and $b = 26$ KW respectively. The second and third scenarios have medium and big bounds of $(a, b) = (14, 40)$ KW and $(a, b) = (28, 54)$ KW, respectively, as shown in table 3.7. In this case, two renewable energy contract capacities are considered (solar and wind powers $K = 2$).

For each set of data the problem is optimized to find the best combination of different types of contract capacities. The contract capacities of traditional, solar, and wind energies with their respective prices are shown in table 3.8, seven values and prices (L=7) for the different types of energy contract capacities are examined $L = 7$. The penalty price is assumed to be $P_p = 6.9\$/KW$. To study the influence of the ecofriendly price, it is necessary to change its value as shown in the graph of figures 3.4 to 3.9.

Period	Scenario1 (KW)	Scenario2 (KW)	Scenario3 (KW)
1	17,6	33.6	38.4
2	19,7	21.1	30
3	19,3	31.7	34.2
4	10,2	31	31.2
5	17	18.2	32.8
6	4,5	17.1	34.2
7	18,4	27	38.8
8	0,8	39	29.3
9	7,2	22.9	51.5
10	1,2	29.2	52.6
11	2,5	19.8	40.8
12	21,4	33.5	40.7
13	18,1	20.6	36.8
14	8,2	27.2	51.4
15	24,7	32.2	37.6
16	0,9	37.2	30.9
17	11,4	38.9	48.3
18	9,9	28.2	38.1
19	19,9	17.6	34.3
20	20,7	17.9	38.5
21	4,9	20.7	30.5
22	12,7	35.9	31.4
23	11,6	20.6	52.5
24	16,8	35.2	52.9

Table 3.7 – Set of demand scenarios in KW

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

Table 3.8 – Peak Power Contract Capacities of Traditional, Solar, and Wind with their respective costs

Comparison

The different scenarios are tested on CPLEX software for linear programming. The comparison is made between the rate of increase of the percentage of renewable energy contract capacities and the percentage of traditional energy contract capacities for the different values of the encouragement factor in the objective function. The percentage change of total cost is calculated as following:

$$\frac{TC_{P_{eco}} - TC_{P_{eco=0}}}{TC_{P_{eco=0}}} * 100$$

The problem is solved with the part of the objective function 3.22 presenting the ecofriendly part for the different scenarios of small, medium, and big demand shown in table 3.14.

As shown in the figures 3.4 and 3.7, for the first scenario of low demand, starting from $P_{eco} = 0$ the percentage of renewable energy is 28.57%, the traditional energy is 71.43%, and the total cost is 5658.79 $. As the value of P_{eco} increases from 0 to 2, the total cost increases continuously reaching 6058 $ with a percentage of change equal to 7.05 %, while the traditional energy and the renewable energy remain constant. At the value of $P_{eco} = 2$ the traditional energy and the renewable energy change step wise, they decrease to 40% and increase to 60 % respectively. As the P_{eco} changes from 2 to 6, the factors vary in the same sense with respect to the values, but for the percentages of the traditional energy and renewable energy increase to 45% and decrease to 55% respectively. While P_{eco} changes from 6 to 11, the total cost decreases continuously from

6328 \$ reaching 6016 \$ and the percentage change decreases from 11.82% to 6.31%. As for the traditional energy and the renewable energy, they remain constant, but at the value of $P_{eco} = 11$ the traditional energy and the renewable energy change step wise, they decrease to 30% and increase to 70 % respectively.

For scenarios 2 and 3, the same sense of variation occurs to the studied factors, as shown in figures 3.5, 3.6, 3.8, and 3.9. It is noticeable that there is a significant change of the total cost by 81.34 % for scenario 3 at the value of $P_{eco} = 40$.

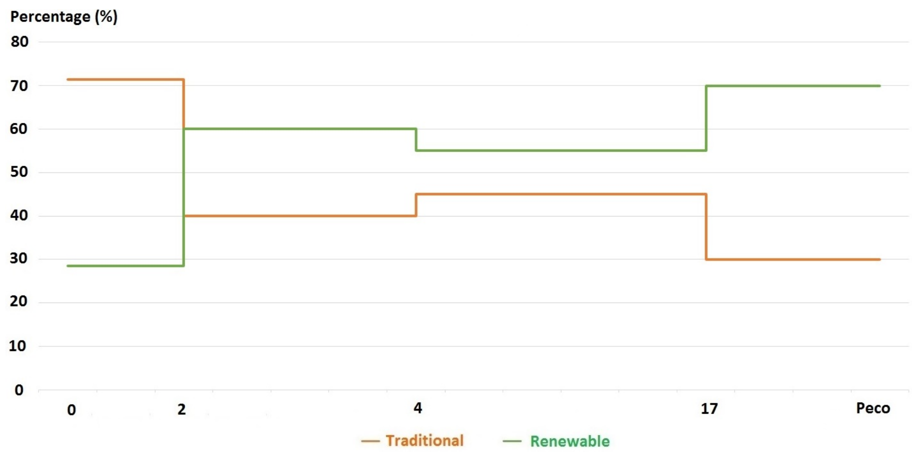


Figure 3.4 – Variation of the traditional and renewable energy contract capacity percentage(%) for demand scenario 1

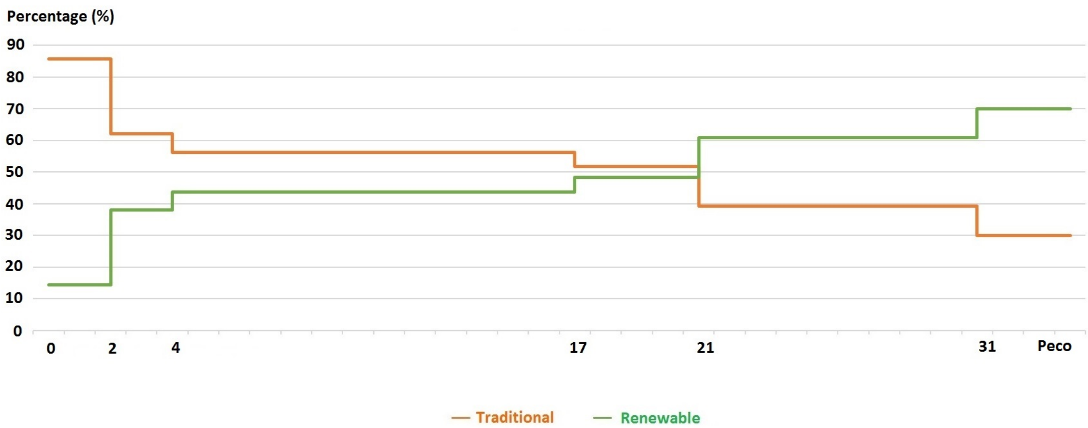


Figure 3.5 – Variation of the traditional and renewable energy contract capacity percentage(%) for demand scenario 2

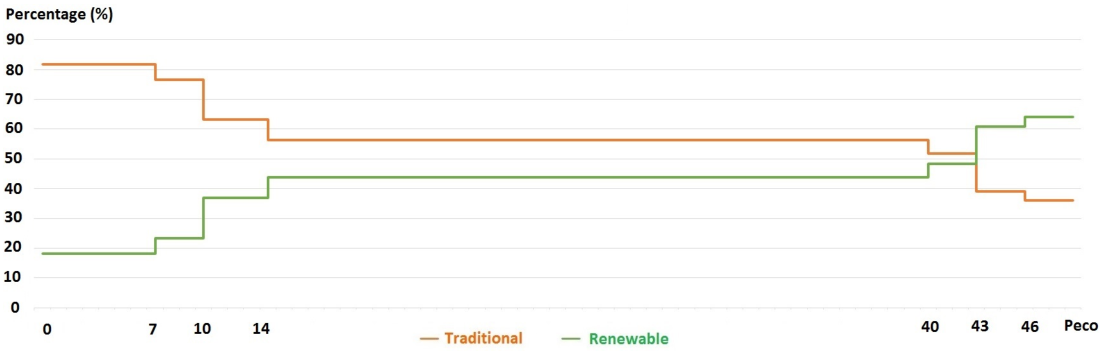


Figure 3.6 – Variation of the traditional and renewable energy contract capacity percentage(%) for demand scenario 3

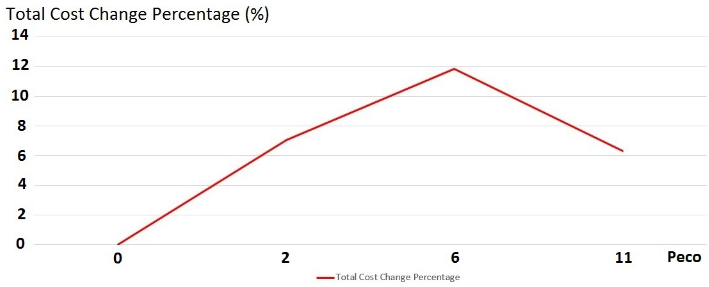


Figure 3.7 – Total cost change variation for demand scenario 1

Discussion

There is a tradeoff between the total cost and the percentage of renewable energy used. Introducing the ecofriendly factor into the objective function increases the usage of renewable energy in the capacity contracts, but it also increases the total cost. The higher the value of the demand scenarios the lower is the increase in the renewable energy percentage used. The excess demand changes independently whether the ecofriendly factor is introduced or not, but it is small in all cases. For very high values of the ecofriendly factor, the total cost decreases with the use of high amounts of renewable energy sources. For very high demand the total cost is very high when we have average values of ecofriendly factor. So when there are higher demands a large amount of money is needed to support the use of renewable energy or it is better to use traditional energy.

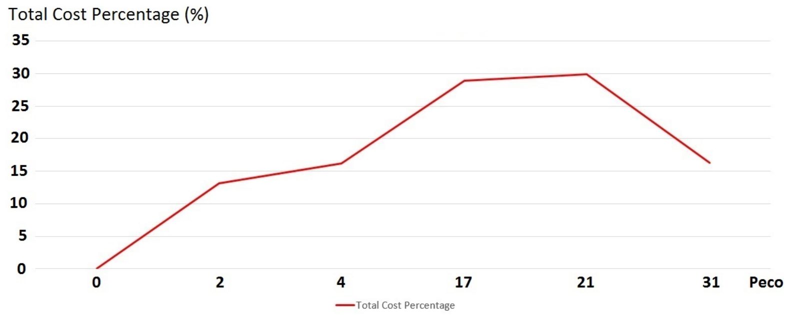


Figure 3.8 – Total cost change variation for demand scenario 2

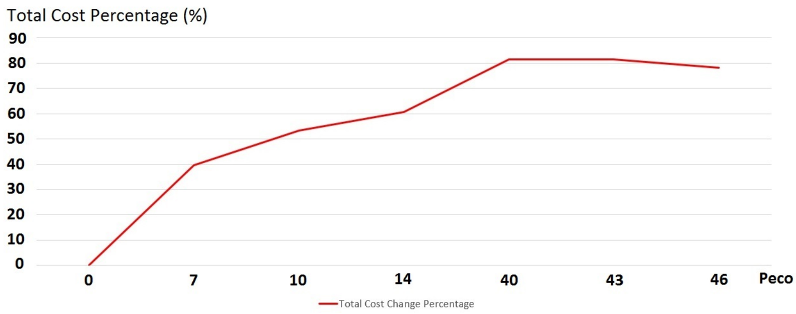


Figure 3.9 – Total cost change variation for demand scenario 3

3.4 Contract Capacity Optimization Under Demand Uncertainty

In this study, the penalty for excess peak power demand over the total contract capacity values is studied, this excess in power is multiplied by the penalty price P_p in (\$/ unit of power). Stochastic features are introduced to the demand, since the consumer's energy demand is a future expectation. The types of cost considered are contract capacity cost, penalty cost, and ecofriendly cost. Governments support the use of renewable energy for the consumers, and the consumers such as industries themselves support the use of renewable energy because they want to be seen as environmentally friendly for marketing purposes.

This support is represented by the ecofriendly cost P_{eco}, which gives a discount when using more renewable energy, and raises the price when using additional traditional energy. Continuous values of the contract capacities are considered, there are traditional contract capacities and different types of renewable energy contract capacities such as solar, thermal, wind, hydroelectric, biomass, bio-fuels, etc. K is the total number of these renewable energy contract capacity types. In the following calculation, a nonlinear model is proposed for this problem. The indexes, parameters and variables of the proposed model are listed in table 3.9.

Indexes	
$t(t = 1, ..., T)$	Index of periods
$k(l = 1, ..., K)$	Index of type of renewable energies
Variables	
X_t	Excess demand at period t
$Trad_t$	Power capacity of traditional contract at period t
$Ren_{k,t}$	Power capacity of renewable contract type k at period t
Parameters	
T	Total number of periods
L	Total number of contracts
K	Total number of renewable power contract capacity types
P_p	Penalty price in $/unit of power
P_{eco}	Ecofriendly price in $/unit of power
$Ptrad$	Price of traditional contract in $/unit of power
$Pren_k$	Price of renewable energy contract of type k in $/unit of power
$\tilde{D}_t$	Random peak power demand at period t
x	Possible value of $\tilde{D}_t$
$f_{\tilde{D}_t}(x)$	Probability density function of $\tilde{D}_t$

Table 3.9 – Indices, parameters, and variables of the nonlinear model.

3.4.1 Mathematical Model

The objective of this model is to find the optimal solution that encourages the use of renewable energy sources. The objective function represents the total cost, it is composed of three parts. The first is composed of the total contract capacities cost, the second is penalty cost, and the third is the ecofriendly encouragement cost. In this optimization model, the optimal solution of the total contract capacities of the different types should be found to satisfy the power demand of the consumer at minimum cost.

$$\sum_{t=1}^{T}(Ptrad * Trad_t + \sum_{k=1}^{K} Pren_k * Ren_{t,k}) \tag{3.31}$$

The first part of the objective function shown in equation (3.31) represents the sum of the prices of the different chosen contracts. The variables $Trad_t$ and $Ren_{t,k}$ will take the value of the optimal combination of traditional and renewable energy contract capacities to be charged at their respective prices $Ptrad$ and $Pren_k$ for each period t.

$$\sum_{t=1}^{T} P_{eco} * (Trad_t - \sum_{k=1}^{K} Ren_{k,t}) \tag{3.32}$$

Equation (3.32) of the second part of the objective function represents the ecofriendly encouragement factor, the more the traditional energy used, the more the consumer pays. On the other hand, the more the consumer uses renewable energy sources, the greater the consumer's discount is.

$$\sum_{t=1}^{T} \int_{Trad_t + \sum_{k=1}^{K} Ren_{k,t}}^{\infty} P_p * (x - Trad_t - \sum_{k=1}^{K} Ren_{t,k}) f_{\tilde{D}_t}(x) dx \tag{3.33}$$

The last part of the objective function in equation (3.33) represents the penalty cost of the total excess demand estimation for all periods. The penalty price P_p in (\$/unit of power) is multiplied by the estimated demand exceeding the total optimal contract capacity combination. The probability of excess demand exceeding the total contract capacities are illustrated in figure 3.10 considering normal distribution. When the demand is less than total contract capacity combination no penalty is charged. The integration starts from the chosen total contract capacities until the maximum value attainable by the demand of energy. The excess demand estimation is illustrated in figure 3.3 as X_t.

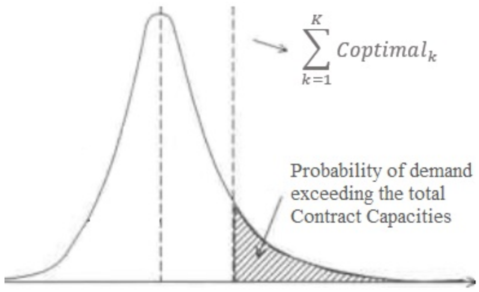


Figure 3.10 – Illustration of probability excess demand

The objective is to find the optimal combination of the different types of contract capacities of the multi-sources of energy with minimum costs that satisfy the given demand. The mathematical model is described as follows:

$$\begin{aligned} Minimize \quad & \sum_{t=1}^{T}(Ptrad * Trad_t + \sum_{k=1}^{K} Pren_k * Ren_{t,k}) + \sum_{t=1}^{T} P_{eco} * (Trad_t - \sum_{k=1}^{K} Ren_{k,t}) \\ & + \sum_{t=1}^{T} \int_{Trad_t + \sum_{k=1}^{K} Ren_{k,t}}^{\infty} P_p * (x - Trad_t - \sum_{k=1}^{K} Ren_{t,k}) f_{\tilde{D}_t}(x) dx \end{aligned} \tag{3.34}$$

Subject to:

$$Trad_t \geq Trad_{min} \qquad \forall\, t = 1, ..., T \tag{3.35}$$

$$Ren_{k,t} \geq Ren_{min} \qquad \forall\, t = 1, ..., T, k = 1, ..., K, \tag{3.36}$$

$$Trad_t \leq Trad_{max} \qquad \forall\, t = 1, ..., T \tag{3.37}$$

$$Ren_{k,t} \leq Ren_{max} \qquad \forall\, t = 1, ..., T, k = 1, ..., K, \tag{3.38}$$

Constraints 3.35 to 3.38 are to define the minimum and the maximum value of the traditional contract capacity and the different types of renewable energy contract capacities.

3.4.2 Optimization Approach

In this study, the interior point method for solving nonlinear constrained optimization problem is described and analyzed. The overview of the optimization approach is summarized by describing the model, proposing the barrier function with KKT conditions, using Newton's method and Interior point method.

Consider the following model:

$$\begin{aligned} Minimize \quad & f(x) \\ s.t. \quad & c(x) = 0 \\ & x \geq 0 \end{aligned} \tag{3.39}$$

Where $f : R^n \longrightarrow R, c : R^n \longrightarrow R^m$ are smooth functions having derivatives of all orders everywhere in its domain, n is the total number of variables and m is the total number of constraints. The interior point strategy associates a logarithmic barrier to the objective function and constraints to solve it and obtain the solution:

$$\begin{aligned} Minimize \quad & \varphi^{\mu}(x) = f(x) - \mu \sum_{i=1}^{n} \log x^{(i)} \\ s.t. \quad & c(x) = 0 \end{aligned} \tag{3.40}$$

The following nonlinear system is caused by the Karush–Kuhn–Tucker (KKT) conditions of the barrier problem (3.40):

$$\begin{pmatrix} \nabla f(x) + \nabla c(x)\lambda - z \\ -\mu X^{-1} e + z \\ c(x) \end{pmatrix} = 0 \tag{3.41}$$

$\lambda \in R^m$ and $0 \leq z \in R^n$ represent the Lagrangian multipliers and $X = diag(x1, x2, ..., xn)$. Multiplying the second row of 3.41 by X , the system obtained is:

$$\begin{pmatrix} \nabla f(x) + \nabla c(x)\lambda - z \\ Xz - \mu e \\ c(x) \end{pmatrix} = 0 \tag{3.42}$$

This may be viewed as a perturbed KKT system for the original problem (3.39). The optimality error for the barrier problem is defined based on (3.42) as:

$$E_{\mu}(x, \lambda, z) = \left\{ \frac{||\nabla f(x) + \nabla c(x)\lambda - z||}{S_d}, \frac{||Xz - \mu e||}{S_C}, ||C(x)|| \right\}$$

With scaling parameters $S_d, S_c \geq 1$ defined as

$$S_d = max\left\{ S_{max}, \tfrac{||\lambda||_1 + ||Z||_1}{m+n} \right\} / S_{max}, \quad S_c = max\left\{ S_{max}, \tfrac{||Z||_1}{n} \right\} / S_{max}$$

Where $S_{max} > 1$. Correspondingly, $E_0(x, \lambda, z)$ is used to measure the optimality error for the original problem 3.39.

Primal–dual interior point methods as mentioned by Qiu and Chen (2018) [124] apply Newton's method to the perturbed KKT system and modify step-size so that the inequality $(x, z) \geq 0$ is satisfied strictly. A primal–dual linear system is given as:

$$\begin{pmatrix} H & \nabla c(x) & -I \\ Z & 0 & X \\ \nabla c(x)^T & 0 & 0 \end{pmatrix} \begin{pmatrix} d_x \\ d_\lambda \\ d_z \end{pmatrix} = - \begin{pmatrix} \nabla f(x) + \nabla c(x)\lambda - z \\ Xz - \mu e \\ c(x) \end{pmatrix} \tag{3.43}$$

Where H is the Hessian of the Lagrangian function and $Z = diag(z1, ..., zn)$. Eliminating d_z by $d_z = -z + \mu X^{-1}e - X^{-1}Zd_x$, and defining $\lambda^+ = \lambda + d_\lambda$, we have the iteration

$$\begin{pmatrix} H + X^{-1}Z & \nabla c(x) \\ \nabla c(x)^T & 0 \end{pmatrix} \begin{pmatrix} d_x \\ \lambda^+ \end{pmatrix} = - \begin{pmatrix} \nabla \varphi^\mu(x) \\ c(x) \end{pmatrix} \tag{3.44}$$

It is easy to see that the step generated by this system coincides with the solution of the following primal-dual quadratic programming subproblem

$$\begin{aligned} min \quad & \nabla \varphi^\mu(x)^T d + \frac{1}{2} d^T \tilde{W} d \\ s.t. \quad & c(x) + \nabla c(x)^T d = 0 \end{aligned} \tag{3.45}$$

Where $\tilde{W} = H + X^{-1}Z$. Step computation of the algorithm is based on this model, $\lambda^+ = \lambda + d_\lambda$, $x^+ = x + d_x$, and $z^+ = z + d_z$. The parameter K_ϵ needs to be selected and the barrier parameter μ should be updated according to the procedure in literature [125, 126, 127] for fast convergence. The algorithm is expressed in table 3.10

This algorithm can solve linear and nonlinear convex optimization problems. In this study the objective function is the total cost and the constraints are the boundaries of the different types of contracts. To prove the convexity of the problem we should study the hessian matrix of the total cost since it is a multivariable function. The total cost is a function of Traditional and Renewable contract capacity variables. The determinant of the hessian matrix should be positive and the diagonal components of the matrix should be also positive. Based on Leibniz integral rule for partial derivation of the total cost $\nabla^2 TC$ is calculated and the followings are obtained:

Algorithm 2
initialization:
Choose the starting point (x_0, λ_0, z_0)
Select barrier parameter
$\mu_0 > 0$
parameter
$K_\epsilon > 0$
stop tolerance
$\epsilon > 0$
Set $j = 0$
While($E_0(x_j, \lambda_j, z_j) > \epsilon,$**)**
{
If **(**$E_{\mu_j}(x_{j+1}, \lambda_{j+1}, z_{j+1}) \leq K_\epsilon \mu_j$**)**
{
Calculate
$\lambda_{j+1} = \lambda_j + d\lambda$
$x_{j+1} = x_j + dx$
$z_{j+1} = z_j + dz$
}
}
Choose $\mu_{j+1} \in (0, \mu_j)$
Set $j = j + 1$

Table 3.10 – Interior Point Algorithm

$$\frac{\partial TC}{\partial Trad} = P_{trad} + P_{eco} - P_p * (1 - F_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) \tag{3.46}$$

$$\frac{\partial^2 TC}{\partial^2 Trad} = P_p * f_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) \tag{3.47}$$

$$\frac{\partial TC}{\partial Ren_k} = Pren_k - P_{eco} - P_p * (1 - F_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) \tag{3.48}$$

$$\frac{\partial^2 TC}{\partial^2 Ren_k} = P_p * f_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) \tag{3.49}$$

$$\frac{\partial^2 TC}{\partial Ren_k \partial Trad} = P_p * f_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) \tag{3.50}$$

$$\frac{\partial^2 TC}{\partial Ren_k \partial Ren_{k'}} = P_p * f_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) \tag{3.51}$$

The hessian matrix becomes as follows:

$$H = \begin{pmatrix} \frac{\partial^2 TC}{\partial^2 Trad} & \frac{\partial^2 TC}{\partial Ren_1 \partial Trad} & \cdots & \frac{\partial^2 TC}{\partial Ren_k \partial Trad} \\ \frac{\partial^2 TC}{\partial Trad \partial Ren_1} & \frac{\partial^2 TC}{\partial^2 Ren_1} & \cdots & \frac{\partial^2 TC}{\partial Ren_k \partial Ren_1} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial^2 TC}{\partial Trad \partial Ren_k} & \frac{\partial^2 TC}{\partial Ren_1 \partial Ren_k} & \cdots & \frac{\partial^2 TC}{\partial^2 Ren_k} \end{pmatrix} \tag{3.52}$$

The components of the hessian matrix are all the same, so the determinant is equal to 0, and the diagonal components (3.47) and (3.49) are strictly positive since $P_p > 0$ and $f_{\tilde{D}}(Trad + \sum_{k=1}^{K} Ren_k)) > 0$ then the problem is convex.

3.4.3 Numerical Results

Experiment design

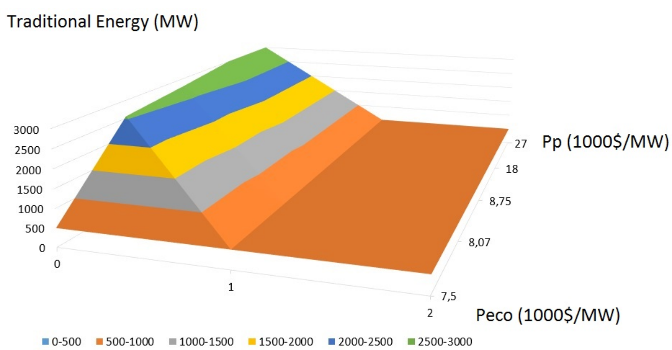


Figure 3.11 – Variation of the optimal traditional energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for Grand-Est region

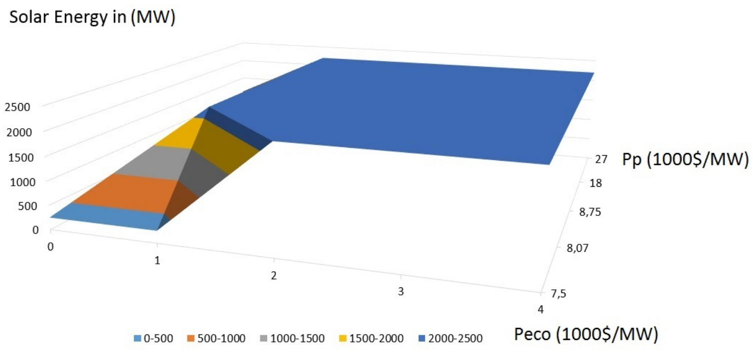


Figure 3.12 – Variation of the optimal solar energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for Grand-Est region

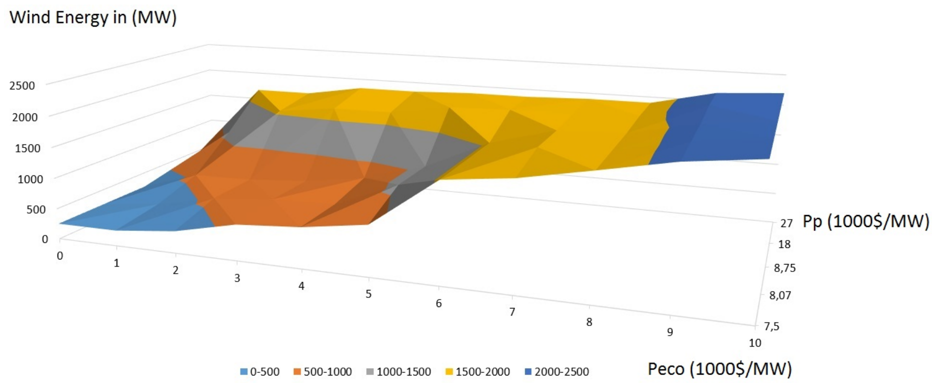


Figure 3.13 – Variation of the optimal wind energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for Grand-Est region

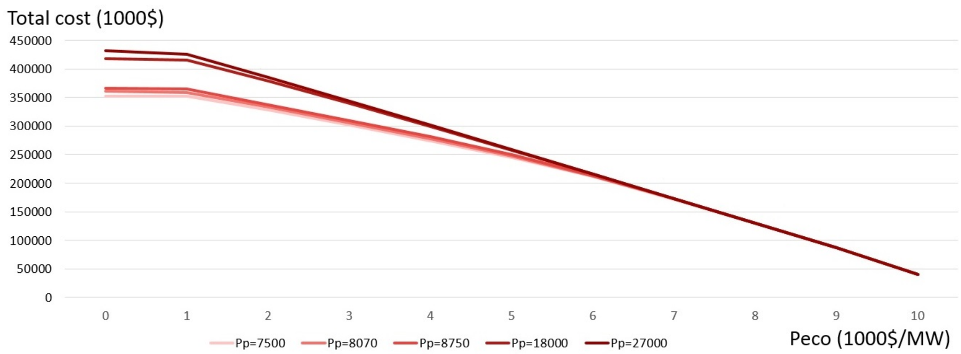


Figure 3.14 – Variation of the total cost with respect to P_{eco} and P_p in ($/MW) for the case of uncertainty for Grand-Est region

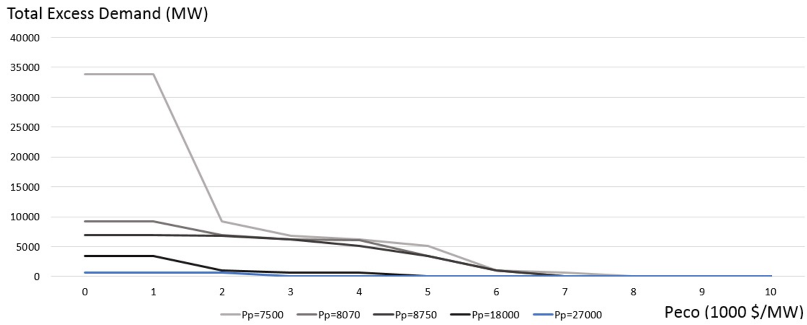


Figure 3.15 – Variation of the total excess demand with respect to P_{eco} and P_p in case of uncertainty for Grand-Est region

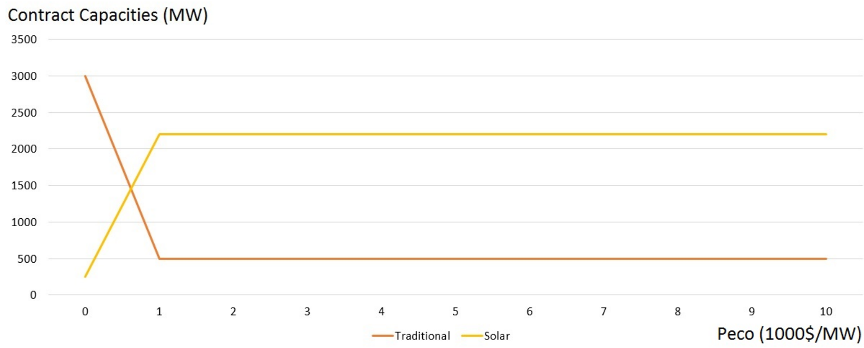


Figure 3.16 – Variation of the optimal traditional and solar energy contract capacity with respect to P_{eco} and for all σ values for Grand-Est region

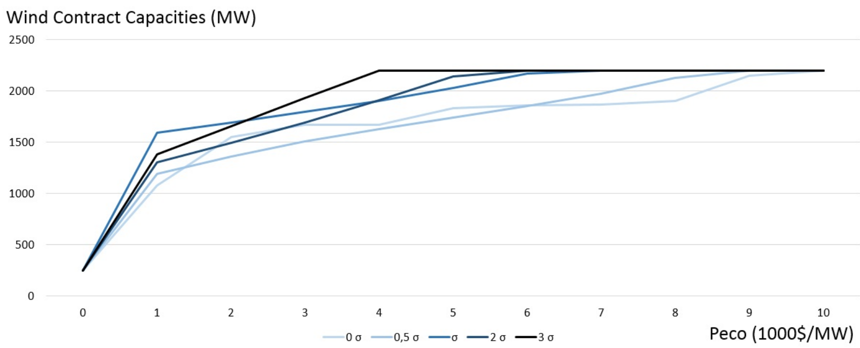


Figure 3.17 – Variation of the optimal wind energy contract capacity with respect to P_{eco} and σ for Grand-Est region

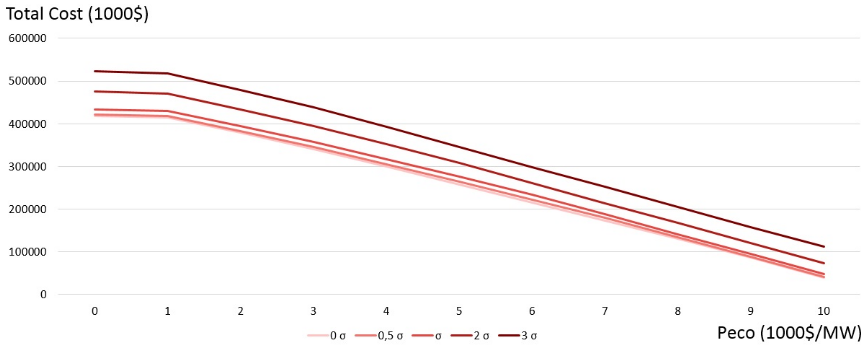


Figure 3.18 – Variation of the total cost with respect to P_{eco} and σ for Grand-Est region

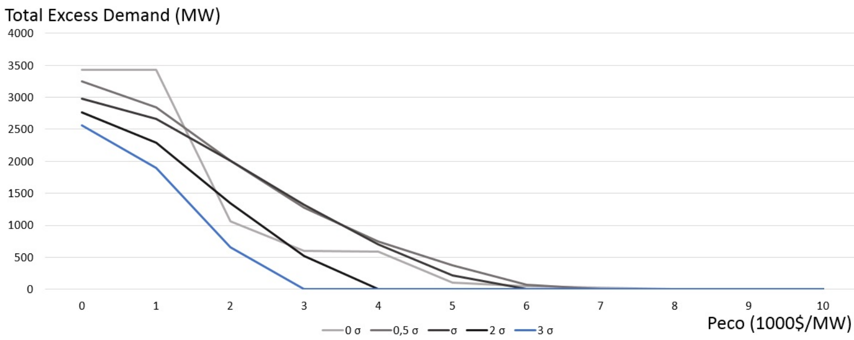


Figure 3.19 – Variation of the total excess Demand with respect to P_{eco} and σ for Grand-Est region

The model and numerical experiments design are inspired from the work of Feng et al. [121]. In their work, the authors tried to find the optimal contract under uncertainty in case of one period demand and one kind of energy source for different probability distributions. The proposed model is tested based on real data representing the monthly energy consumption of Grand-Est Region (in France) [123] for 2018. The data may follow any type of distribution, here the data are assumed to follow a normal distribution density function:

$$\tilde{D}_t \sim \mathcal{N}(\mu,\, \sigma^2)\,.$$

The normal distribution density function is used because its parameters directly represent the mean and the variance, by changing the variance the effect of uncertainty will be tested directly. The mean value of each period of the demands are shown in table 3.14. In this study the contracts are assumed to be constant in all periods. So the following constraints are added:

$$Trad_t = Trad_{t+1} \qquad \forall\, t = 1, ..., T-1 \tag{3.53}$$

$$Ren_{k,t+1} = Ren_{k,t} \qquad \forall\, t = 1, ..., T-1, k = 1, ..., K, \tag{3.54}$$

In this case, two renewable energy contract capacities are considered (solar and wind energies $K = 2$). For the set of data the problem is optimized to find the best combination of different types of contract capacities. The effect of the penalty price on the optimal solution in one type of traditional energy is well known, but in the presence of multi types of renewable energy contracts, it needs to be discovered. To study the influence of the ecofriendly price, penalty price and uncertainty it is necessary to change the values of P_{eco}, P_p, and σ as shown in the graph of figures 3.11 to 3.19. The values of the parameters of the model are assumed as shown in table 3.11. These parameters are presented by the prices in \$/MW, the boundaries are the maximum and minimum values in MW achievable via the different types of contract capacities of traditional, solar and wind energy types.

Contract Capacity Type	Traditional	Solar	Wind
Price in (\$/MW)	7640	8500	9000
Minimum value in (MW)	500	250	250
Maximum value in (MW)	3000	2200	2200

Table 3.11 – Assumed contract capacity prices and bounds

When studying the effect of ecofriendly price P_{eco} and penalty price P_p a certainty case of $\sigma = 0$ is considered and the values of P_p are shown and described in table 3.18. The penalty prices studied are the intermediate values of the traditional and renewable contract capacity prices, with 2 and 3 times the wind contract capacity price, these values are applied as shown in figures 3.11 to 3.13.

Penalty price	P_{p1}	P_{p2}	P_{p3}	P_{p4}	P_{p5}
Price value in ($\$/MW$)	7500	8070	8750	18000	30000
In comparison with the contract capacity price	$P_{p1} < P_{Trad}$	$P_{Trad} < P_{p2} < P_{Sol}$	$P_{Sol} < P_{p3} < P_{Wind}$	$P_{p4} > P_{Wind}$	$P_{p5} > P_{p4}$
Calculation with respect to contract capacity price	-	$\frac{P_{Trad}+P_{Sol}}{2}$	$\frac{P_{Sol}+P_{Wind}}{2}$	$2 * P_{Wind}$	$3 * P_{Wind}$

Table 3.12 – Assumed penalty prices value and description

Meanwhile, when analyzing the effect of ecofriendly price P_{eco} and uncertainty, the value of the penalty price remains constant at P_p=18000 \$/MW equal two times of the highest price of contract capacities P_{Wind}=9000\$/MW. The energy demands are stochastic and they follow a normal distribution of average value presented in table 3.14, the standard deviation is changed to study the effect of uncertainty on the optimal solution. The values of table 3.14 are the energy demand in MW of the Grand-Est region of France for the year 2018. The value of the standard deviation of the data in table 3.14 is calculated to be $\sigma = \sigma_3 = 596.9702$, so the values of the standard deviations representing the uncertainty studied are multiple of σ_3 as shown in table 3.13, the different values of σ are tested as shown in figures 3.16 to 3.19.

Standard deviation	σ_1	σ_2	σ_3	σ_4	σ_5
Value	0	298.4851	596.9702	1193.9404	1790.9106
In comparison with respect to σ_3	0 σ_3	0.5 σ_3	1 σ_3	2 σ_3	3 σ_3

Table 3.13 – Standard deviation values and description (own results)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Demand (MW)	4533	4601	4570	3494	3343	3272	3361	3053	3259	3779	4253	4370

Table 3.14 – Energy demand of Grand-Est for 2018 [123]

Discussion

The problem is solved on MATLAB software using an interior point algorithm. The initial point for the algorithm used is equal to the lower bound $Trad_{min}$ = 500 MW, Sol_{min} = 250 MW, and $Wind_{min}$ = 250 MW. The comparison is made between the rate of change of the different types of contract capacities. The effect of P_{eco} and P_p on the optimal solution is studied by changing their values.

Figures 3.11 to 3.15 present the variation of the optimal contract capacity types, total cost, and total excess demand with respect to P_{eco} and P_p in case of certainty $\sigma = 0$, the effect of P_p on the optimal solution is examined. For the values of penalty price less than the traditional energy price, which is the minimum between the different types of contract capacities, the optimal solution is the minimum value of the contract capacities $Trad_{min} = 500$ MW, $Sol_{min} = 250$ MW, and $Wind_{min} = 250$ MW. That is because the penalty is low, so even if the demand exceeds the contract capacities significantly the price of the penalty would be cheaper than that of the contract capacities.

As P_p increases above the minimum price of the contract capacities, in this case the traditional energy, the optimal solution of the contract capacities increases, starting with the traditional energy from 500 MW until 3000 MW as shown in figure 3.11, but when P_{eco} increases the optimal traditional energy drops to a minimum 500 MW, since P_{eco} discourages the use of traditional energy by increasing the cost.

As P_p increases the optimal solar contract capacity rises from 250 MW to 1120 MW for $P_{eco} = 0$. As the P_{eco} rises the optimal solar contract capacity goes up from 250MW to 2200MW in one step, since it is cheaper than the wind contract price as presented in figure 3.12. The wind energy contract capacity increases continuously with P_{eco} since it is the most expensive contract capacity, as can be seen in figure 3.13. As P_p augments the optimal wind energy contract capacity augments more rapidly with P_{eco} reaching saturation $Wind_{max} = 2200$ MW, to compensate the high value of the penalty price imposed on the excess demand.

When P_{eco} increases the total cost decreases in general as shown in figure 3.14. As P_p increases the total cost increases and have the same sense of variation as function of P_{eco}, but for $P_{eco} \geq 6000\$/\mathrm{MW}$ the total cost is approximately the same for all values of P_p, that is because the optimal renewable energy contracts become higher because of their cheap price and cover all the expected demand, so there will be no excess demand to pay penalty over and the total cost represent the price of the contracts.

The total excess demand decreases as P_{eco} increases for all values of P_p as presented in figure 3.15. The P_{eco} increases the optimal renewable contract capacities that cover the estimated demand. As P_p rises the total excess demand reduces, the optimal contract capacity combination increase to minimize the excess demand so the user is not charged a high penalty.

Figures 3.16 and 3.17 represent the variation of the different types of contract capacities with respect to P_{eco} and σ considering constant penalty price of $P_p = 18000$ \$/MW, two times the wind contract capacity price. Concerning the study of the influence of uncertainty, when P_{eco} rises the optimal traditional energy contract drops from a maximum 3000 MW to a minimum 500 MW, while the optimal solar energy contract increases from 250 MW to 2200 MW since it is cheaper. The values and the variation of the traditional and solar contract capacities with respect to P_{eco} are the same for all values of σ as viewed in figure 3.16.

In figure 3.17, as the uncertainty increases the increase of wind energy with P_{eco} reaches saturation at $Wind_{max}$ =2200 MW much faster, since the increase of uncertainty gives a higher value of the expected demand, so higher values of contract capacities are needed to compensate the high expected demand.

Based on figure 3.18, the total costs obviously decrease with P_{eco} since it is encouraging the use of renewable energy after all, but as the value of σ rises the total costs increase, that is due to the high value of the expected excess demand, so the user is charged for the high contract capacity to compensate for the excess demand or the penalty for the expected demand exceeding the total contract capacities.

The total excess demand (TED) is calculated by the difference of the average demand exceeding the total capacity as follows: $TED = \sum_{t=1}^{T} max(0, E[\tilde{D}] - Trad - \sum_{k=1}^{K} Ren_k)$. The total excess demand decreases with P_{eco} since there is enough contract capacity when encouraging the use of renewable energy to cover the expected demand. With the variation of uncertainty the total excess demand decreases more rapidly by reason of the increase of the expected demand with uncertainty, so the total optimal contract capacities increase so that the user isn't charged a high penalty as seen in figure 3.19.

Factor	$Trad$	Sol	$Wind$	Total contracts	Total cost	Total excess demand
P_{eco}	-	+	+	+	-	-
P_p	+	+	+	+	+	-
σ	+	+	+	+	+	-

Table 3.15 – Variation of contract capacities, total cost, and total excess demand with respect to P_{eco}, P_p, and σ (own results)

The table 3.15 shows the variation of total contract capacities, total cost, and total excess demand with respect to P_{eco}, P_p, and σ, the positive sign shows increase, and the negative sign signify decrease. Penalty price is subjected to government laws, and the uncertainty depends on the user consumption, so these results show that in the case of a high penalty, low values of P_{eco} are needed to increase the use of renewable energy. When there is enough data on the demand of energy, high amounts of support of P_{eco} are needed to encourage renewable energy use because the expected demand will be low.

Different Experiments

To test if the model gives the same results, two different data cases are examined. For the first case, the mean value of each period of demands is generated randomly, the random generation follows a continuous uniform density function. The lower bound and upper bound are $(a, b) = (28, 54)$ KW, as shown in table 3.16 there are 24 periods in total $T = 24$, the data is taken from the literature [116] and [128].

Period	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Demand Average (KW)	38.4	30	34.2	31.2	32.8	34.2	38.8	29.3	51.5	52.6	40.8	40.7	36.8	51.4	37.6	30.9	48.3	38.1	34.3	38.5	30.5	31.4	52.5	52.9

Table 3.16 – Set of demand scenarios in KW

The prices, the maximum and minimum values of the different types of contract capacities are shown in table 3.17.

Contract Capacity Type	Traditional	Solar	Wind
Price in ($/KW)	7.64	8.5	9
Minimum value in (KW)	6	3	3
Maximum value in (KW)	36	26	26

Table 3.17 – Contract capacity prices and bounds for random generated demand

When studying the effect of P_{eco} and P_p a certainty case of $\sigma = 0$ is considered and the values of P_p are shown and described in table 3.18, these values are applied as shown in figures 3.11 to 3.13.

Penalty price	P_{p1}	P_{p2}	P_{p3}	P_{p4}	P_{p5}
Price value in ($/KW$)	7.5	8	8.75	18	30
In comparison with the contract capacity price	$P_{p1} < P_{Trad}$	$P_{Trad} < P_{p2} < P_{Sol}$	$P_{Sol} < P_{p3} < P_{Wind}$	$P_{p4} > P_{Wind}$	$P_{p5} > P_{p4}$

Table 3.18 – Penalty prices value and description

Meanwhile, when analysing the effect of P_{eco} and uncertainty, the value of the penalty price remains constant at $P_p = 15.28$ $\$/KW$. The demand of energy is stochastic and follows a normal distribution of average value presented in table 3.16 and the standard deviation is changed to study the effect of uncertainty on the optimal solution. The value of the standard deviation of the data in table 3.16 is $\sigma = \sigma_3 = 8.1009$ so the values studied are shown in table 3.19. The different values of σ are tested as shown in figures 3.16 to 3.19.

Standard deviation	σ_1	σ_2	σ_3	σ_4	σ_5
Value	0	4.0504	8.1009	16.2018	24.3027
In comparison with respect to σ_3	$0 * \sigma_3$	$0.5 * \sigma_3$	$= 1 * \sigma_3$	$2 * \sigma_3$	$3 * \sigma_3$

Table 3.19 – Standard deviation value and description

The results presented in figures from 3.20 to 3.26 show that the effect of P_p, the uncertainty, and $Peco$ on the different parameters is the same in case of more periods and low values of demand.

For the second case, there are 12 sets of demand $T = 12$ representing the consumption of

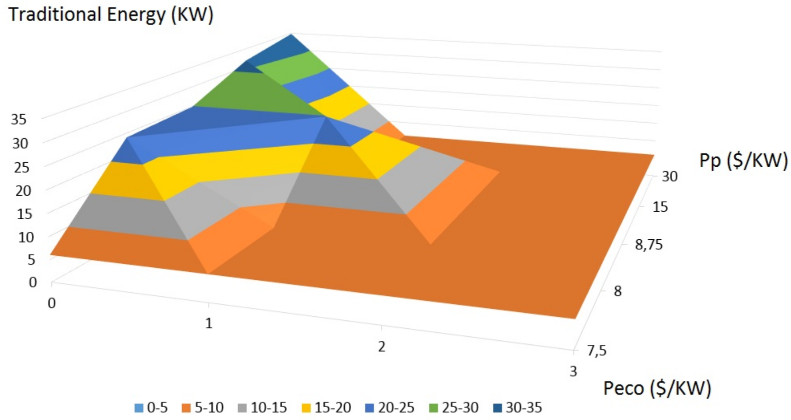


Figure 3.20 – Variation of the traditional energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for random demand

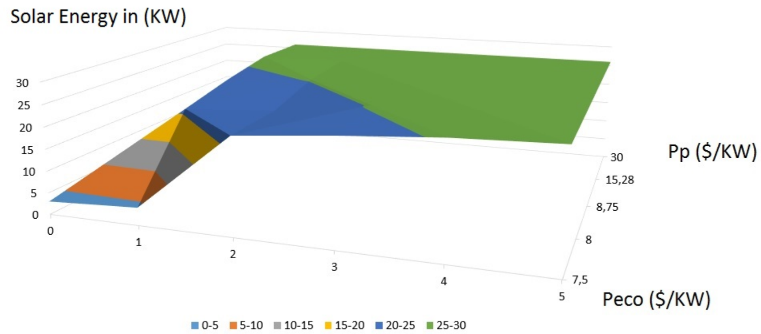


Figure 3.21 – Variation of the solar energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for random demand

energy of each month in France for 2018 [123], each one follows a normal distribution density function. The data has very high values in MW. The contract capacities prices and the penalty prices are the same as that of the case of Grand-Est shown in tables 3.17 and 3.18. But for the uncertainties σ values are different. The value of the standard deviation of the data in table 3.20 is $\sigma = \sigma_3 = 7281.8$ so the values studied are shown in table 3.19. The different values of σ are tested as shown in figures 3.23 to 3.26.

The results presented in figures from 3.27 to 3.33 show that the effect of P_p, the uncertainty, and $Peco$ on the different parameters is the same in case of high values of demand.

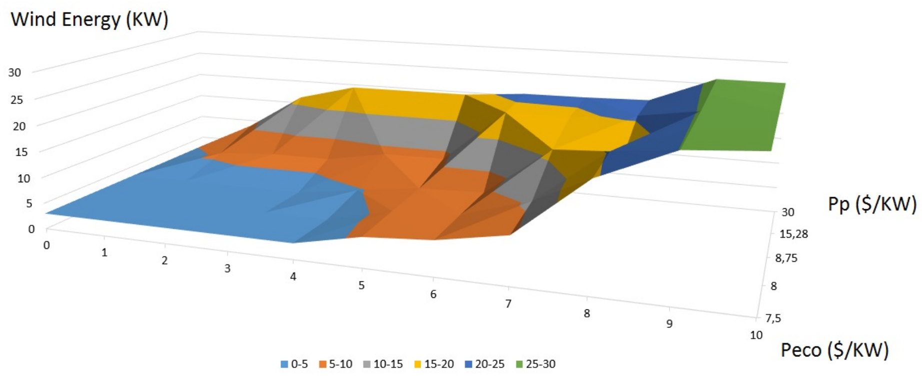


Figure 3.22 – Variation of the wind energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for random demand

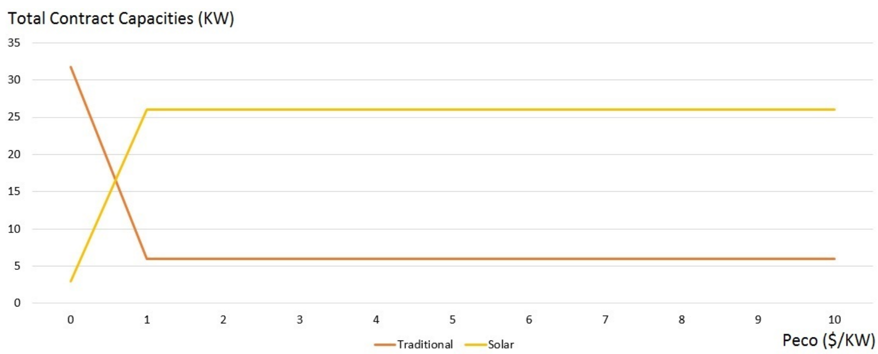


Figure 3.23 – Variation of the traditional and solar energy contract capacity with respect to P_{eco} and σ for random demand

Month	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
Demand (MW)	48807	50236	48484	36236	33949	32553	34514	32384	32620	37052	43814	47562

Table 3.20 – Energy demand of France for 2018 in MW [123]

The prices and the maximum and minimum values of the different types of contract capacities are shown in table 3.21.

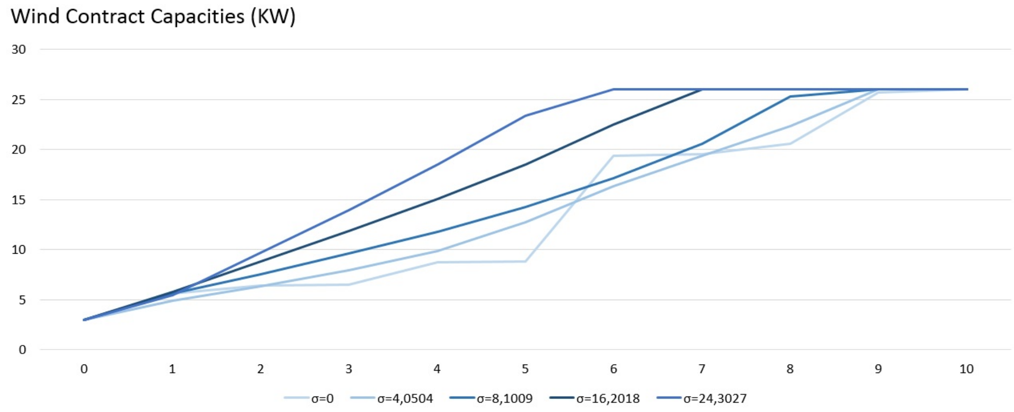


Figure 3.24 – Variation of the wind energy contract capacity with respect to P_{eco} and σ for random demand

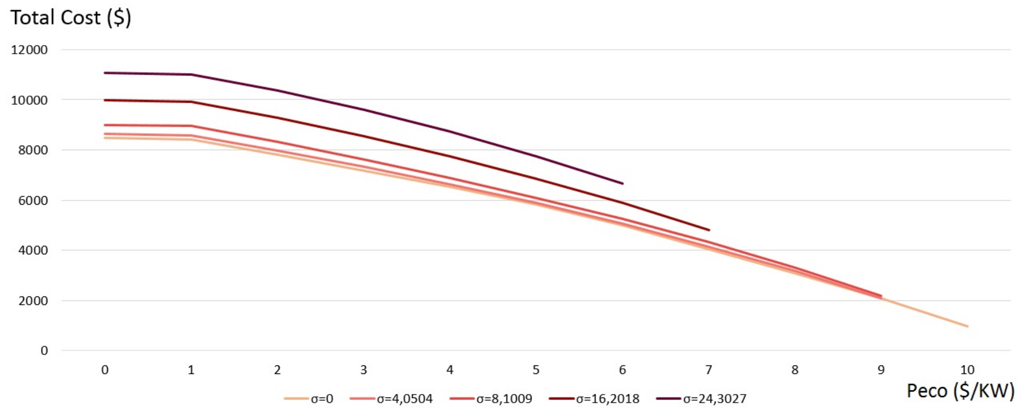
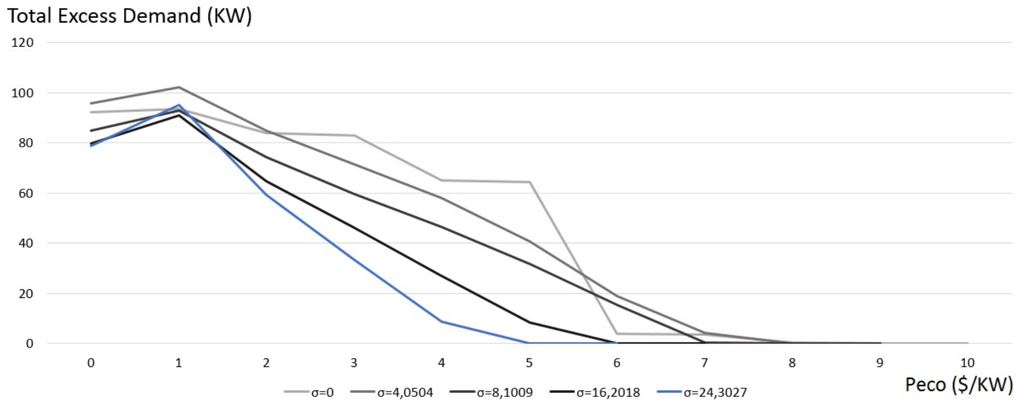


Figure 3.25 – Variation of the Total Cost with respect to P_{eco} and σ for random demand

Contract Capacity Type	Traditional	Solar	Wind
Price in ($/MW)	7640	8500	9000
Minimum value in (MW)	5000	2500	2500
Maximum value in (MW)	30000	25000	25000

Table 3.21 – Contract capacity prices and bounds for energy demand of France



demand.jpg

Figure 3.26 – Variation of the Total Excess Demand with respect to P_{eco} and σ for random demand

Standard deviation	σ_1	σ_2	σ_3	σ_4	σ_5
Value	0	3640.5	7281.8	14563.6	21845.4
In comparison with respect to σ_3	$0 * \sigma_3$	$0.5 * \sigma_3$	$= 1 * \sigma_3$	$2 * \sigma_3$	$3 * \sigma_3$

Table 3.22 – Standard deviation value and description for energy demand of France

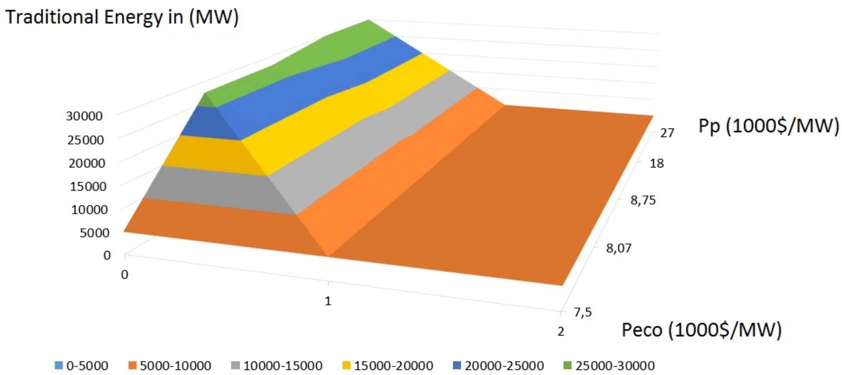


Figure 3.27 – Variation of the traditional energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for France

The information presented in figures 3.11 to 3.33 illustrate the influence of the different factors on the optimal solution such as the ecofriendly factor, the penalty price, and uncertainty in demand. The ecofriendly factor increases the renewable energy contract capacities and decreases the traditional energy contract capacities and the total cost. And this combination of contract

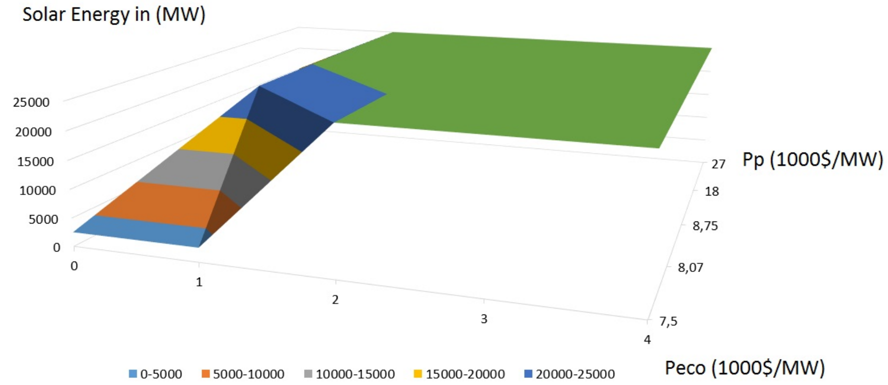


Figure 3.28 – Variation of the solar energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for France

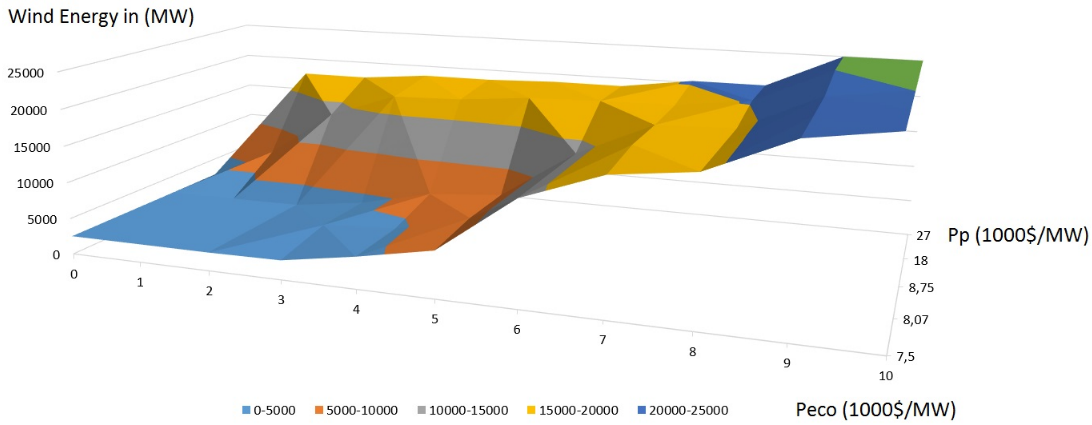


Figure 3.29 – Variation of the wind energy contract capacity with respect to P_{eco} and P_p in case of uncertainty for France

capacity increase in total with the increase of the penalty price and the uncertainty.

The threshold of the increase of a type of contract is when the penalty price matches the price of this type of contract capacity. As the penalty price increase over that of the contract with the maximum price the optimal value of the contract capacity combination increases so that the customers are not charged high penalties. Uncertainty increases the expected excess demand so the optimal contract capacity combination increases for minimum cost with less excess demand, and the total cost increases with uncertainty.

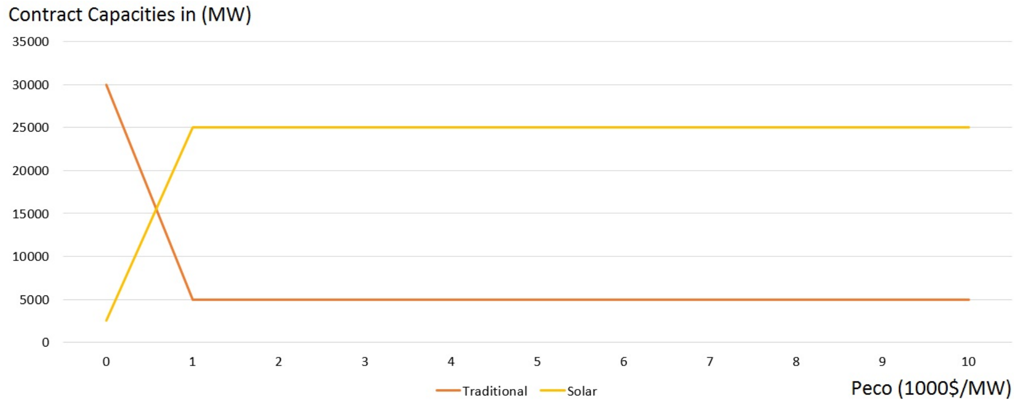


Figure 3.30 – Variation of the traditional and solar energy contract capacity with respect to P_{eco} and σ for France

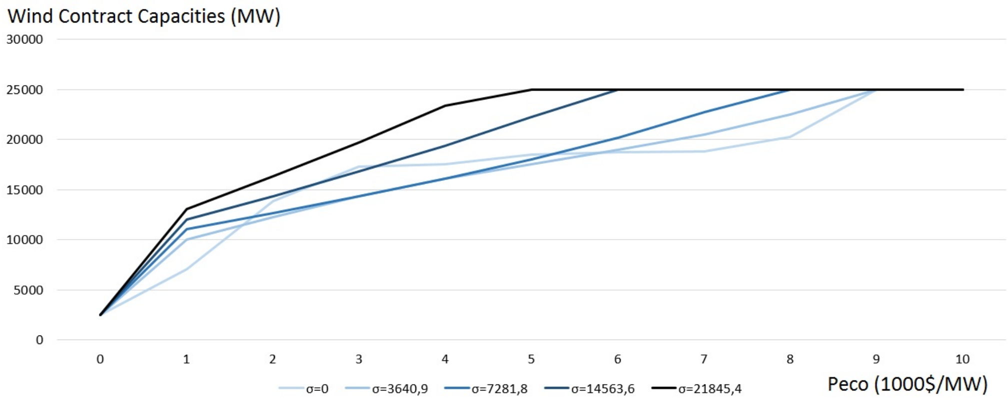


Figure 3.31 – Variation of the wind energy contract capacity with respect to P_{eco} and σ for France

Different distributions

The problem is tested on two other different probability density functions, gamma and log-normal distributions, to illustrate the generality of the model and compare the results between them. The parameters of the gamma and log-normal distributions are calibrated so that the same mean and standard deviations are tested. The results of the optimal wind contract capacity, total cost, and the total excess demand are presented in figures 3.34, 3.35, and 3.38 respectively, in the case of gamma distribution, for the case of the log-normal distribution they are presented in figures 3.34, 3.35, and 3.38.

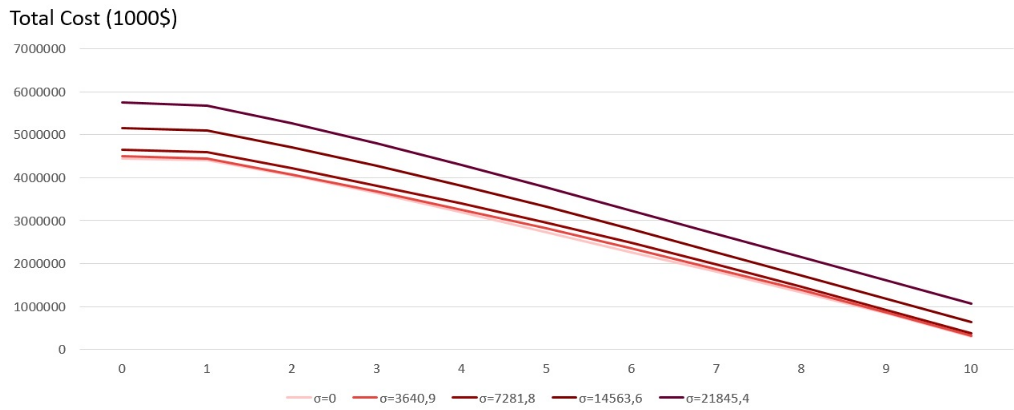


Figure 3.32 – Variation of the Total Cost with respect to P_{eco} and σ for France

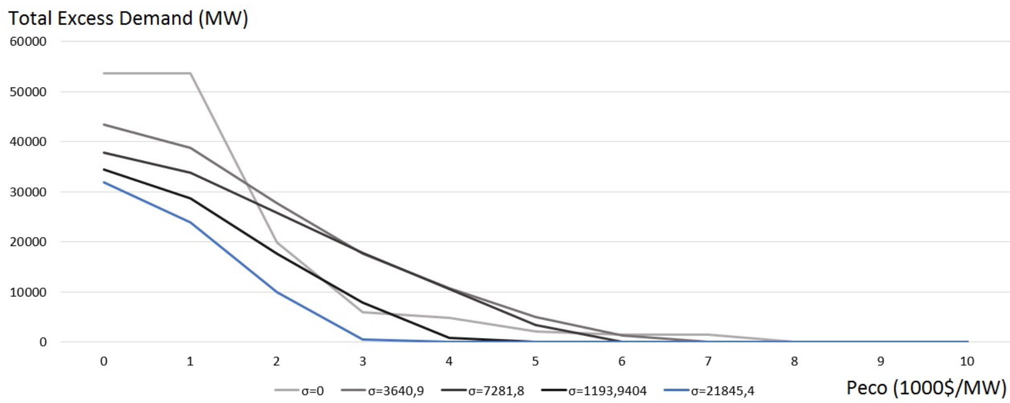


Figure 3.33 – Variation of the Total Excess Demand with respect to P_{eco} and σ for France

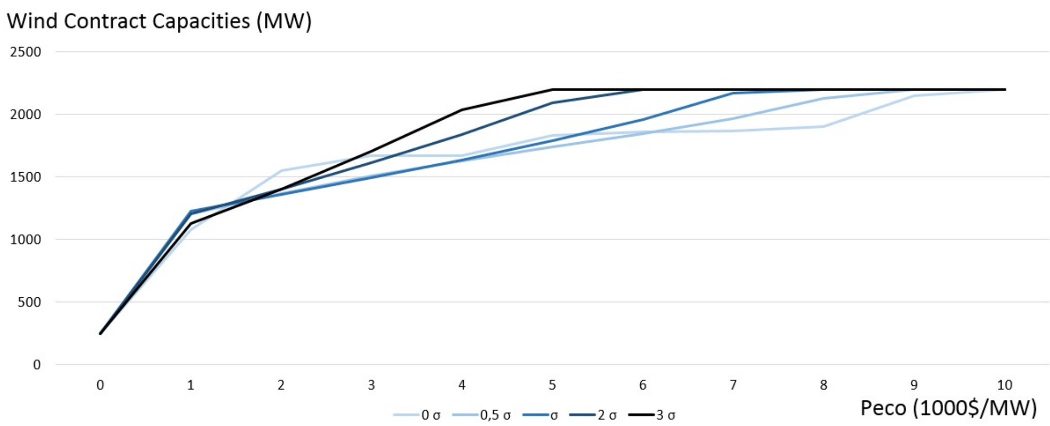


Figure 3.34 – Variation of the optimal wind energy contract capacity with respect to P_{eco} and σ in the case of gamma distribution (own results)

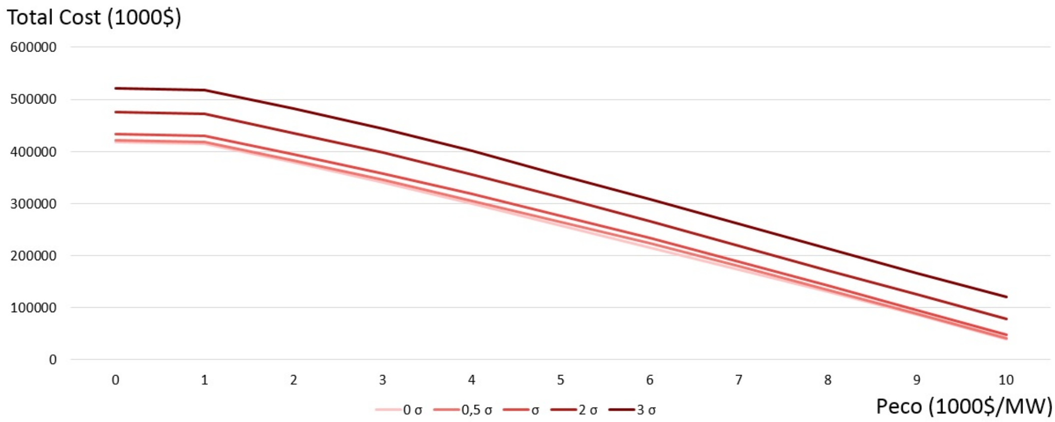


Figure 3.35 – Variation of the optimal total cost with respect to P_{eco} and σ in the case of gamma distribution (own results)

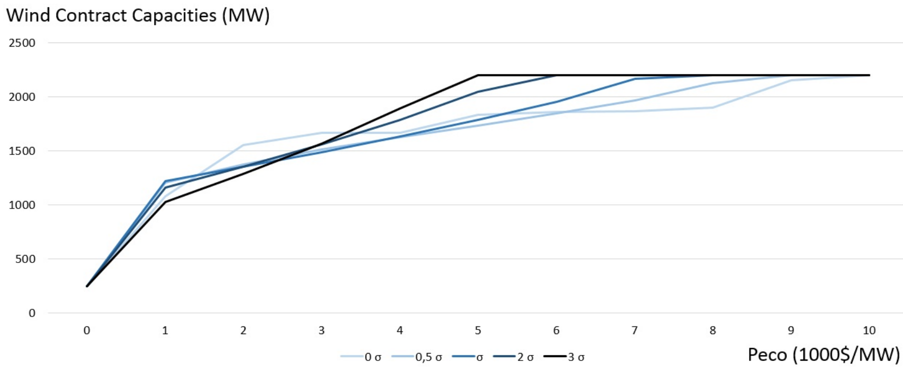


Figure 3.36 – Variation of the optimal wind energy contract capacity with respect to P_{eco} and σ in the case of log-normal distribution (own results)

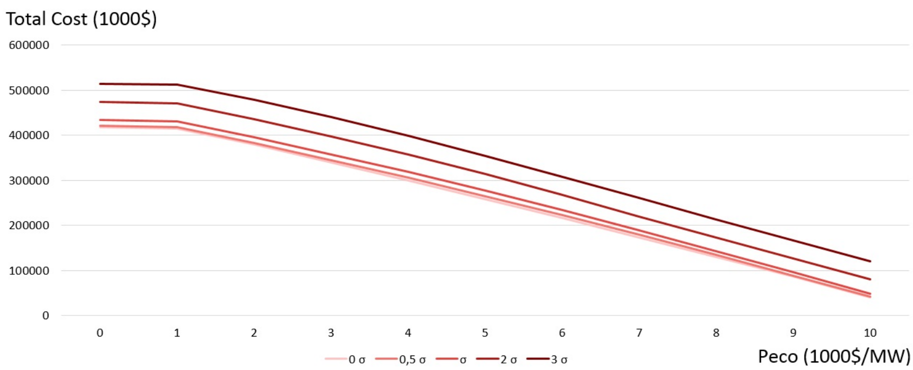


Figure 3.37 – Variation of the optimal total cost with respect to P_{eco} and σ in the case of log-normal distribution (own results)

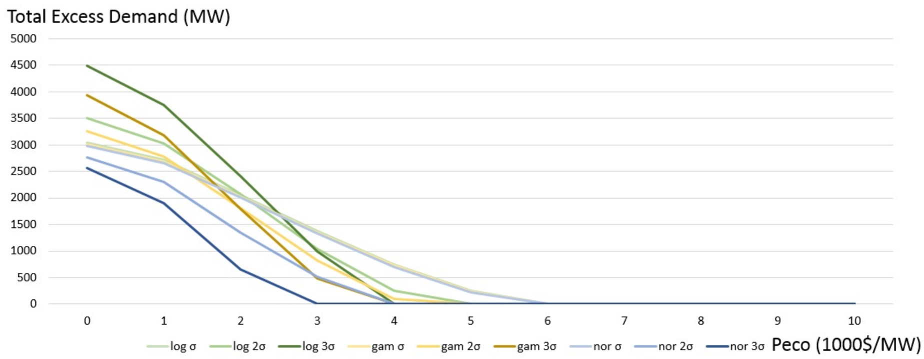


Figure 3.38 – Variation of the optimal total excess demand with respect to P_{eco} and σ for the different distributions (own results)

The optimal traditional and solar wind contract capacities in the case of gamma and log-normal distributions are approximately the same as in figure 3.16. The results in general obtained from the gamma and log-normal distribution are approximately the same as the results obtained from the normal distribution. But in the case of total excess demand, for σ it is the same for the different distributions, but for 2σ and 3σ the log-normal has the highest total excess demand, second is the gamma distribution, then the normal distribution as presented in figure 3.38. So the influence of uncertainty on the expected excess demand changes from one type of probability distribution to other depending on its form, but it is not significant enough to change the optimal contract capacities and the total cost.

In the case with gamma distribution, the function is $f_{\tilde{D}_t}(x|a,b) = \frac{1}{b^a\Gamma(a)}x^{a-1}e^{\frac{-x}{b}}$. So the objective function becomes:

$$\sum_{t=1}^{T}(Ptrad * Trad_t + \sum_{k=1}^{K} Pren_k * Ren_{t,k}) + \sum_{t=1}^{T} P_{eco} * (Trad_t - \sum_{k=1}^{K} Ren_{k,t}) +$$

$$\sum_{t=1}^{T}\int_{Trad_t+\sum_{k=1}^{K} Ren_{k,t}}^{\infty} P_p * (x - Trad_t - \sum_{k=1}^{K} Ren_{t,k})\frac{1}{b^a\Gamma(a)}x^{a-1}e^{\frac{-x}{b}}dx$$

The parameters a and b of the gamma distribution function have been calibrated to have the same mean μ of the demand presented in the table 3.14 and standard deviations studied in table 3.13.

$$a = (\frac{\mu}{\sigma})^2$$

$$b = \frac{\sigma^2}{\mu}$$

With log-normal distribution the function is $f_{\tilde{D}_t}(x|a,b) = \frac{1}{xb\sqrt{2\pi}} e^{\frac{-(\log x - a)^2}{2b^2}}$. So the objective function becomes:

$$\sum_{t=1}^{T}(Ptrad * Trad_t + \sum_{k=1}^{K} Pren_k * Ren_{t,k}) + \sum_{t=1}^{T} P_{eco} * (Trad_t - \sum_{k=1}^{K} Ren_{k,t}) +$$

$$\sum_{t=1}^{T} \int_{Trad_t + \sum_{k=1}^{K} Ren_{k,t}}^{\infty} P_p * (x - Trad_t - \sum_{k=1}^{K} Ren_{t,k}) \frac{1}{xb\sqrt{2\pi}} e^{\frac{-(\log x - a)^2}{2b^2}} dx$$

The parameters a and b of the log-normal distribution function have been calibrated in the manner to have the same mean μ of the demand presented in the table 3.14 and standard deviations studied in table 3.13.

$$a = \log(\frac{\mu^2}{\sqrt{\sigma^2 + \mu^2}})$$

$$b = \sqrt{\log(\frac{\sigma^2}{\mu^2 + 1})}$$

3.5 Summary and Conclusion

In this chapter, energy contract capacity optimization has been dealt with in cases of certainty and uncertainty. For the certainty case, to introduce the multistage penalty in the model of Ferdavini et al. [1] a new algorithm is proposed. The algorithm is tested and compared to linear programming and is applicable to discrete contract capacity problems. In the case of multi-sources of energy, we have formulated a model to optimize the total cost by choosing the best contract capacities combination. The multi-sources contract capacities are composed mainly of traditional and one or more types of renewable energy. An ecofriendly factor is introduced to increase the percentage of renewable energy used in the contract capacities combination. This model is applied on randomly generated data, the results show that there is an improvement in the use of renewable energy after introducing the ecofriendly factor, but for very high demand a large value of subsidy is needed for the use of renewable energy.

Dealing with uncertainty in energy demand, in this chapter a model is formulated to optimize the total cost for choosing the best contract capacity combination of multi-sources of energy. To solve the model we used an interior point algorithm taking into account the cost of the different types of contract capacities, the penalty price of the excess demand, ecofriendly encouragement for the use of renewable energy, and uncertainty in the energy demand. The multi-sources of energy contract capacities are composed mainly of traditional and one or more types of renewable energy, such as solar and wind in the case studied.

Uncertainty is studied for the demand of energy and changing the ecofriendly factor at the same time, the stochastic features are examined in different probability distributions such as normal, gamma, and log-normal probability distributions. As the uncertainty increases the expected excess demand gets higher and eventually the contract capacities of all types including renewable energy sources and total cost rise, while the total excess demand reduce. Therefore, when there is a lack of data concerning the demand of energy or high uncertainty for any reason, a small ecofriendly assistant is enough to have more renewable energy in the contract capacity combination, but with high total cost and vice versa.

4 Conclusion and Perspectives

Outline of the current chapter

4.1 Conclusion

The increase in pollution and global warming is due to the world's reliance on traditional energy depending on the fossil fuels. Moreover, societies and governments are seeking independence from conventional energy due to its political influence and its inability to meet increasing energy demands. Governments are distributing sustainable green energy sources in their regions to meet rising energy demands and reduce pollution. The use of renewable energy nowadays is becoming so common that there are contract capacities for each type of energy. Therefore, increasing the use of renewable energy in the different regions of a country and facilitating the different aspects, such as contract capacities with encouraging their use, not only contributes to achieving sustainability targets, but also contributes to reducing the overall carbon emission levels significantly.

The main objective of this thesis is to propose a general optimization model with probability assignment for the distribution of locations of multi-sources of energy in a country. Moreover, this thesis provides optimization models and solutions for deterministic and stochastic cases of multi-sources of energy contract capacity optimization, to integrate the availability of the energy sources with the stochastic peak power demands, this problem is combined with the contract capacity selection problem under the inspiration of real life practices.

Chapter 1 reviews the literature of the energy problems and methods to solve them, the review confirms that the problems handled in this thesis have not been studied before in the literature. In Section 1.4, the location optimization of facilities and renewable energy power plants are reviewed and it is shown that no general optimization method of multi-source of energy applicable for any country has been proposed yet. Moreover, in Section 1.5.7 contract capacity optimization problems and methods to solve them are also reviewed, showing that the inclusion of multi-sources of energy in contracting has seldom been considered. So the application of multi-sources of energy contracting strategy with uncertainty consideration is the other novelty of our study.

Chapter 2 provides a general goal programming model for governments to locate various types of power plants. Therefore, any country can decide the optimal mix for a variable numbers of powers plant types in a variable number of locations given the statistical data concerning the different criteria. Control flow is used to solve the goal programming problem several times by changing the weight of the different types of criteria, the probability of distribution of each type of power plant to each place by adding these solutions and dividing them by the total. Since the parameters of the alternatives vary with respect to the place, the proposed method can solve variable instances close to actual conditions. The constraints are relaxed to find more feasible solutions with better objective functions. A better method of Data Envelopment Analysis based on the criteria is proposed to extract more efficient solutions.

Finally in chapter 3, we introduced a new algorithm which is an improvement of the model, ferdavini et al. [1] proposed, to solve multistage penalty problems for contract capacities, the method is applicable in case of certainty and discrete contracts, the approach is compared with linear programming to show the effectiveness of the method. We introduced multisources of energy in contract capacity selection, the optimal solution is obtained handling different factors such as the contract price, penalty price, and ecofriendly encouragement using linear programming. The method is applied for deterministic cases with discrete contracts on small, medium and high values of random generated demands, the results indicate that a high value of ecofriendly factor is needed to use more renewable contract capacity in case of high demand.

Considering stochastic features in energy demand, we proposed a nonlinear optimization method to optimize the selection of multi-sources of energy contract capacity considering uncertainty in energy demand. An interior point algorithm is used and the problem is proved to be convex so that the obtained solution is global. Different instances and various probability distribution functions for the demand are tested, we study the influence of uncertainty on the optimal solution by calibrating the parameters of the probability distribution function, so that the effect of penalty price and the ecofriendly factor on the optimal solution are examined. The penalty price increases with the optimal contract capacity starting from the contract with minimum price, until the penalty price exceeds the contract with the maximum price, the total contract capacities in combination increase, that is to ensure that the demand does not exceed the total contract capacities and large penalty costs are incurred. However, in the presence of the ecofriendly factor as it increases with the increase of the penalty price, the renewable energy contract capacities increases and traditional energy contract capacity decreases in the overall combination of contract capacities, this combination increases in total with the penalty price. So in situations having high penalty prices it is not necessary to have large ecofriendly support to encourage the use of renewable energy in the contract capacity. But for low penalty price a significant subsidy is needed to ensure more renewable energy in the contract capacity combination. As the uncertainty increases the expected excess demand gets higher and eventually the contract capacities of all types, including renewable energy sources, and total cost rises and excess demand declines. Therefore, in the absence of data concerning the demand of energy or high uncertainty for any reason, a small ecofriendly assistant is enough to have more renewable energy in the contract capacity combination, although with high total cost and vice versa. The total cost increases with the penalty price and uncertainty which are uncontrollable parameters, but the ecofriendly factor is controllable and the total cost decreases with respect to it, this study shows what value of ecofriendly factor to choose in the presence of low or high values of penalty price and uncertainty.

Renewable energy generation is subject to uncertainty because it depends on the weather such as solar and wind energy. To handle uncertainty in energy generation and demand a robust optimization is needed for the producer to decide the maximum contract capacity of each type of energy, so in Appendix 1, a two-stage mixed-integer linear robust program with recourse model is proposed.

Overall, this thesis contributes in the fields of location optimization of multi-sources of energy and in the optimization of multi-sources of energy contract capacity.

4.2 Perspectives

In this thesis, several doors are opened for future research projects based on the studies we have conducted. We would like to suggest perspectives that researchers could develop in future studies.

There are several future research directions in the location optimization of multi-sources of energy power plants that can be developed from this thesis. The model can be extended by considering the presence of fuzzy data. Fuzzy data is an excellent way to model uncertainties which can be an important aspect of any problem that deals with sustainability criteria. Another direction for future research would be to test the model based on real case applications considering different countries and geographical areas. More criteria can be introduced to make the model adaptable and applicable in those countries having special aspects. Different location optimization methods can be applied to the multi-sources of energy and a comparison between them in the objective value, the criteria, and time of simulation would be interesting.

The multi-sources of energy contract capacities offered to the consumers by the energy producer should be determined based on the availability of renewable energy. Renewable energies, especially solar and wind energies, depend on the weather, the climate changes each year due to the green house effect and pollution in general, so that makes the energy produced by renewable energy sources difficult to determine. Keeping in mind that the energy demand is also uncertain since it depends on the user, it is the responsibility of the energy producer to find a set of contracts of different types of renewable energy for the consumer to choose. After the consumer chooses a certain contract the producer is obliged to satisfy the demand of energy as written in the contract. This means there is a need for a storage battery system to compensate the lack of energy in the worst case scenario, when the demand for energy exceeds the sources of energy. This system charges the extra energy from the sources to supply the demand of energy when required. To determine this set of contracts different parameters should be examined such as, the available renewable energy produced, the demand for energy, and traditional energy.

Traditional energy availability can be considered certain, the objective is to find the maximum contract capacities of the renewable energies under uncertainty with the minimum necessary traditional contract capacity which will also satisfy the demand under uncertainty. In some cases the renewable energy sources capacity contracts are discrete. This leads to the use of a robust optimization method for decision making under uncertainty modeled as a two-stage mixed-integer linear program with recourse inspired by Billionnet et al. [2, 19]. The preliminary model developed in the case of this perspective is introduced in Appendix 1. The work is presented as an appendix because we are still working on this problem.

Part II

French version

French Summary

Outline of the current chapter

Introduction

Les sources d'énergie se composent d'énergies renouvelables et de sources d'énergie traditionnelles. Les centrales d'électricté provenant de sources renouvelables sont combinées dans le réseau électrique avec centrales d'énergie non renouvelable. Multi-sources d'énergie composées également de stockage d'énergie et de la demande d'énergie telle que les industries et les résidences.

Les sources d'énergie non renouvelables contribuent au réchauffement de la planète en raison des émissions de CO2 dues à la combustion de combustibles fossiles. Elles augmentent également les différents aspects de la pollution en général. De plus, les sources d'énergie traditionnelles sont limitées et ne permettront pas de suivre l'augmentation des besoins énergétiques à l'avenir. Pour ces raisons,et dans un but d'indépendance par rapport au pétrole, la société et les gouvernements exigent, le recours aux sources d'énergies renouvelables au lieu des sources d'énergies traditionnelles, car celles ci sont écologiques et éternelles.

L'Union européenne (UE) définit des objectifs énergétiques pour 2020, 2030 et 2050 afin de surveiller systématiquement la consommation énergétique des pays de l'UE. La directive de l'UE sur les énergies renouvelables fixe un objectif contraignant à 20% de consommation finale d'énergie provenant de sources renouvelables d'ici 2020.

Cet objectif peut être atteint décarbonant le système énergétique, en utilisant des objectifs de réduction des émissions plutôt qu'en poursuivant les politiques actuelles, en augmentant la part des énergies renouvelables et en utilisant l'énergie plus efficacement, en investissant tôt dans les infrastructures et en les remplaçant immédiatement par des alternatives à faible émission de CO2.

Pour atteindre un scénario de développement durable et atteindre les objectifs mentionnés, il convient d'optimiser les multiples sources d'énergie d'une manière efficace et compatible avec chaque pays. Pour réduire les émissions de carbone de n'importe quel pays, il est important d'investir dans des centrales d'énergie renouvelable dans les différentes régions du pays qui répondent à la demande en énergie et à d'autres critères économiques et sociaux.

De nos jours, les contrats d'électricité se distinguent en différents types tels que les contrats traditionnels et les contrats d'énergie renouvelable, donc le choix de valeurs élevées des contrats d'énergie renouvelable aidera à atteindre les objectifs européens. Les industries sont également intéressées à améliorer leur réputation en utilisant les énergies renouvelables pour leur production.

Pour une répartition optimale des centrales d'énergies renouvelables sur le territoire, des questions importantes se posent, auxquelles il est nécessaire de répondre.

- Sur la base de quels critères les centrales d'énergie renouvelable devraient-elles être réparties ?
- Comment peut-on attribuer plusieurs centrales électriques à une même région géographique ?

Pour adapter la production et la demande en énergie, celles-ci doivent être équilibrées en adaptant les tarifs proposés au client. Ces tarifs doivent donc suivre des stratégies de tarification et des options de production d'énergie. En signant un contrat, l'accord de fourniture d'énergie est préservé, ce qui signifie que les consommateurs d'énergie sont confrontés au questionmement

"Quelle est l'option de capacité qui peut satisfaire mes besoins en énergie ?" Pour utiliser les sources d'énergies renouvelables sur le marché, celles-ci sont ajoutées à la politique de choix de la capacité contractuelle. Il faut également garder à l'esprit que la demande d'énergie est incertaine puisqu'elle dépend de l'utilisateur. En conséquence, on peut reformuler la question par "Comment modéliser et choisir les capacités des contrats avec multiples sources d'énergie d'une manière respectueuse de l'environnement en prenant en compte l'incertitude ?". D'autre part, la production d'énergie renouvelable comme l'énergie solaire ou l'éolien dépend des conditions météorologiques, ce qui lui confère un aspect stochastique. "Comment le producteur d'énergie peut-il décider de la capacité contractuelle maximale de plusieurs sources d'énergie en cas d'incertitude dans la production et la demande d'énergie ?"

Dans cette étude, nous avons modélisé quatre problèmes d'optimisation et proposé des réponses aux questions pour augmenter l'utilisation des énergies renouvelables :

1. Localisation de centrales de production de plusieurs type d'energie. L'approche utilisée est Goal Programming et l'analyse de contrôle de flux.
   Sur la base de quels critères les centrales d'énergie renouvelable devraient-elles être distribuées ? Comment les multi-sources de centrales électriques d'énergie peuvent-elles être assignées à un seul endroit ?

2. Optimisation de la production d'énergie pour la demande d'énergie en tenant compte des critères du développement durable.
   Quelle est l'option de capacité qui peut satisfaire les besoins en énergie ?

3. La capacité contractuelle d'énergie multi-sources avec un facteur écologique et des incertitudes.
   Comment modéliser et choisir des capacités de contrats énergétiques multi-sources de manière durable en tenant compte de l'incertitude ?

4. 2-Stage robust mixed integer linear programming pour l'incertitude dans la production et la demande d'énergie.
   Comment le producteur d'énergie peut-il décider de la capacité contractuelle maximale de plusieurs sources d'énergie en cas d'incertitude dans la production et la demande d'énergie ?

Le primier objectif de la thèse est de faire un modèle général pour attribuer de manière optimale les différents types de centrales électriques aux différents endroits ayant dans différents critères. Ce modèle devrait avoir quelques améliorations et peut donner l'énergie de profil de chaque endroit en trouvant la probabilité d'attribuer une centrale électrique à cet endroit. Le deuxième objectif est de concevoir un modèle pour les consommateurs d'énergie afin d'optimiser les capacités contractuelles des multiples sources énergétiques d'une manière respectueuse de l'environnement pour encourager l'utilisation des énergies renouvelables. Le troisième objectif est de trouver la combinaison optimale de contrats énergétiques multisources dans un contexte d'incertitude de la demande énergétique. Le quatrième objectif est de trouver la capacité contractuelle maximale de plusieurs sources d'énergie, compte tenu de l'incertitude sur la production et la demande d'énergie.

Etat de l'art

Pour les multiples sources d'énergie, Ramon et Cristobal [3] ont développé un modèle de programmation par objectif, basé sur un réseau de multi-sources multi-sink, afin de localiser cinq types différents de centrales d'énergie renouvelable pour la production d'électricité dans cinq endroits situés dans la région autonome de Cantabrie, dans le Nord de l'Espagne. L'objectif est de répartir de manière optimale les centrales d'énergie renouvelable sur chaque site, en minimisant les déviations totales par rapport aux critères environnementaux, sociaux, et économiques. Les objectifs représentent différents critères tels que l'électricité produite, le coût d'investissement, la quantité d'émissions de CO_2 évitées, l'acceptation sociale, le nombre d'emplois offerts, la distance entre les centrales et l'exploitation avec coût de maintenance.

Le modèle a été amélioré en étendant la région faisable en introduisant des valeurs cibles comme mentionné par Chang [108], où il peut éviter la sous-estimation de la valeur cible et obtenir des résultats qui sont plus proches des conditions réelles. Il a introduit une normalisation pour éviter le biais involontaire vers les objectifs. Par rapport au modèle de Ramón et Cristóbal, les critères sont meilleurs dans le modèle de Chang après avoir élargi la région faisable et normalisé l'objectif. On constate qu'en ajoutant des pondérations à la fonction objectif, la méthode proposée peut facilement servir d'aide à la décision pour déterminer la meilleure solution ou la plus appropriée pour à des problèmes d'outil objectifs multiples. Afin d'élargir le champ d'application faisable, chaque objectif du problème multi-objectifs peut être divisé en plusieurs niveaux d'aspiration pour mieux répondre aux exigences de gestion. Ces contraintes peuvent également être facilement ajoutées dans le modèle de programmation d'objectifs à Multi Choice Goal Programming– multi-source multi-sink (MCGP-MSMS) normalisé pour refléter les situations du monde réel. Le modèle de programmation MCGP-MSMS normalisé fournit un moyen pratique et robuste de choisir l'emplacement optimal pour les centrales d'énergie renouvelable. Une fonction d'utilité linéaire est donnée comme fonction d'appartenance, pour représenter le taux d'acceptation sociale de l'installation des éoliennes. Il s'agit de trouver un équilibre entre les exigences des résidents et les considérations liées à la construction. Cela montre que le modèle proposé offre des caractéristiques réalisables pour permettre à un décideur de faire face à de multiples problèmes de prise de décision.

Le réseau grec de production d'énergie renouvelable dans 52 préfectures a été conçu de manière optimale par Zografidou et al. [4], ils appliquent un modèle de programmation à objectifs (GP) pondérés 0-1, en tenant compte des critères environnementaux, sociaux et économiques. Ils ont utilisé l'approche DEA (Data Envelopment Analysis), en utilisant le front de pareto, afin de filtrer les meilleures structures de réseau possible. Pour évaluer la probabilité de localiser les différentes centrales électriques aux différents endroits, le problème est résolu avec des poids différents par étapes incrémentales dans la gamme de chaque poids pour les critères économiques, sociaux et environnementaux. Une probabilité d'affectation de chaque centrale électrique à chaque endroit est formulée sur la carte de la Grèce. Différentes permutations des poids des critères environnementaux, sociaux et économiques des déviations de la fonction objective sont proposées. Finalement, pour calculer les différentes probabilités, la moyenne des différentes solutions de ces combinaisons de poids est calculée.

Pour les clients du secteur de l'électricité, l'adaptation des exigences du système aux offres du marché de l'énergie est l'une des décisions importantes qui doivent être prises [116]. De nombreux clients industriels optent pour une demande contractuelle maximale. Une telle facture d'électricité se compose de coût d'énergie et de coût de capacité. Le coût d'énergie est basée sur les kilowattheures, tandis que le coût de capacité est basé sur la demande maximale consommée au cours de chaque période le temps d'utilisation (TOU). Si le pic de demande ne dépasse pas la capacité contractuelle, le coût habituel de capacité contractuelle est prélevé. En revanche, si le pic de demande dépasse la capacité contractuelle, une pénalité de deux à trois fois le tarif de base est appliquée [5]. Par conséquent, le choix d'une capacité contractuelle excessivement faible imposera des frais de capacité élevés, tandis que le choix d'une capacité contractuelle excessivement élevée peut entraîner une charge de capacité de base inutile. Par conséquent, les clients qui consomment beaucoup d'électricité ont accordé beaucoup d'attention aux décisions optimales en matière de capacité contractuelle.

Pour déterminer la capacité contractuelle d'électricité de clients industriels à Taïwan, Chen et al. [5] ont utilisé une approche de programmation linéaire. Ils ont formulé le problème comme un programme linéaire et l'ont resolu en utilisant le logiciel LINDO. Puisqu'aucune littérature antérieure n'a prouvé que le problème était NP difficile, ils ont considéré que le problème peut probablement être résolu dans un temps polynomial. Les auteurs ont examiné la charge de capacité, l'ajustement du facteur de puissance, l'augmentation des frais de construction et la diminution non autorisée des capacités contractuelles dans le problème de l'optimisation. Une redevance fixe de capacité sera perçue si le pic de demande ne dépasse pas la capacité contractuelle. De plus, il y a une surcharge pour la demande excédentaire : Un dépassement de moins de 10% de la capacité contractuelle est facturé au double du taux de la capacité contractuelle. Si le dépassement est au de la 10%, la pénalité est le triple du taux de base. Les auteurs ont proposé deux modèles : le premier modèle détermine la capacité contractuelle de pointe et le second détermine à la fois la capacité de pointe et la capacité hors pointe. La méthode est appliquée à deux cas réels, pour une université et pour une usine de papier, pour démontrer que le modèle peut minimiser la facture d'électricité de clients industriels avec un temps de calcul inférieur à 0,06 sec.

Pour les machines industrielles, la planification optimale de la production et le choix du contrat énergétique ont été déterminés par Rodoplu et al. [116] qui minimisent les coûts de production et d'énergie en respectant les contraintes des systèmes de production et les conditions contractuelles des fournisseurs d'énergie. Le niveau de tolérance de pénalité est supposé être de 10 % au-dessus et en-dessous de la valeur de la puissance chaire. Les capacités contractuelles de pointe des énergies traditionnelles et renouvelables sont prises en compte. Ils ont appliqué leur méthode sur un cas particulier avec trois machines afin de choisir de manière optimale les différents contrats de capacité de multi-sources d'énergie pour une planification optimale de la production et un coût minimum. Trois types de sources d'énergie (traditionnelle, solaire, éolienne) sont utilisés.Toutes les énergies (traditionnelles et renouvelables) sont vendues par le fournisseur. Dans le modèle proposé, la valeur optimale du contrat est décrite comme une variable de décision. L'objectif est de choisir la meilleure valeur contractuelle pour chaque source d'énergie en minimisant les coûts et en satisfaisant la demande externe.

Optimisation de la localisation de multiples sources d'energie

Un modèle général pour l'optimisation de la localisation de multiples sources d'energie par un gouvernement a été proposé. La méthode de résolution développée est une méthode de programmation à objectifs multiples pour optimiser l'emplacement d'un nombre variable de centrales électriques dans un nombre variable d'endroits. La fonction objectif vise à minimiser les déviations totales des critères autour des intervalles désirés. Nous effectuons plusieurs combinaisons de poids assigné aux différents critères pour générer plusieurs solutions. Ensuite, on calcule la fréquence de distribution des centrales électriques aux différents endroits. Dans cette approche, il est prouvé que l'utilisation du DEA directement sur les critères donne des résultats plus efficaces que son utilisation sur les écarts. Le modèle proposé s'inspire des travaux de [3, 108, 4].

Description du problème

Les chercheurs appliquent la programmation par objectifs à des cas particuliers d'optimisation de localisation de plusieurs sources d'énergie, avec un nombre limité de centrales électriques et d'emplacements. Un modèle généralisé de programmation par objectifs (GP) est proposé pour localiser un nombre variable n de différents types de centrales électriques (alternatives) dans un nombre variable m d'emplacements différents avec un nombre total de connexions c. Les attributs pris en compte pour évaluer ces systèmes d'énergie renouvelable dans ce modèle sont : l'électricité produite (PP), le coût d'investissement (INV), les tonnes d'émissions de CO2 évitées par an (TCO2/an), les emplois créés (JOB), les coûts de fonctionnement et de maintenance (OM), la distance entre usines (DIS) et l'acceptation sociale (SA). L'acceptabilité sociale est exprimée sur une échelle de 1 (acceptation faible) à 10 (acceptation élevée). L'objectif est de s'écarter le moins possible des objectifs. X_{ij} est une variable binaire égale à 1 si la centrale électrique de type i est assignée à l'emplacement j et zéro sinon. d^+ et d^- sont des écarts positifs et négatifs par rapport aux objectifs et S est l'ensemble des types de centrales et des lieux.

Pour généraliser le modèle, nous avons tenté de linéariser le modèle, de relaxer les contraintes, d'élargir la région réalisable et de rendre le lieu des critères dépendant de sorte que les contraintes deviennent comme suit :

$$\begin{cases} \sum_{i,j \in S} PP_{ij} * X_{ij} + d^-_{PP} - d^+_{PP} = y^{PP} \\ y^{PP} + e^-_{PP} - e^+_{PP} = G^{PP}_{max} \\ G^{PP}_{min} \leq y^{PP} \leq G^{PP}_{max} \end{cases}$$

$$\begin{cases} \sum_{i,j \in S} INV_{ij} * X_{ij} + d^-_{INV} - d^+_{INV} = y^{INV} \\ y^{INV} + e^-_{INV} - e^+_{INV} = G^{INV}_{min} \\ G^{INV}_{min} \leq y^{INV} \leq G^{INV}_{max} \end{cases}$$

$$\begin{cases} \sum_{i,j \in S} CO_{2ij} * X_{ij} + d^-_{CO_2} - d^+_{CO_2} = y^{CO_2} \\ y^{CO_2} + e^-_{CO_2} - e^+_{CO_2} = G^{CO_2}_{max} \\ G^{CO_2}_{min} \leq y^{CO_2} \leq G^{CO_2}_{max} \end{cases}$$

$$\begin{cases} \sum_{i,j \in S} JOB_{ij} * X_{ij} + d^-_{JOB} - d^+_{JOB} = y^{JOB} \\ y^{JOB} + e^-_{JOB} - e^+_{JOB} = G^{JOB}_{max} \\ G^{JOB}_{min} \leq y^{JOB} \leq G^{JOB}_{max} \end{cases}$$

$$\begin{cases} \sum_{i,j \in S} OM_{ij} * X_{ij} + d^-_{OM} - d^+_{OM} = y^{OM} \\ y^{OM} + e^-_{OM} - e^+_{OM} = G^{OM}_{min} \\ G^{OM}_{min} \leq y^{OM} \leq G^{OM}_{max} \end{cases}$$

$$\begin{cases} \sum_{i,j \in S} DIS_{j\acute{j}} * Z_{j\acute{j}} + d^-_{DIS} - d^+_{DIS} = y^{DIS} \\ y^{DIS} + e^-_{DIS} - e^+_{DIS} = G^{DIS}_{min} \\ G^{DIS}_{min} \leq y^{DIS} \leq G^{DIS}_{max} \end{cases}$$

$$\sum_{i,j \in S} SA_{ij} * X_{ij} + d^-_{SA} - d^+_{SA} = y^{SA}$$

Où $x \in X \subset R^n, d^+$ et d^- sont des écarts positifs et négatifs de la fonction de réalisation $f(x)$ par rapport au niveau d'aspiration du vecteur y, e^+ et e^- sont des écarts positifs et négatifs du niveau de réalisation y du vecteur du niveau d'objectif scalaire g_{max} ou g_{min}.

La technique de normalisation est introduite pour éviter tout biais de la fonction objectif. Les écarts sont divisés par la valeur cible maximale. La fonction objectif devient donc la suivante :

$$\begin{cases} w_{ECON}(\sum_{ECON} \frac{1}{G^{Max}_{ECON}} * (d^+_{ECON} + d^-_{ECON} \\ +e^+_{ECON} + e^-_{ECON})) + w_{ENV}(\sum_{ENV} \frac{1}{G^{Max}_{ENV}} * \\ (d^+_{ENV} + d^-_{ENV} + e^+_{ENV} + e^-_{ENV})) + w_{SOC} \\ (\sum_{SOC} \frac{1}{G^{Max}_{SOC}} * (d^+_{SOC} + d^-_{SOC} + e^+_{SOC} + e^-_{ENV})) \end{cases}$$

Avec la somme des poids egale à 1 :

$$w_{ECON} + w_{ENV} + w_{SOC} = 1$$

De plus, les différents réseaux qui ont été créés pour chaque ensemble de poids sont les suivants :

$$net^w_{ij} = X^*_{ij}, \forall i, j \in S$$

L'étape suivante de l'analyse proposée est la carte des énergies renouvelables pour toutes les représentations de l'importance du poids dans la fonction objectif. Les représentations de tous les réseaux ont été stockées dans une matrice pour toutes les itérations, à savoir net^w_{ij}. La somme de toutes les représentations des réseaux, divisée par le total est utilisée pour calculer la fréquence.

$$fr_{ij} = \sum_{w=1}^{W} \frac{net_{ij}^{w}}{|W|}$$

Nous considérons $x_{w,in}$ la matrice des entrées et $y_{w,out}$ la matrice contenant les sorties qui seront utilisées dans Data Envelopment Analysis (DEA). Les variables faibles qui correspondent aux objectifs qui seront minimisés qui servent dans donnés d'entrés tandis que celles qui correspondent aux objectifs maximisés servent de sortie.

Dans notre cas $x_{w,in}$ est une matrice d'entrées de taille $300 * 4$ et $y_{w,out}$ est une matrice de sorties de taille $300 * 9$ sous la forme suivante :

$$x_{w,in} = [d^{+}_{INV} \;\; e^{+}_{INV} \;\; d^{+}_{OM} \;\; e^{+}_{OM}]$$

$$y_{w,out} = [d^{-}_{PP} \, e^{-}_{PP} \, d^{-}_{JOB} \, e^{-}_{JOB} \, d^{-}_{CO_2} \, e^{-}_{CO_2} \, d^{-}_{DIS} \, e^{-}_{DIS} \, d^{-}_{SA}]$$

Par expérience, nous nous rendons compte que le remplacement des écarts par les critères conduit directement à des solutions plus efficaces comme suit :

$$x_{w,in} = [INV \;\; OM]$$

$$y_{w,out} = [PP \;\; JOB \;\; CO_2 \;\; DIS \;\; SA]$$

Ensuite, nous choisissons le maximum de la soustraction entre les sorties et les entrées normalisées pour extraire la solution la plus efficace comme suit :

$$max \sum w_{out} * y_{w,out} - \sum w_{in} * x_{w,in}$$

Analyse de la méthode

Les contraintes étaient trop strictes là où il n'y a qu'un nombre limité de solutions, il est donc nécessaire de trouver soigneusement les valeurs appropriées des objectifs. Ceci permet de trouver la solution appropriée pour l'optimisation mono objectif. La relaxation des contraintes donne une variété de solutions avec de meilleures valeurs objectives.

Le temps d'exécution augmente de quelques secondes à quelques minutes à mesure que le nombre de centrales et de connexions augmentent, mais lorsque le nombre de connexions atteint 100 ou plus et que le nombre de centrales atteint 200 ou plus, le temps d'exécution atteint 1 heure.

Pour trouver une solution déterministe pour les repartition des centrales, la méthode DEA est choisie pour extraire les solutions avec des sorties maximales et des entrées minimales des différentes solutions obtenues. L'application de la méthode DEA directement sur les critères donne des solutions plus efficaces que son application sur les écarts.

Optimisation de la capacité contractuelle de multiples sources énergetiques

Optimisation de la capacité contratuelle avec pénalité multi-étapes

Présentation du problème

Les producteurs d'énergie proposent des capacités contractuelles pour couvrir les pics de demande d'énergie, mais lorsque la demande d'énergie dépasse la capacité contractuelle, une pénalité est imposée. Dans le cas d'une pénalité à plusieurs étapes, puisque la demande dépasse les seuils de capacité du contrat, des taux de pénalité plus élevés sont imposés. Dans cette approche, un algorithme est proposé pour trouver la capacité contractuelle optimale en cas de pénalité à plusieurs niveaux, le modèle s'inspire du travail [1].

En supposant que le coût de la capacité contractuelle est constant, et en triant la demande d'énergie par ordre décroissant, la fonction objectif s'exprime en fonction du coût contractuel, du coût de pénalité, de l'indice de période, de la demande d'énergie et de la capacité contractuelle. Elle s'écrit :

$$(\gamma - \beta) * P^{CC} * \sum_{m=1}^{N_{E1}} D(m) + \beta * P^{CC} * \sum_{m=1}^{N_{E2}} D(m) + (N_m - \alpha * (\gamma - \beta) * N_{E1} - \beta * N_{E2}) * P^{CC} * C$$

Les coûts des pénalités n'étant pas connus au préalable pour chaque période en cas de pénalité

Algorithm 1

initialization :
Choisissez le point de départ $N_2 = Round\_Up(\frac{N_m}{\beta})$

Trouver N_1 de telle sorte que :
$D(N_1) > \alpha * D(N_2)$

Calculez $A(N_E)$
$= \sum_{m=1}^{N_m} P^{CC}(m) - \sum_{m=1}^{N_1} \gamma * P^{CC}(m) - \sum_{N_1+1}^{N_2} \beta * P^{CC}(m)$

While $(A(N_E) < 0$ Et $N_2 \geq Round\_Up(\frac{N_m}{\gamma}))$
{
$N_2 = N_2 - 1$
chercher N_1 de telle sorte que
$D(N_1) > \alpha * D(N_2)$
Calculez $A(N_E)$
$= \sum_{m=1}^{N_m} P^{CC}(m) - \sum_{m=1}^{N_1} \gamma * P^{CC}(m) - \sum_{N_1+1}^{N_2} \beta * P^{CC}(m)$
}

Choisissez $C_{optimal} \in [D(N_2 + 1); D(N_2 - 1)]$

Calculez $TC(C_{optimal})$

Tableau 4.1 – Algorithme pour optimiser la capacité contractuelle avec des pénalités en deux niveaux

à plusieurs niveaux, un nouvel algorithme est proposé pour trouver la capacité contractuelle optimale. La capacité contractuelle optimale se trouve dans l'intervalle $[D(N_2 + 1); D(N_2 - 1)]$. On trouve l'indice selon N_2 l'algorithme 4.1.

Discussion

L'algorithme a été comparé au solveur commercial IBMILOG CPLEX. Les données relatives à la demande d'énergie proviennent de la region Grand-Est et de la France, et les valeurs des coûts de pénalité ont été modifiées. Les résultats montrent que la solution optimale se situe dans l'intervalle $[D(N_{E2} + 1); D(N_{E2} - 1)]$, ce qui est confirmée par la méthode de programmation linéaire qui donne une solution exacte, et le temps de calcul de l'algorithme proposé est bien inférieur à la méthode de programmation linéaire 4.1.

La contractualisation de la demande d'énergie dans le respect de l'environnement

Définition du problème et objectif

Dans cette approche, la pénalité pour l'excédent du pic de demande sur les valeurs totales de la capacité contractuelle est étudiée. Cet excédent est multiplié par le prix de pénalité P_p et les clients peuvent modifier leur demande contractuelle à chaque période. Sur la base de [5] nous prenons la même hypothèse de diminution non autorisée des capacités contractuelles. Les types de coûts pris en compte sont les coûts fixes de capacité, les coûts de pénalité et les coûts écologiques. Le coût de respect de l'environnement permet de bénéficier d'un rabais lorsque l'on utilise davantage d'énergie renouvelable, et de payer plus cher lorsque l'on utilise des énergies plus polluantes. Les valeurs discrètes des contrats de capacité sont prises en compte. Dans ce qui suit, un modèle de programmation linéaire est proposé pour ce problème.

Le modèle mathématique proposé est le suivant :

$$Min \qquad \sum_{t=1}^{T}\sum_{l=1}^{L}(Wtr_{t,l} * Ptrad_l) + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{k=1}^{K}(Wren_{t,l,k} * Pren_{l,k}) +$$
$$P_{eco} * (\sum_{t=1}^{T}\sum_{l=1}^{L}(Wtr_{t,l} * Trad_l - \sum_{k=1}^{K} Wren_{t,l,k} * Ren_{l,k})) + \sum_{t=1}^{T} P_p * X_t$$

Tels que :

$$Wtr_{t+1,l} \geq Wtr_{t,l} \qquad \forall\, t = 1, ..., T-1, l = 1, ..., L$$

$$Wren_{t+1,l,k} \geq Wren_{t,l,k} \qquad \forall\, t = 1, ..., T-1, l = 1, ..., L, k = 1, ..., K$$

$$\sum_{l=1}^{L} Wtr_{t,l} = 1 \qquad \forall\, t = 1, ..., T$$

$$\sum_{l=1}^{L} Wren_{t,l,k} = 1 \qquad \forall\, t = 1, ..., T, k = 1, ..., K$$

$$X_t + \sum_{l=1}^{L}(Wtr_{t,l} * Trad_l + \sum_{k=1}^{K} Wren_{t,l,k} * Ren_{k,l}) \geq D_t$$
$$\forall\, t = 1, ..., T$$

$$X_t \geq 0 \qquad \forall\, t = 1, ..., T$$

Analyse des résultats

Trois scénarios différents de données de demande sont générés pour tester le modèle. Pour ces scénarios, des demandes aléatoires pour 24 périodes sont générées. La probabilité de distribution suit une fonction de densité uniforme et continue, et pour chaque scénario, on suppose des limites inférieure et supérieure petites, moyennes et élevées.

Il y a un compromis à faire entre le coût total et le pourcentage d'énergie renouvelable utilisé. L'introduction du facteur écologique dans la fonction objectif augmente l'utilisation des énergies renouvelables dans les contrats de capacité, mais elle augmente également le coût total. Plus la valeur de demande est élevée, moins l'augmentation du pourcentage d'énergie renouvelable utilisée est importante. Et la demande excédentaire change indépendamment pour introduire ou non le facteur écologique, mais elle est faible dans tous les cas.

Pour des valeurs très élevées de facteur écologique, le coût total diminue pour l'utilisation d'une grande quantité de sources d'énergies renouvelables. Pour une demande très élevée, le coût total est très élevé lorsque nous avons des valeurs moyennes de facteur écologique. Ainsi, lorsque la demande est élevée, une grande quantité d'argent est nécessaire pour soutenir l'utilisation des énergies renouvelables ou il est préférable d'utiliser les énergies traditionnelles.

Optimisation de la capacité contractuelle sous demande incertaine

Définition du problème et objectif

Des caractéristiques stochastiques sont introduites dans la demande, puisque la demande d'énergie du consommateur est une prévision. Les types de coûts pris en compte sont le coût de capacité contractuelles, le coût de pénalité et le coût écologique. Dans cette étude, la pénalité de dépassement de la capacité contractuelle par le pic de demande est étudiée, et l'effet de l'incertitude et du coût écologique sur la solution optimale a également été examiné. Les valeurs continues des capacités contractuelles sont prises en compte, il existe des capacités contractuelles traditionnelles et dans différents types de capacités contractuelles d'énergies renouvelables. Un modèle d'optimisation non linéaire utilisant une méthode de points intérieurs est proposé pour ce problème.

$$Min \quad \sum_{t=1}^{T}(Ptrad * Trad_t + \sum_{k=1}^{K} Pren_k * Ren_{t,k}) + \sum_{t=1}^{T} P_{eco} * (Trad_t - \sum_{k=1}^{K} Ren_{k,t}) + \sum_{t=1}^{T} \int_{Trad_t + \sum_{k=1}^{K} Ren_{k,t}}^{\infty} P_p * (x - Trad_t - \sum_{k=1}^{K} Ren_{t,k}) f_{\tilde{D}_t}(x)dx$$

Tels que :

$$Trad_t \geq Trad_{min} \qquad \forall\, t = 1, ..., T$$

$$Ren_{k,t} \geq Ren_{min} \qquad \forall\, t = 1, ..., T, k = 1, ..., K,$$

$$Trad_t \leq Trad_{max} \qquad \forall\, t = 1, ..., T$$

$$Ren_{k,t} \leq Ren_{max} \qquad \forall\, t = 1, ..., T, k = 1, ..., K,$$

Discussion

Le coût de la pénalité augmente la combinaison optimale de la capacité contractuelle à partir du moment où le coût de la pénalité est égal au coût minimum du contrat jusqu'à ce que le coût de la pénalité dépasse le coût maximum du contrat. La demande ne doit pas dépasser la capacité contractuelle totale, faute de quoi l'utilisateur sera pénalisé par des coûts élevés. Mais en présence du facteur écologique qui augmente avec l'augmentation du coût de la pénalité, les capacités contractuelles d'énergie renouvelable augmentent et les capacités contractuelles d'énergie traditionnelle diminuent dans la combinaison des capacités contractuelles ; cette combinaison augmente au total avec le coût de la pénalité. Ainsi, dans les situations où les coûts de pénalité sont élevés, il n'est pas nécessaire de disposer d'un large soutien écologique pour encourager l'utilisation d'énergies renouvelables dans la capacité contractuelle. Mais pour un coût de pénalité peu élevé, un montant important est utilisé pour avoir plus d'énergie renouvelable dans la combinaison de capacité contractuelle.

L'incertitude est étudiée pour la demande d'énergie et le changement du facteur écologique en même temps, les caractéristiques stochastiques sont examinées dans différentes distributions de probabilités telles que les distributions normales, gamma et log-normales. Au fur et à mesure que l'incertitude augmente, la demande excédentaire prévue augmente, mais également les capacités contractuelles de tous les types, y compris les sources d'énergie renouvelables et la hausse des coûts totaux, tandis que la demande excédentaire totale diminue. Par conséquent, en cas de manque de données concernant la demande d'énergie ou d'incertitude élevée pour n'importe quelle raison que ce soit, un assistant l'environnement est suffisant pour avoir plus d'énergie renouvelable dans la combinaison des capacités contractuelles mais avec un coût total élevé et vice versa. Le coût total augmente avec le coût de pénalité et l'incertitude qui sont des paramètres incontrôlables, mais le coût de respect de l'environnement est contrôlable et le coût total diminue par rapport au coût respectueux de l'environnement, de sorte que cette étude montre en présomption de valeurs faibles ou élevées du coût de pénalité et de l'incertitude quelle valeur écologique choisir.

Conclusion et perspectives

L'augmentation de la pollution et du rechauffement climatique mondial est à cause de la dépendance du monde à l'égard des énergies traditionnelles qui dépendent des combustibles fossiles. De plus, les sociétés et les gouvernements exigent l'indépendance énergétique conventionnelle en raison de son influence politique et de sa nature limitée. Les gouvernements ont tendance à distribuer des sources d'énergie vertes et durables dans leurs régions en raison de la forte augmentation de la consommation d'énergie et de la pollution. L'utilisation des énergies renouvelables est de plus en plus courante de nos jours, car il existe des capacités contractuelles pour chaque type d'énergie. De ce fait, augmenter l'utilisation des énergies renouvelables dans les différentes régions d'un pays et faciliter les différents aspects de l'énergie renouvelable, tels que les capacités contractuelles en encourageant leur utilisation, contribue non seulement à atteindre les objectifs de durabilité, mais aussi à réduire considérablement les niveaux globaux des émissions de carbone.

L'objectif principal de cette thèse est de proposer un modèle général d'optimisation de la distribution multi-sources de la localisation énergétique dans un pays avec assignation de probabilité. De plus, cette thèse fournit des modèles d'optimisation et des solutions pour des cas déterministes et stochastiques d'optimisation de la capacité d'un contrat énergétique multi-sources, pour intégrer la disponibilité des sources d'énergie à l'énergie de pointe stochastique, le problème traité est combiné avec le problème de sélection de capacité contractuelle en s'inspirant des pratiques réelles.

Cette thèse passe en revue la littérature sur les problèmes énergétiques et les méthodes pour les résoudre. L'optimisation de la localisation des installations et des centrales d'énergie renouvelable est passée en revue et il est démontré qu'aucune méthode d'optimisation générale avec multiple source d'énergie applicable à un pays n'a été proposée. De plus, les problèmes d'optimisation de la capacité contractuelle et les méthodes pour les résoudre sont également passés en revue, et l'inclusion de sources d'énergie multiples dans les contrats a rarement été envisagée. L'autre nouveauté de notre étude est donc l'application d'une stratégie d'optimisation énergétique multi-sources qui tient compte de l'incertitude.

Un modèle de programmation par objectifs général est fourni aux gouvernements pour l'implantation de divers types de centrales électriques. Ainsi, n'importe quel pays peut décider de la combinaison optimale pour un nombre variable de types de centrales électriques dans un nombre variable d'emplacements, compte tenu des données statistiques sur les différents critères. Le flux de contrôle est utilisé pour résoudre le problème de programmation par objectifs plusieurs fois en changeant le poids des différents types de critères, la probabilité de distribution de chaque type de centrale à chaque endroit en ajoutant ces solutions et en les divisant par le total. Comme les paramètres des alternatives varient en fonction du lieu, la méthode proposée peut résoudre des cas variables proches des conditions réelles. Les contraintes sont relaxées pour trouver des solutions plus réalisables avec de meilleures fonctions objectifs. Une meilleure méthode d'analyse du développement des données basée sur les critères est proposée pour extraire des solutions plus efficaces.

Nous avons introduit un nouvel algorithme qui est une amélioration du modèle, proposé par ferdavini et al. [1], pour résoudre les problèmes de pénalités en plusieurs étapes pour les capacités contractuelles, la méthode est applicable en cas de contrats sûrs et discrets, l'approche est comparée à la programmation linéaire pour montrer l'efficacité de la méthode. Nous avons introduit plusieurs sources d'énergie dans la sélection de la capacité contractuelle, la solution optimale est obtenue en tenant compte de différents facteurs tels que le prix du contrat, le prix de pénalité, et l'encouragement écologique en utilisant la programmation linéaire. La méthode est appliquée pour les cas déterministes avec des contrats discrets sur des petites, moyennes et grandes valeurs de demandes générées au hasard, les résultats indiquent qu'une valeur élevée de facteur écologique est nécessaire pour utiliser une capacité contractuelle plus renouvelable en cas de forte demande.

Compte tenu des caractéristiques stochastiques de la demande d'énergie, nous avons proposé une méthode d'optimisation non linéaire afin d'optimiser la sélection de la capacité de contrats énergétiques multisources compte tenu de l'incertitude de la demande énergétique. Un algorithme de points intérieurs est utilisé et le problème s'avère convexe de sorte que la solution obtenue est globale. Différentes instances et différentes fonctions de distribution de probabilités pour la demande sont testées, nous étudions l'influence de l'incertitude sur la solution optimale en calibrant les paramètres de la fonction de distribution de probabilités, afin d'examiner l'effet du coût de pénalité et le facteur écologique sur la solution optimale. Le coût de pénalité augmente la capacité contractuelle optimale à partir du contrat à coût minimum, jusqu'à ce que le coût de pénalité dépasse le contrat à coût maximum, la combinaison des capacités contractuelles en augmentation totale, c'est-à-dire que la demande ne doit pas dépasser les capacités contractuelles totales et être payée par des coûts de pénalité élevés. Mais en présence du facteur écologique qui augmente avec l'augmentation du coût de la pénalité, les capacités contractuelles d'énergie renouvelable augmentent et les capacités contractuelles d'énergie traditionnelle diminuent dans la combinaison de la capacité contractuelle, cette combinaison augmente au total avec le coût de la pénalité. Ainsi, dans les situations où les coûts de pénalité sont élevés, il n'est pas nécessaire de disposer d'un large soutien écologique pour encourager l'utilisation d'énergies renouvelables dans la capacité contractuelle. Mais pour un coût de pénalité peu élevé, un montant important est utilisé pour avoir plus d'énergie renouvelable dans la combinaison de capacité contractuelle. Au fur et à mesure que l'incertitude augmente, la demande excédentaire prévue augmente, mais également les capacités contractuelles de tous les types, y compris les sources d'énergies renouvelables et la hausse des coûts totaux, tandis que la demande excédentaire totale diminue. Par conséquent, en cas de manque de données concernant la demande d'énergie ou d'incertitude élevée pour quelle raison que ce soit, assistant est suffisant pour avoir plus d'énergie renouvelable dans la combinaison des capacités contractuelles mais avec un coût total élevé et vice versa. Le coût total augmente avec le prix de pénalité et l'incertitude qui sont des paramètres incontrôlables, mais le facteur écologique est contrôlable et le coût total diminue par rapport à lui, de sorte que cette étude montre en présence de valeurs faibles ou élevées de prix de pénalité et d'incertitude quelle valeur du facteur écologique à choisir.

La production d'énergie renouvelable est sujette à l'incertitude parce qu'elle dépend des conditions météorologiques telles que l'énergie solaire et éolienne. Pour faire face à l'incertitude de la production d'énergie et à la demande, le producteur a besoin d'une optimisation robuste pour décider de la capacité contractuelle maximale de chaque type d'énergie, on propose un programme robuste linéaire à deux étapes à nombres entiers mixtes avec recours.

Globalement, cette thèse contribue dans les domaines de l'optimisation de l'implantation de multi-sources d'énergie et de l'optimisation de la capacité des contrats énergétiques multisources.

Plusieurs orientations de recherche futures peuvent se dégager de cette thèse. Le modèle peut être étendu en considérant la présence de données floues. Les données floues sont un excellent moyen de modéliser les incertitudes qui peuvent être un aspect important de tout problème lié aux critères de durabilité. Une autre orientation pour les recherches futures consisterait à tester le modèle à partir d'applications réelles dans différents pays et zones géographiques.

Il serait intéressant d'appliquer directement le 2-Stage robust mixed integer linear programming sur des données réelles pour trouver la capacité contractuelle maximale des différents types d'énergie. De plus, il est important de comparer la méthode proposée avec d'autres méthodes d'optimisation robustes pour trouver la meilleure méthode d'optimisation robuste.

Bibliography

[1] A. K. Ferdavani, R.-A. Hooshmand, and H. B. Gooi. "Analytical solution for demand contracting with forecasting-error analysis on maximum demands and prices". In: *IET Generation, Transmission & Distribution* 12.12 (2018), pp. 3097–3105 (cit. on pp. v, 56, 82, 83, 85, 88, 90, 91, 130, 132, 149, 156, 168).

[2] A. Billionnet, M.-C. Costa, and P.-L. Poirion. "Robust optimal sizing of a hybrid energy stand-alone system". In: *European Journal of Operational Research* 254.2 (2016), pp. 565–575 (cit. on pp. 4, 16, 34, 135).

[3] J. R. San Cristóbal. "A goal programming model for the optimal mix and location of renewable energy plants in the north of Spain". In: *Renewable and Sustainable Energy Reviews* 16.7 (2012), pp. 4461–4464 (cit. on pp. 8, 47, 58, 64, 142, 145).

[4] E. Zografidou et al. "Optimal design of the renewable energy map of Greece using weighted goal-programming and data envelopment analysis". In: *Computers & Operations Research* 66 (2016), pp. 313–326 (cit. on pp. 8, 37, 47, 48, 58, 74, 75, 143, 145).

[5] C.-Y. Chen and C.-J. Liao. "A linear programming approach to the electricity contract capacity problem". In: *Applied Mathematical Modelling* 35.8 (2011), pp. 4077–4082 (cit. on pp. 8, 51–53, 90, 91, 94, 144, 151).

[6] A. Billionnet, M.-C. Costa, and P.-L. Poirion. "2-Stage Robust MILP with continuous recourse variables". In: *Discrete Applied Mathematics* 170 (2014), pp. 21–32 (cit. on pp. 9, 33).

[7] Y. Gaoua. "Modèles mathématiques et techniques d'optimisation non linéaire et combinatoire pour la gestion d'énergie d'un système multi-source: vers une implantation temps-réel pour différentes structures électriques de véhicules hybrides". PhD thesis. École Doctorale Systèmes (Toulouse); 154236462, 2014 (cit. on p. 12).

[8] Y. Gaoua, S. Caux, and P. Lopez. "Energy management for an electric vehicle based on combinatorial modeling". In: *Proceedings of 2013 International Conference on Industrial Engineering and Systems Management (IESM)*. IEEE. 2013, pp. 1–6 (cit. on p. 12).

[9] Y. Gaoua, S. Caux, and P. Lopez. "A combinatorial optimization approach for the electrical energy management in a multi-source system". In: *2nd International Conference on Operations Research and Enterprise Systems (ICORES 2013)*. 2013, pp. 55–59 (cit. on p. 12).

[10] S. Caux, Y. Gaoua, and P. Lopez. "A combinatorial optimisation approach to energy management strategy for a hybrid fuel cell vehicle". In: *Energy* 133 (2017), pp. 219–230 (cit. on p. 13).

[11] W.-H. Tsai et al. "Applying a mathematical programming approach for a green product mix decision". In: *International Journal of Production Research* 50.4 (2012), pp. 1171–1184 (cit. on p. 13).

[12] M. Deshmukh and S. Deshmukh. “Modeling of hybrid renewable energy systems”. In: *Renewable and Sustainable Energy Reviews* 12.1 (2008), pp. 235–249 (cit. on p. 13).

[13] W. B. Powell. “Energy and uncertainty: Models and algorithms for complex energy systems”. In: *AI Magazine* 35.3 (2014), pp. 8–22 (cit. on p. 13).

[14] M. Elsied et al. “Gestion de l’énergie et optimisation du système multisources basée sur l’algorithme génétique”. In: *Symposium de Génie Électrique 2014*. 2014 (cit. on p. 14).

[15] A. Gupta, R. Saini, and M. Sharma. “Modelling of hybrid energy system—Part I: Problem formulation and model development”. In: *Renewable Energy* 36.2 (2011), pp. 459–465 (cit. on p. 14).

[16] V. V. Prabhu, D. Trentesaux, and M. Taisch. *Energy-aware manufacturing operations*. 2015 (cit. on p. 14).

[17] Š. Bojnec and D. Papler. “Economic efficiency, energy consumption and sustainable development”. In: *Journal of Business Economics and Management* 12.2 (2011), pp. 353–374 (cit. on p. 15).

[18] Z. Zhou et al. “A two-stage stochastic programming model for the optimal design of distributed energy systems”. In: *Applied Energy* 103 (2013), pp. 135–144 (cit. on p. 15).

[19] H. Bilil, G. Aniba, and M. Maaroufi. “Multiobjective optimization of renewable energy penetration rate in power systems”. In: *Energy Procedia* 50 (2014), pp. 368–375 (cit. on pp. 15, 135).

[20] N. Apostolopoulos and P. Liargovas. “Regional parameters and solar energy enterprises: Purposive sampling and group AHP approach”. In: *International Journal of Energy Sector Management* 10.1 (2016), pp. 19–37 (cit. on p. 16).

[21] W. Ogryczak, K. Studziński, and K. Zorychta. “A solver for the multi-objective transshipment problem with facility location”. In: *European Journal of Operational Research* 43.1 (1989), pp. 53–64 (cit. on pp. 17, 43, 45).

[22] T. Logenthiran, D. Srinivasan, and A. M. Khambadkone. “Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system”. In: *Electric Power Systems Research* 81.1 (2011), pp. 138–148 (cit. on pp. 18, 21).

[23] G. Osório et al. “Scheduling model for renewable energy sources integration in an insular power system”. In: *Energies* 11.1 (2018), p. 144 (cit. on p. 18).

[24] K. Mitra and G. Dutta. “A two-part dynamic pricing policy for household electricity consumption scheduling with minimized expenditure”. In: *International Journal of Electrical Power & Energy Systems* 100 (2018), pp. 29–41 (cit. on pp. 19, 24).

[25] R. Niemi, J. Mikkola, and P. Lund. “Urban energy systems with smart multi-carrier energy networks and renewable energy generation”. In: *Renewable energy* 48 (2012), pp. 524–536 (cit. on p. 19).

[26] S. Malkawi, D. Azizi, et al. “A multi-criteria optimization analysis for Jordan’s energy mix”. In: *Energy* 127 (2017), pp. 680–696 (cit. on pp. 19, 47).

[27] E. S. Barbieri et al. “Concurrent optimization of size and switch-on priority of a multi-source energy system for a commercial building application”. In: *Energy Procedia* 81 (2015), pp. 45–54 (cit. on p. 20).

[28] A. Safaei, F. Freire, and C. H. Antunes. “A model for optimal energy planning of a commercial building integrating solar and cogeneration systems”. In: *Energy* 61 (2013), pp. 211–223 (cit. on p. 20).

[29] J. R. Galvão et al. "Cogeneration supply by bio-energy for a sustainable hotel building management system". In: *Fuel processing technology* 92.2 (2011), pp. 284–289 (cit. on p. 20).

[30] S. Caron and G. Kesidis. "Incentive-based energy consumption scheduling algorithms for the smart grid". In: *2010 First IEEE International Conference on Smart Grid Communications*. IEEE. 2010, pp. 391–396 (cit. on pp. 21, 22).

[31] L. Wang et al. "Robust multi-objective optimization for energy production scheduling in microgrids". In: *Engineering Optimization* 51.2 (2019), pp. 332–351 (cit. on pp. 21, 22).

[32] S.-J. Ahn et al. "Power scheduling of distributed generators for economic and stable operation of a microgrid". In: *IEEE Transactions on Smart Grid* 4.1 (2013), pp. 398–405 (cit. on p. 22).

[33] D. Zhang et al. "Optimal design of CHP-based microgrids: Multiobjective optimisation and life cycle assessment". In: *Energy* 85 (2015), pp. 181–193 (cit. on p. 22).

[34] A.-H. Mohsenian-Rad et al. "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid". In: *IEEE transactions on Smart Grid* 1.3 (2010), pp. 320–331 (cit. on p. 22).

[35] E. Celebi and J. D. Fuller. "A model for efficient consumer pricing schemes in electricity markets". In: *IEEE Transactions on Power Systems* 22.1 (2007), pp. 60–67 (cit. on pp. 23, 24).

[36] S. Poletti and J. Wright. "Real Time Pricing and Market Power: A New Zealand Case Study". In: (2017) (cit. on p. 24).

[37] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen. "A medium-term decision model for DisCos: Forward contracting and TOU pricing". In: *IEEE Transactions on Power Systems* 30.3 (2014), pp. 1143–1154 (cit. on p. 24).

[38] S. Huang and G. Hu. "Biomass supply contract pricing and environmental policy analysis: A simulation approach". In: *Energy* 145 (2018), pp. 557–566 (cit. on p. 24).

[39] M. Sulaima et al. "Optimum Enhance Time of Use (ETOU) for Demand Side Electricity Pricing in Regulated Market: An Implementation Using Evolutionary Algorithm". In: *Indonesian Journal of Electrical Engineering and Computer Science* 8.1 (2017), pp. 253–261 (cit. on p. 24).

[40] X. Luo et al. "Robust optimization-based generation self-scheduling under uncertain price". In: *Mathematical Problems in Engineering* 2011 (2011) (cit. on p. 24).

[41] A. A. Bruzzone et al. "Energy-aware scheduling for improving manufacturing process sustainability: A mathematical model for flexible flow shops". In: *CIRP annals* 61.1 (2012), pp. 459–462 (cit. on pp. 25, 28).

[42] M. Aghelinejad, Y. Ouazene, and A. Yalaoui. "Complexity analysis of energy-efficient single machine scheduling problems". In: *Operations Research Perspectives* 6 (2019), p. 100105 (cit. on pp. 25, 27).

[43] M. M. Aghelinejad, Y. Ouazene, and A. Yalaoui. "Energy efficient scheduling problems under Time-Of-Use tariffs with different energy consumption of the jobs". In: *IFAC-PapersOnLine* 51.11 (2018), pp. 1053–1058 (cit. on pp. 25, 26).

[44] M. Aghelinejad, Y. Ouazene, and A. Yalaoui. "Machine and production scheduling under electricity time varying prices". In: *2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE. 2016, pp. 992–996 (cit. on pp. 25, 26).

[45] F. Shrouf et al. “Optimizing the production scheduling of a single machine to minimize total energy consumption costs”. In: *Journal of Cleaner Production* 67 (2014), pp. 197–207 (cit. on p. 26).

[46] M. M. Aghelinejad, Y. Ouazene, and A. Yalaoui. “Preemptive scheduling of a single machine with finite states to minimize energy costs”. In: *International Conference on Optimization and Decision Science*. Springer. 2017, pp. 591–599 (cit. on p. 26).

[47] M. Aghelinejad, Y. Ouazene, and A. Yalaoui. “Production scheduling optimisation with machine state and time-dependent energy costs”. In: *International Journal of Production Research* 56.16 (2018), pp. 5558–5575 (cit. on p. 26).

[48] O. Masmoudi et al. “Lot-sizing in flow-shop with energy consideration for sustainable manufacturing systems”. In: *IFAC-PapersOnLine* 48.3 (2015), pp. 727–732 (cit. on p. 27).

[49] O. Masmoudi et al. “A multi-level capacitated lot-sizing problem with energy consideration”. In: *2015 International Conference on Industrial Engineering and Systems Management (IESM)*. IEEE. 2015, pp. 1352–1359 (cit. on p. 27).

[50] O. Masmoudi et al. “Multi-item capacitated lot-sizing problem in a flow-shop system with energy consideration”. In: *IFAC-PapersOnLine* 49.12 (2016), pp. 301–306 (cit. on p. 27).

[51] O. Masmoudi et al. “Lot-sizing in a multi-stage flow line production system with energy consideration”. In: *International Journal of Production Research* 55.6 (2017), pp. 1640–1663 (cit. on p. 27).

[52] O. Masmoudi et al. “Solving a capacitated flow-shop problem with minimizing total energy costs”. In: *The International Journal of Advanced Manufacturing Technology* 90.9-12 (2017), pp. 2655–2667 (cit. on p. 27).

[53] S. Zanoni, L. Bettoni, and C. H. Glock. “Energy implications in a two-stage production system with controllable production rates”. In: *International Journal of Production Economics* 149 (2014), pp. 164–171 (cit. on p. 28).

[54] S. A. Mansouri, E. Aktas, and U. Besikci. “Green scheduling of a two-machine flowshop: Trade-off between makespan and energy consumption”. In: *European Journal of Operational Research* 248.3 (2016), pp. 772–788 (cit. on p. 28).

[55] C. Gahm et al. “Energy-efficient scheduling in manufacturing companies: A review and research framework”. In: *European Journal of Operational Research* 248.3 (2016), pp. 744–757 (cit. on p. 28).

[56] R. Yokoyama et al. “A revised method for robust optimal design of energy supply systems based on minimax regret criterion”. In: *Energy conversion and management* 84 (2014), pp. 196–208 (cit. on pp. 29, 33).

[57] C. Ning and F. You. “Data-Driven Adaptive Robust Optimization Framework for Unit Commitment under Renewable Energy Generation Uncertainty”. In: *2019 American Control Conference (ACC)*. IEEE. 2019, pp. 4734–4739 (cit. on pp. 29, 32).

[58] L. Wang et al. “Robust optimisation scheduling of CCHP systems with multi-energy based on minimax regret criterion”. In: *IET Generation, Transmission & Distribution* 10.9 (2016), pp. 2194–2201 (cit. on pp. 29, 31).

[59] R. A. Jabr. “Robust transmission network expansion planning with uncertain renewable generation and loads”. In: *IEEE Transactions on Power Systems* 28.4 (2013), pp. 4558–4567 (cit. on p. 29).

[60] K. Shimizu and E. Aiyoshi. “Necessary conditions for min-max problems and algorithms by a relaxation procedure”. In: *IEEE Transactions on Automatic Control* 25.1 (1980), pp. 62–66 (cit. on p. 29).

[61] H. Gao et al. “A security-constrainted dispatching model for wind generation units based on extreme scenario set optimization”. In: *Power System Technology* 6 (2013), p. 018 (cit. on p. 29).

[62] A. Barvinok. *A course in convexity.* Vol. 54. American Mathematical Soc., 2002 (cit. on p. 29).

[63] R. Jiang, J. Wang, and Y. Guan. “Robust unit commitment with wind power and pumped storage hydro”. In: *IEEE Transactions on Power Systems* 27.2 (2011), pp. 800–810 (cit. on p. 30).

[64] Y. Xiang, J. Liu, and Y. Liu. “Robust energy management of microgrid with uncertain renewable generation and load”. In: *IEEE Transactions on Smart Grid* 7.2 (2015), pp. 1034–1043 (cit. on p. 30).

[65] S. A. Alavi, A. Ahmadian, and M. Aliakbar-Golkar. “Optimal probabilistic energy management in a typical micro-grid based-on robust optimization and point estimate method”. In: *Energy Conversion and Management* 95 (2015), pp. 314–325 (cit. on p. 31).

[66] K. Akbari et al. “Optimal investment and unit sizing of distributed energy systems under uncertainty: A robust optimization approach”. In: *Energy and Buildings* 85 (2014), pp. 275–286 (cit. on p. 31).

[67] L. Xie et al. “Short-term spatio-temporal wind power forecast in robust look-ahead power system dispatch”. In: *IEEE Transactions on Smart Grid* 5.1 (2013), pp. 511–520 (cit. on p. 32).

[68] A. Khodaei, S. Bahramirad, and M. Shahidehpour. “Microgrid planning under uncertainty”. In: *IEEE Transactions on Power Systems* 30.5 (2014), pp. 2417–2425 (cit. on p. 32).

[69] R. Gupta and N. K. Gupta. “A robust optimization based approach for microgrid operation in deregulated environment”. In: *Energy Conversion and Management* 93 (2015), pp. 121–131 (cit. on p. 33).

[70] R. Wang, P. Wang, and G. Xiao. “A robust optimization approach for energy generation scheduling in microgrids”. In: *Energy Conversion and Management* 106 (2015), pp. 597–607 (cit. on p. 33).

[71] A. Furková and K. Surmanová. “Stochastic frontier analysis of regional competitiveness”. In: *Metody Ilościowe w Badaniach Ekonomicznych* 12.1 (2011), pp. 67–76 (cit. on p. 35).

[72] G. E. Battese and T. J. Coelli. “A model for technical inefficiency effects in a stochastic frontier production function for panel data”. In: *Empirical economics* 20.2 (1995), pp. 325–332 (cit. on p. 35).

[73] E. Kraft and D. Tırtıroğlu. “Bank efficiency in Croatia: A stochastic-frontier analysis”. In: *Journal of comparative economics* 26.2 (1998), pp. 282–300 (cit. on p. 36).

[74] R. Jacobs. “Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis”. In: *Health care management science* 4.2 (2001), pp. 103–115 (cit. on p. 36).

[75] W. Greene. “Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization’s panel data on national health care systems”. In: *Health economics* 13.10 (2004), pp. 959–980 (cit. on p. 36).

[76] K. Cullinane et al. “The technical efficiency of container ports: Comparing data envelopment analysis and stochastic frontier analysis”. In: *Transportation Research Part A: Policy and Practice* 40.4 (2006), pp. 354–374 (cit. on p. 36).

[77] T. Coelli. “A guide to DEAP version 2.1: a data envelopment analysis (computer) program”. In: *Centre for Efficiency and Productivity Analysis, University of New England, Australia* (1996) (cit. on p. 37).

[78] Y.-b. Ji and C. Lee. “Data envelopment analysis”. In: *The Stata Journal* 10.2 (2010), pp. 267–280 (cit. on p. 38).

[79] R. D. Banker, A. Charnes, and W. W. Cooper. “Some models for estimating technical and scale inefficiencies in data envelopment analysis”. In: *Management science* 30.9 (1984), pp. 1078–1092 (cit. on p. 38).

[80] R. Z. Farahani, M. SteadieSeifi, and N. Asgari. “Multiple criteria facility location problems: A survey”. In: *Applied Mathematical Modelling* 34.7 (2010), pp. 1689–1709 (cit. on p. 39).

[81] N. Srinivas and K. Deb. “Muiltiobjective optimization using nondominated sorting in genetic algorithms”. In: *Evolutionary computation* 2.3 (1994), pp. 221–248 (cit. on p. 41).

[82] M. Ehrgott and X. Gandibleux. “A survey and annotated bibliography of multiobjective combinatorial optimization”. In: *OR-Spektrum* 22.4 (2000), pp. 425–460 (cit. on p. 41).

[83] E. L. Ulungu and J. Teghem. “Multi-objective combinatorial optimization problems: A survey”. In: *Journal of Multi-Criteria Decision Analysis* 3.2 (1994), pp. 83–104 (cit. on p. 41).

[84] R. K. Klimberg and S. J. Ratick. “Modeling data envelopment analysis (DEA) efficient location/allocation decisions”. In: *Computers & Operations Research* 35.2 (2008), pp. 457–474 (cit. on pp. 42, 43).

[85] M. Labbé et al. “Multicriteria Semi-obnoxious Network Location Problems (MSNLP) with Sum and Center Objectives”. In: (2000) (cit. on p. 42).

[86] J. Puerto and R. Fernández. “A convergent approximation scheme for efficient sets of the multi-criteria Weber location problem”. In: *Top* 6.2 (1998), pp. 195–204 (cit. on p. 42).

[87] E. Melachrinoudis, H. Min, and X. Wu. “A multiobjective model for the dynamic location of landfills”. In: *Location Science* 3.3 (1995), pp. 143–166 (cit. on p. 42).

[88] E. Fernández and J. Puerto. “Multiobjective solution of the uncapacitated plant location problem”. In: *European Journal of Operational Research* 145.3 (2003), pp. 509–529 (cit. on p. 42).

[89] H. Aras, Ş. Erdoğmuş, and E. Koç. “Multi-criteria selection for a wind observation station location using analytic hierarchy process”. In: *Renewable Energy* 29.8 (2004), pp. 1383–1392 (cit. on p. 42).

[90] M. A. Badri. “Combining the analytic hierarchy process and goal programming for global facility location-allocation problem”. In: *International journal of production economics* 62.3 (1999), pp. 237–248 (cit. on p. 42).

[91] L. Guo and Y. He. “Integrated multi-criterial decision model: a case study for the allocation of facilities in Chinese agriculture”. In: *Journal of Agricultural Engineering Research* 73.1 (1999), pp. 87–94 (cit. on p. 42).

[92] O. H. Barda, J. Dupuis, and P. Lencioni. “Multicriteria location of thermal power plants”. In: *European Journal of Operational Research* 45.2-3 (1990), pp. 332–346 (cit. on p. 42).

[93] D. Yong. “Plant location selection based on fuzzy TOPSIS”. In: *The International Journal of Advanced Manufacturing Technology* 28.7-8 (2006), pp. 839–844 (cit. on p. 43).

[94] A. G. Pereira, G. Munda, and M. Paruccini. “Generating alternatives for siting retail and service facilities using genetic algorithms and multiple criteria decision techniques”. In: *Journal of Retailing and Consumer Services* 1.1 (1994), pp. 40–47 (cit. on p. 43).

[95] W. Ogryczak, K. Studziński, and K. Zorychta. “DINAS: a computer-assisted analysis system for multiobjective transshipment problems with facility location”. In: *Computers & operations research* 19.7 (1992), pp. 637–647 (cit. on p. 43).

[96] L. Raisanen and R. M. Whitaker. “Comparison and evaluation of multiple objective genetic algorithms for the antenna placement problem”. In: *Mobile Networks and Applications* 10.1-2 (2005), pp. 79–88 (cit. on p. 43).

[97] S. C. Leung. “A non-linear goal programming model and solution method for the multi-objective trip distribution problem in transportation engineering”. In: *Optimization and Engineering* 8.3 (2007), pp. 277–298 (cit. on p. 44).

[98] M. Karatas. “A multi-objective facility location problem in the presence of variable gradual coverage performance and cooperative cover”. In: *European Journal of Operational Research* 262.3 (2017), pp. 1040–1051 (cit. on p. 44).

[99] F. Torfi, R. Z. Farahani, and S. Rezapour. “Fuzzy AHP to determine the relative weights of evaluation criteria and Fuzzy TOPSIS to rank the alternatives”. In: *Applied Soft Computing* 10.2 (2010), pp. 520–528 (cit. on p. 45).

[100] M. Solimanpur and M. A. Kamran. “Solving facilities location problem in the presence of alternative processing routes using a genetic algorithm”. In: *Computers & Industrial Engineering* 59.4 (2010), pp. 830–839 (cit. on p. 45).

[101] S. Bojić et al. “Location allocation of solid biomass power plants: Case study of Vojvodina”. In: *Renewable and Sustainable Energy Reviews* 26 (2013), pp. 769–775 (cit. on p. 46).

[102] G. Villacreses et al. “Wind farms suitability location using geographical information system (GIS), based on multi-criteria decision making (MCDM) methods: The case of continental Ecuador”. In: *Renewable energy* 109 (2017), pp. 275–286 (cit. on p. 46).

[103] M. L. Sabo et al. “Spatial energy predictions from large-scale photovoltaic power plants located in optimal sites and connected to a smart grid in Peninsular Malaysia”. In: *Renewable and Sustainable Energy Reviews* 66 (2016), pp. 79–94 (cit. on p. 46).

[104] H. Bjørnebye, C. Hagem, and A. Lind. “Optimal location of renewable power”. In: *Energy* 147 (2018), pp. 1203–1215 (cit. on p. 46).

[105] M. Wagner, J. Day, and F. Neumann. “A fast and effective local search algorithm for optimizing the placement of wind turbines”. In: *Renewable Energy* 51 (2013), pp. 64–70 (cit. on p. 46).

[106] S. Silva, L. Alçada-Almeida, and L. C. Dias. “Biogas plants site selection integrating Multicriteria Decision Aid methods and GIS techniques: A case study in a Portuguese region”. In: *biomass and bioenergy* 71 (2014), pp. 58–68 (cit. on p. 46).

[107] E. Zografidou et al. “A financial approach to renewable energy production in Greece using goal programming”. In: *Renewable energy* 108 (2017), pp. 37–51 (cit. on p. 47).

[108] C.-T. Chang. “Multi-choice goal programming model for the optimal location of renewable energy facilities”. In: *Renewable and Sustainable Energy Reviews* 41 (2015), pp. 379–389 (cit. on pp. 47, 48, 142, 145).

[109] E. Ali, S. A. Elazim, and A. Abdelaziz. “Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations”. In: *Renewable energy* 101 (2017), pp. 1311–1324 (cit. on p. 47).

[110] A. Hamze et al. “Multi-sources energy plants location using goal-programming and flow control analysis approach”. In: *Codit2019-PapersOnLine* (2019) (cit. on p. 49).

[111] “Taiwan Power Company,Rate Schedules”. In: (2006) (cit. on p. 50).

[112] “Taiwan Power Company, Electricity Tariff Book”. In: (2006) (cit. on p. 50).

[113] “Ministry of Power Industry of the People’s Republic of China”. In: *Power Supply Business Rules* 7.8 (2012), p. 85. URL: http://www.nea.gov.cn/2012-01/04/c_131262676.htm (cit. on p. 50).

[114] J. E. N. (Ltd. “Policy for Resetting Contract Demand”. In: (). URL: http://jemena.com.au/ (cit. on p. 50).

[115] D. Feng et al. “Demand response in China”. In: *Three-Year Action Plan of Big Data Research and Development, Shanghai Sci. Technol. Comm., Shanghai, China.* (2013-2015). URL: http://www.stcsm.gov.cn/gk/ghjh/333008.htm (cit. on p. 51).

[116] M. Rodoplu, T. Arbaoui, and A. Yalaoui. “Energy Contract Optimization for the Single Item Lot Sizing Problem in a Flow-Shop Configuration and Multiple Energy Sources”. In: *IFAC-PapersOnLine* 51.11 (2018), pp. 1089–1094 (cit. on pp. 51, 52, 55, 58, 118, 143, 144).

[117] T.-Y. Lee and C.-L. Chen. “Iteration particle swarm optimization for contract capacities selection of time-of-use rates industrial customers”. In: *Energy conversion and management* 48.4 (2007), pp. 1120–1131 (cit. on pp. 52–54).

[118] M. Tsay, W. Lin, and J. Lee. “Optimal contracts decision of industrial customers”. In: *International Journal of Electrical Power & Energy Systems* 23.8 (2001), pp. 795–803 (cit. on p. 53).

[119] H.-T. Yang and P.-C. Peng. “Improved Taguchi method based contract capacity optimization for industrial consumer with self-owned generating units”. In: *Energy conversion and management* 53.1 (2012), pp. 282–290 (cit. on p. 55).

[120] A. K. Ferdavani and H. Gooi. “The very fast method for contracted capacity optimization problem in Singapore”. In: *2016 IEEE Region 10 Conference (TENCON)*. IEEE. 2016, pp. 2100–2103 (cit. on p. 56).

[121] D. Feng et al. “Optimal demand contracting strategy under uncertainty and its implication for advanced pricing”. In: *IEEE Transactions on Smart Grid* 7.4 (2016), pp. 1876–1885 (cit. on pp. 57, 113).

[122] J.-C. Hwang et al. “CSO and PSO to solve optimal contract capacity for high tension customers”. In: *2009 International Conference on Power Electronics and Drive Systems (PEDS)*. IEEE. 2009, pp. 246–251 (cit. on p. 57).

[123] France. *Eco2mix Download*. https://www.rte-france.com/fr/eco2mix/eco2mix-telechargement. [Online; accessed 27-July-2019]. 2019 (cit. on pp. 90–92, 113, 115, 120, 121).

[124] S. Qiu and Z. Chen. “An interior point method for nonlinear optimization with a quasi-tangential subproblem”. In: *Journal of Computational and Applied Mathematics* 334 (2018), pp. 77–96 (cit. on p. 108).

[125] A. El-Bakry et al. “On the formulation and theory of the Newton interior-point method for nonlinear programming”. In: *Journal of Optimization Theory and Applications* 89.3 (1996), pp. 507–541 (cit. on p. 108).

[126] H. Yamashita and H. Yabe. “Superlinear and quadratic convergence of some primal-dual interior point methods for constrained optimization”. In: *Mathematical Programming* 75.3 (1996), pp. 377–397 (cit. on p. 108).

[127] R. H. Byrd, G. Liu, and J. Nocedal. “On the local behavior of an interior point method for nonlinear programming”. In: *Numerical analysis* 1997 (1997), pp. 37–56 (cit. on p. 108).

[128] A. Hamze et al. “Optimization of energy demand contracting strategy with ecofriendly consideration”. In: *7th IEEE International Conference on Advanced Logistics and Transport Marrakesh Morocco June* (2019) (cit. on p. 118).

Energy and Uncertainty: Stochastic Modeling and Optimization of Multi-sources Energy Systems

Abstract

World energy demand is still mostly satisfied by traditional sources of fossil energy. Nevertheless, over the last decade, hybrid or multi-sources energy systems have become viable alternatives for energy production because they capitalize on the strengths of conventional energy sources as well as the ecofriendly benefits of renewable energy sources. The need to consider this type of hybrid system can be justified by the fact that renewable energy resources, in addition to being more expensive, are often disturbed by seasonal variations and cannot be considered as a reliable continuous source of energy. As part of this thesis, we carried out a review of the literature of different optimization problems related to systems with multi-sources of energy. At first, we worked on the problem of localization of multi-source energy systems. The objective was to establish an energy profile or potential of a geographical area by considering economic, social and environmental criteria. Then, we are interested in optimizing energy contracts to meet global consumption needs by considering "ecofriendly" aspects of these contracts. We have proposed mathematical models and resolution methods for optimizing the choice of multi-sources energy contracts considering deterministic and random demands.

Keywords: power resources, uncertainty, mathematical optimization, energy consumption, localization theory

Résumé

La demande énergétique mondiale est encore majoritairement satisfaite par les sources traditionnelles d'énergie fossile. Néanmoins, au cours de la dernière décennie, les systèmes énergétiques multi-sources sont devenus des alternatives viables pour la production de l'énergie car ils permettent de capitaliser sur les points forts des sources conventionnelles mais également sur les sources d'énergie renouvelables. L'intérêt de considérer ce type de systèmes hybrides réside dans le fait que les ressources d'énergie renouvelables, en plus de leurs coûts, sont souvent impactées par des variations saisonnières et ne peuvent être considérées comme un apport d'énergie continu et déterministe. Nous avons réalisé, dans le cadre de cette thèse, une revue de la littérature des différents problèmes d'optimisation en relation avec les systèmes énergétiques multi-sources. Dans un premier temps, nous avons travaillé sur la problématique de la localisation des systèmes énergétiques multi-sources. L'objectif est établir un profil ou un potentiel énergétique d'une zone géographique en considérant des critères économiques, sociaux et environnementaux. Ensuite, nous nous sommes intéressés à l'optimisation des contrats d'énergie pour répondre au besoin global de consommation en considérant des aspects «écoresponsables» de ces contrats. Nous avons proposé des modèles mathématiques et des méthodes de résolution pour l'optimisation du choix des contrats d'énergie multi-sources en considérant à la fois des demandes déterministes et des demandes aléatoires.[1]

Mots clés : ressources énergétiques, incertitude, optimisation mathématique, consommation d'énergie, localisation, théorie de la

ROSAS

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Abbas HAMZE

Doctorat : Optimisation et Sûreté des Systèmes
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Energie et incertitudes : modélisation et optimisation stochastique des systèmes énergétiques multi-sources

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