공학석사학위논문

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Abstract

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Today's companies are forced to deal with uncertainty daily, especially deep uncertainty. Unfortunately, this complicates long-term strategic planning. Deep uncertainty has been assessed in numerous studies using different approaches, mostly in fields such as water resource planning. However, it has never been applied to strategic facility allocation problems.

The purpose of this paper is to investigate deep uncertainty and its applicability in a newly presented facility allocation problem, using the Non-dominated Sorting Genetic Algorithm (NSGA II) to find the Pareto front solutions. A study case is presented to give insights and new perspectives in the light of our findings.

Keywords: Facility allocation problems, Multi-objective Optimization, Deep uncertainty, Genetic algorithm, Robust decision-making.

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Chapter 1. Introduction

The primary goal of virtually every company has always been to maximize shareholder value by generating as much profit as possible. However, given the difficulties in estimating operating costs and predicting sales, companies find difficulties in predicting exogenous variables such as demand and tariffs, which have a significant influence on the company's future strategies and operational goals.

Under deep uncertainty, companies face significant challenges concerning decision-making, planning, and strategy design especially when uncertainty is hovering over costs and demand. Exporting companies, for instance, need to deal with unpredictable tariffs fluctuations due to the political agenda of a country, or international political instability in general. Tariff fluctuations and new markets' eventual penetration are two factors, among others, impacting company performance. Strategic decisions should be made in light of the existing data on these factors. However, data can be unavailable, incomplete or unreliable (Mezias et al., 2009). Hence, the use of simulation models to mimic the reality as much as possible is justified.

Traditionally, simulation models are used to predict future consequences, and decisions are optimized in light of these predictions. However, under deep uncertainty, models should be used in an exploratory fashion, "for 'what-could-happen-if' scenario generation, for learning about system behavior; for exploratory rather than predictive purposes" (Kwakkel, 2017). Although the use of models is generally explained by the need to simplify real systems or the lack of information on these systems, “the use of models to make predictions can be seriously misleading if there are profound uncertainties” (Kwakkel et al., 2013). In 2001, Ben-Haim called this type of uncertainty "severe uncertainty," and Lempert was the first to call it “deep uncertainty” in 2003; and since then the term “deep uncertainty” became the most used expression. Kwakkel et al., (2010) define this notion as “a situation where one can incompletely enumerate multiple possibilities without being able or willing to rank order the possibilities in terms of how likely or plausible they are judged to be” (Kwakkel et al., 2010). This is mainly due to the inherent complexity of the system under study. In other words, the system cannot be fully observed because many components interact in a variety of ways, leading to the need for a different approach to deal with such uncertainties.

Research on designing robust strategies across a plethora of irreducible uncertainties has produced, among others, the technique called Exploratory Modeling and Analysis (EMA), developed by the RAND Corporation, and an open source toolkit for exploratory modeling was implemented in Python by Kwakkel (2017). EMA can be understood as searching or sampling over a set of models that are plausible, given a priori knowledge or are otherwise of interest. Moreover, EMA was explicitly used to investigate the impact of deep uncertainty in specific fields, especially in environmental systems problems and adaptive policymaking.
Kwakkel and Pruyt (2013) stated that

> “EMA aims at offering decision support even in the face of many irreducible uncertainties, by systematically exploring the consequences of a plethora of uncertainties – ranging from parametric uncertainties (e.g., parameters ranges), over structural uncertainties (e.g., different

structures and models), to method uncertainties (e.g. different modeling methods)."

In this paper, the EMA concept will be used to explore the different scenarios and different strategies, among which the company may choose when faced with uncertainties in tariffs and demand.

In addition, this paper will address a new version of the facility allocation problem. It is a strategic decision-making problem where one company is unsure whether to invest and grow, or reduce risks and accumulate savings. The company under consideration needs to evaluate its capacity augmentation options, namely the opening of new factories or the closure of the existing ones, in a fixed planning horizon using many scenarios to account for the deep uncertainty.

Even though the options explored in this study are either opening or closing factories, the other potential options are to increase or reduce the company's capacity, such as outsourcing services, industrial park renewal or even short-term options such as extra hours. When more options are given, the problem becomes more realistic but also more complex. The use of simulation software such as ARENA or other available simulation software can help describe the problem better and also permits the deep uncertainty investigation.

Hence, deep uncertainty will be investigated in a particular allocation problem, where tariffs and external demand contribute to deep uncertainty. The purpose of this paper is to investigate this type of uncertainty in the allocation problem as a first. It is a two-objective optimization problem, including profits and robustness as objectives. This approach was chosen to help decision-makers gain insight into a strategic problem and investigate to what extent this approach can be helpful when making long-term decisions.

Knowing that exploratory decision-making approaches for addressing multi-objective and deeply uncertain decision problems is a relatively new area (Moallemi et al., 2018), and inspired by the current events on international trade and the work of Beh et al., (2017), a strategy decision-making problem was designed. By using the NSGAII algorithm, the researcher attempts to find the most robust and profitable solutions to the Pareto front.

The remainder of this paper is structured as follows. The next Chapter contains a literature review on strategic planning, deep uncertainty approach, and location-allocation problems. Chapter 3 contains a description of the considered problem in addition to a brief section on the methodological approach, how the deep uncertainty is incorporated and the definition of the mathematical model. Furthermore, Chapter 4 describes the solution approach including the problem simplification steps. Numerical experiments are described and analyzed in Chapter 5. A concluding Chapter sums up our study and explores further research directions.

Chapter 2. Literature Review

Companies face challenges to cope with the continuous change in meso-level factors such as the environment and market trends, but also in macro-level factors such as political agenda and currency fluctuations. For instance, steel companies facing the recently implemented U.S. tariffs on steel and aluminum are vulnerable to such practices, especially those located in important U.S. trade partners such as Canada and China. Even though some voices condemned these unilateral practices as illegal for violating rules in the General Agreement on Tariffs and Trade (GATT), they were unable to undo these actions, and hence steel companies need to reconsider their strategy.

Political agendas leading to trade wars are unpredictable and very volatile; thus, companies need to evaluate and seize any opportunity to overcome such disruptive occurrences. New markets penetration, for instance, can be one of the opportunities to tackle high tariffs imposition. The implementation of such strategic decisions is often crucial to the company's development and survival.

The problem discussed in this paper falls into the strategic decision-making field. Schwenk (1984) discussed some cognitive simplification processes in strategic decision-making. He gathered the research done by cognitive psychologists and behavioral decision theorists (Hofer et al., 1978; Mason et al., 1981; Mazzolini, 1981) on the matter, discussed the cognitive processes to simplify the decision maker's perceptions of problems, and how the “bounded rationality” effects the decision outcomes at each stage of the strategic decision-making process. These stages, namely goal formulation/problem identification, alternatives generation, and evaluation and selection can also be found in the methodology section of this paper.

Besides the human cognitive limitations, strategic planning problems are complex and ambiguous due to the lack of appropriate and complete datasets (Mezias et al., 2009). Simulation software programs have been widely developed and heavily used in the last decades to overcome those shortcomings. Simulation-based decision support systems are used in a spectrum of domains, including scientific, industrial and medical domains, and are continuously improved to narrow the gap between the real world and simulation models (Reijers et al., 1999), when forecasting techniques fail to capture the uncertainty.

Furthermore, many papers dealt with deep uncertainty in the water system problems using different approaches (Dessai et al., 2007; Matrosov et al., 2013). Beh et al., (2017) used metamodels to reduce the computational burden of the process simulation, such that robustness is included as an objective in the optimization process, which could not have been done without the use of metamodels. Beh et al., (2015) also used an adaptive approach to design the augmentation of the water system of Adelaide. Besides, Kasprzyk et al., (2013) have designed a robust decision-making approach for complex environmental systems, and Matrosov's work (2013) was based on selecting portfolios of water supply and demand management strategies under uncertainty.

Few writers have dealt with deep uncertainty in a context other than environmental issues. For example, Kwakkel et al., (2010) dealt with deep uncertainty in airport strategic planning. Pruyt (2010) used an exploratory system dynamics model to deal with the scarcity of metals and minerals. Furthermore, data mining techniques, such as clustering (Pruyt, 2010) and classification trees (Breiman, 2017), are more and more often used 'to extract decision-relevant information' (Kwakkel et al., 2013), and to help exploratory modeling analysis when a large number of scenarios is investigated.

In addition, location-allocation facility problems refer to a broad category of optimization problems. As defined by Farahani and Hekmatfar (2009), facility location problems "locate a set of facilities (resources) to minimize the cost of satisfying some set of demands (of the customers) with respect to some set of constraints." Depending on the nature of the facility set –i.e., a finite set or a continuous space- the facility location-allocation is said to be discrete or continuous. Furthermore, we can distinguish between static and dynamic (Wesolowsky et al., 1975), capacitated (Sridharan, 1995) and incapacitated (Chudak et al., 2003; Verter, 2011), and between deterministic (Church et al., 1974; Hakimi, 1964) and stochastic (Revelle et al., 1989; Wang et al., 2002) location-allocation facility problems, based on the time variable, the capacity constraint, and whether a variable is probabilistic, respectively.

Mehrez (2016) provided a system whereby facility location problems can be categorized. Owen and Daskin (1998) reviewed stochastic location problems, distinguishing between probabilistic models and scenario planning models. For the latter, researchers incorporated uncertainty into models by assessing their solutions over a number of scenarios. While some researchers attempted to assess uncertainty by post-optimization sensitivity analysis (Labbé et al., 1991), others incorporated uncertainty by evaluating the expected regret, or other performance functions proactively, across all scenarios in classic deterministic problems such as p-median location problems.

As for solution approaches, the methods developed to solve this variety of location-allocation problems vary from exact methods to hybrid metaheuristics. In his book, Daskin (2011) made a review of the solution approaches used in discrete location problems, and Brimberg et al., (2008) compiled the solution methods used to solve the continuous location facility problem.

The major differences between the previous studies and the present one are the incorporation of a robustness index as an objective function, plus the expected performance (the average value of the profit function) across all scenarios. Another major difference is the formulation of a new model of the capacitated allocation problem where the number of facilities to implement is not predetermined and where the closure of certain facilities is possible. Finally, the EMA approach was applied using a wide range of possible scenarios equally likely, and not only best guess scenarios weighted by their occurrence probability.

Chapter 3. Facility Allocation Problem

The allocation facility problem discussed in this paper has slight variations from the well-known facility allocation problem. In The Fault-Tolerant Facility Allocation Problem (Xu et al., 2009) for instance, the purpose is to minimize operating and service accessing costs while planning the allocation of facilities for each site. Unlike the previous problem (FTFAP), the present problem requires to allocate capacity by opening new factories or closing old ones, without considering the factories location.

3.1 Methodology

In this section, we explain our approach steps shown in Figure 3.1. The first decision stage is problem identification, which includes the selection of the objectives and their translation into measurable criteria. These two steps are important because it is the phase when decision makers define their goals and formulate them into mathematical functions with the risk of an inadequate formulation. The two objectives chosen in this study can be modified, but attention should be made when choosing robustness performance criteria for different problems. Moreover, the identification of options step is usually a simple one because the decision makers generally know beforehand the feasible solutions.

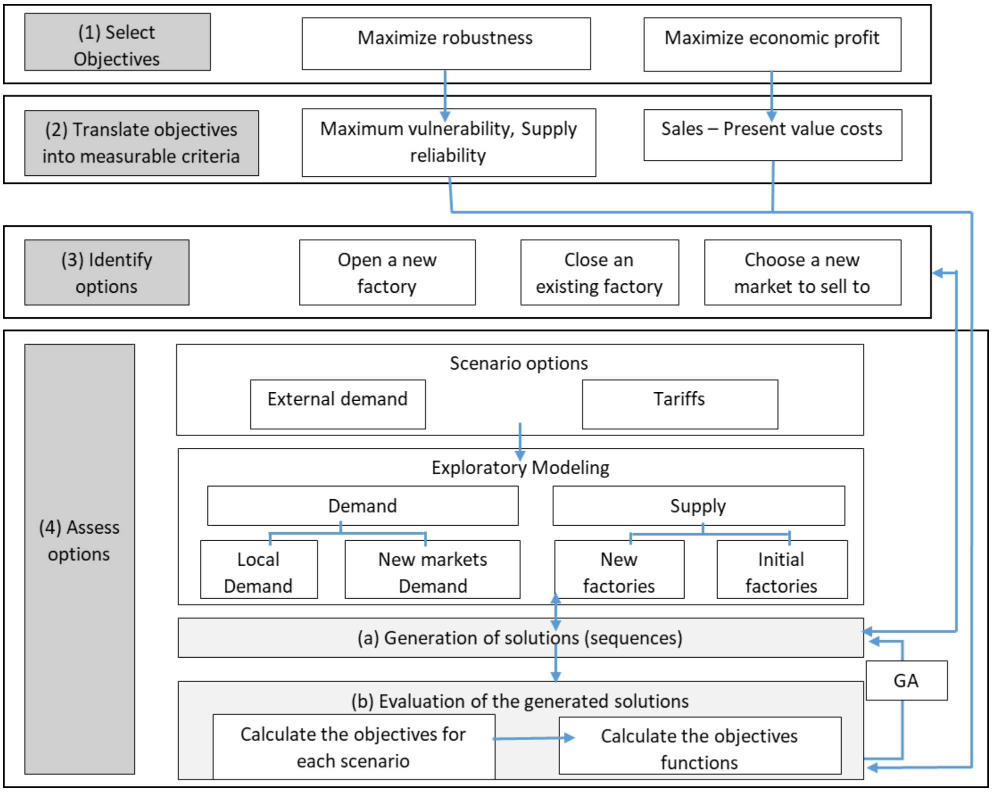

Figure 3.1 Methodology schema

A more adaptive approach would assume that the options would evolve with time and the advent of new technologies, in which event the decision makers will need to evaluate the incorporation of the new solutions proactively. In this study, it is presumed that the company has three options: (i) open new factories (ii) close initial ones or (iii) sell to a new market with uncertain demand. The fourth step, option assessment, consists of using a genetic algorithm (GA) to generate solutions, namely sequence plans, and to select the best solutions based on their performance on a large number of pre-selected scenarios. The mean profit overall scenarios and robustness value are the basis on which solutions are compared. This process of solution generation and evaluation continues until the stopping criterion of the GA is met. These steps allow the deep uncertainty approach to be applied to a new strategic allocation problem. By adapting it to this new problem, the researcher applied it to a study case to see to what extent this approach is suitable for the new problem. The choice of the GA and the solution approach are detailed in the next Chapter.

3.2 Problem description

Consider that a company has a few factories and sells to two types of markets: the local market and a foreign overseas one. High tariffs are suddenly imposed in the foreign market, which makes selling to this market hardly profitable. Thus, the company's decision makers see the urge to adjust their strategy and seek the penetration of new foreign markets, even though they are aware of the risks of irregular and unpredictable demand; see Figure 3.2.

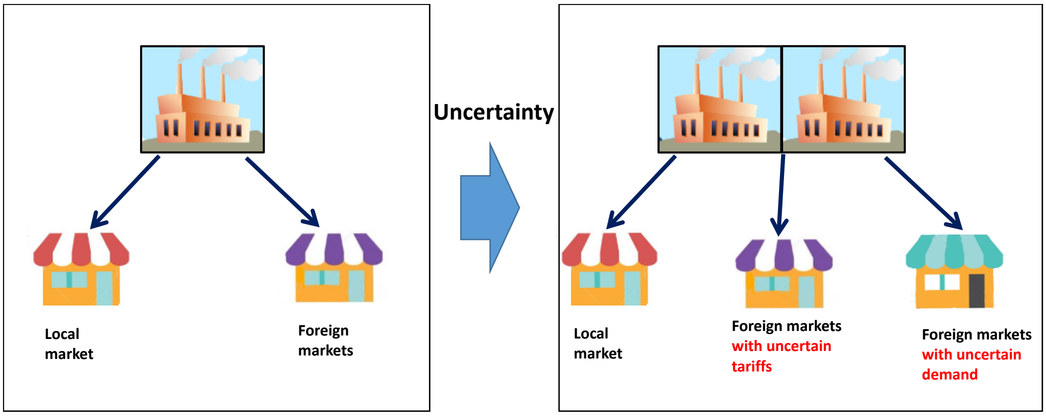

Figure 3.2 Problem description

Given a set of initial factories, a set of eventual new factories, and the corresponding capacities and operating costs, the company needs to identify which factories to open, or which one among the existing factories to close, the quantities to produce, the quantities to sell and to which markets. Some of the existing factories cannot be closed, because they are critically important in the production chain. Since the opening and the closure of factories are long term decisions, this is a multiple-period problem with a fixed planning horizon T and staging intervals. Each staging interval, or period as it is called in the remainder of this paper, is considered a decision stage.

Three types of markets are considered: the local market, a foreign market with uncertain tariffs and a new market with uncertain demand. Each market has specific tariffs, transport cost and selling price, whereas each factory is characterized by its capacity and production cost. The initial factories that can be closed are characterized by their closure costs, while eventual new factories have their proper opening and closing costs.

Furthermore, this is a two-objective optimization problem, with profit and robustness index as the objective functions. The first objective function is defined as the difference between revenues, mainly sales, and the present value of the capital costs and operating costs. The second objective function is roughly defined as a quantitative metric of robustness that depicts the robustness of solutions faced with deep uncertainty, with details given in the subsequent sections.

3.3 Uncertain variables and robustness as an objective function

Unlike the standard robust optimization approach, this paper investigates the robustness of the solutions using performance metrics over many scenarios, in a similar approach to what was done by Beh et al., (2017). In this section, we present in detail the incorporation of robustness as an objective function and how deep uncertainty is designed. The profit objective function is defined in Section 3.5.

3.3.1 Uncertain variables and scenarios

As discussed in the Introduction, tariffs of the foreign markets and demand of the new foreign markets are considered as deeply uncertain variables UV_i in this problem. In general, a combination of n uncertain variables (UV_i i=1, 2, ... n) represents a scenario, such that a particular future scenario is represented as $S_l=[UV_{1,l}, UV_{2,}\ l,..., UV_{n,l}]^T$, where l={1,2..., NS}, and NS is the total number of scenarios (Beh et al., 2017). As mentioned before, deep uncertainty is generally represented via scenarios to account for multiple plausible future trajectories that cannot be associated with a probability or a rank (Maier et al., 2015). Hence, these uncertain variables will take a broad range of values to form a number of scenarios.

3.3.2 Robustness

The definition of robustness used in this study is very similar to the one used in a number of previous studies to assess water resources systems (Beh et al., 2017) (Paton et al., 2014), but is slightly modified here.

Robustness is defined as the fraction of L future scenarios (S_i=1, 2, ..., L) for which the system under consideration was considered to exhibit "acceptable performance"; the latter indicates a performance according to a set of performance criteria, which generally act as constraints in optimization problems (Beh et al., 2017; Paton et al., 2014):

$$R = \frac{Nb\ of\ Scenarios\ where\ performance\ criteria\ are\ met}{Total\ nb\ of\ Scenarios} \qquad (*)$$

The performance criteria are case study dependent and are chosen to assess the performance of the system. More details are given in the following subsection.

3.3.3 Performance criteria

To assess the system performance and to be able to qualify it as "acceptable," decision makers need to agree on the performance metrics and the performance criteria that will be used to assess the system. Two performance metrics were used for this problem -the minimum level of supply reliability C_r and the average vulnerability C_v- with details given in 3.5. The performance metrics are study-case dependent, and the appropriate performance criteria are usually determined with the aid of stakeholder consultation (Wu et al., 2016).

3.3.4 Overall evaluation of solutions

Consider a solution x, a sequence plan, to be evaluated. As mentioned before, this is a two-objective optimization problem, but in general, all the objectives except robustness are to be calculated for the solution x for all the given scenarios. To compare between solutions, the mean of each objective values (except robustness) is calculated. In other words, the final objective function is the mean of the objective values for each scenario. Rather than choosing the mean values, one could choose other functions including but not limited to functions such as the range, the median, and the variance.

Regarding the second objective function, robustness is by definition a calculation of performance metrics over the given scenarios, which means no more action is needed to assess the robustness of the solution x.

3.4 Notations and assumptions

As mentioned in the introduction of Chapter 3, this is a multi-period problem with a fixed planning horizon T and staging interval i. We consider a set of factories J, subdivided into two subsets: a set of existing factories J_I and a set of eventual new factories J_E. Another subset of factories J_C represents the factories that can be closed. The complement of the set J_C contains factories that cannot be closed due to their critical importance in the production chain (e.g., headquarters, mining sites ...).

In short, $J = J_I \cup J_E$, $J_E \subseteq J_C \subseteq J$, and $J_I \cap J_E = \emptyset$.

i refers to the period index, k to the market index and j to the factories index. More notations are summed up in the following table:

Costs:	
$C_{prod, j}$	Production costs for factory j per unit
$C_{exp,j}$	Costs for opening a factory $j \in J_E$
$C_{close, j}$	Costs for closing a factory $j \in J_c$
$C_{t,k}$	Transportation costs for the market k
$f_{i, k}$	Tariffs for the market k in period i
Decision variables:	
$y_{i,j}$	Binary, opening decision of factory j in period i,
$x_{i, j}$	Binary, closure decision of factory j in period i
$Q_{i, j}$	Integer, quantity produced by factory j in period i
$X_{i, k}$	Integer, quantity sold to market k in period i
$z_{i,j}$	Binary, indicates factory j state in period i: {1}if open {0} if closed
Other data:	
$C_{p, j}$	Capacity of the factory j
NS	Number of scenarios
$D_{i, k}$	Demand of the market k in period i
$P_{i, k}$	Selling price for market k in period i

To solve the present problem, the following assumptions were made:

1. No stocking between periods: quantities produced in one period are sold in the same period.

2. Selling prices are constant over the planning horizon.

3. Demand for local and foreign markets with uncertain tariffs are constant.

3.5 Mathematical formulation

3.5.1 Objective Functions:

The profit objective function for a single scenario is formulated as follows:

$$O_s = \sum_{i=1}^{N}\left[\sum_{k=1}^{K}\left(p_{i,k} - C_{t,k} - f_{i,k,s}\right) X_{i,k,s} - \sum_{j=1}^{J}\left(C_{exp,j}\, y_{i,j,s} d + C_{close,j}\, x_{i,j,s} + C_{prod,j} Q_{i,j,s}\right)\right] \quad (1)$$

The profit function for a single scenario is defined as the difference between the sales and the present value of the capital costs and the operating costs. The capital costs include the costs of opening and closing factories, and the operating costs include production costs, transportation costs, and tariffs. To calculate the present value of the capital costs, a discount factor d was used:

$$d = \frac{1}{(1+r)^n}$$

Where r represents the discount rate, and n represents the design life.
As for the robustness function, we use the same definition described above (*). The performance criteria are defined as follows.

- The minimum level of supply reliability C_r is the fraction of periods in which available supply is greater than or equal to demand over the planning horizon:

$$C_r = \frac{1}{T}\sum_{t=1}^{T} I\left(SU_t,\ DM_t\right)$$

Where SU_t is the quantity supplied and DM_t is the demand from all markets in period t. See Chapter 4 for more details on how the quantities supplied $(X_{t,k})$ are calculated.

- The average vulnerability C_v is the average of the supply shortfall per period within the time horizon T

$$C_v = \frac{1}{T}\sum\left\{\frac{\min[(SU_t - DM_t),0]}{DM_t}\right\}$$

The performance criteria are:

$C_r \geq 80\%$

$C_v \leq 30\%$

3.5.2 Formulation

The formulation of the present problem can be stated as follows:

$$Maximize : \frac{1}{NS}\sum_{s=1}^{NS} O_s \tag{2}$$

Maximize R (3)

Subject to:

$$\begin{aligned} &z_{1,j} = y_{1,j},\ \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}} \\ &z_{i,j} = z_{i-1,j} + y_{i,j} - x_{i,j}, 2 \leq \forall \mathrm{i} \leq \mathrm{N} \end{aligned} \tag{4}$$

$$\begin{aligned} &z_{i,j} = z_{i-1,j} - x_{i,j},\ 2 \leq \forall \mathrm{i} \leq \mathrm{N} \\ &z_{1,j} = 1 - x_{1,j},\ \forall \mathrm{j} \in \mathrm{J}_{\mathbf{I}} \end{aligned} \tag{5}$$

$$\sum_{p=1}^{i} y_{p,j} = 0 \Rightarrow x_{i,j} = 0, \forall \mathrm{i}, \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}} \tag{6}$$

$$\begin{aligned} &y_{i,j} = 1 \Rightarrow x_{i,j} = x_{i+1,j} = x_{i+2,j} = 0\ , 1 \leq \forall \mathrm{i} \leq \mathrm{N}-2 \\ &y_{N-1,j} = 1 \Rightarrow x_{N-1,j} = x_{N,j} = 0 \\ &y_{N,j} = 1 \Rightarrow x_{N,j} = 0, \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}}, \forall \mathrm{i} \end{aligned} \tag{7}$$

$$y_{i,j} = 1 \Rightarrow (x_{i,j'} = 0\ \forall \mathrm{j}' \in \mathrm{J}_{\mathbf{C}}),\ \forall \mathrm{i},\ \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}} \tag{8}$$

$$\begin{aligned} &Q_{i,j} \leq Cp_j\ (z_{i,j} - y_{i,j}),\ \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}},\ \forall \mathrm{i} \\ &Q_{i,j} \leq Cp_j\ z_{i,j},\ \forall \mathrm{j} \in \mathrm{J}_{\mathbf{I}},\ \forall \mathrm{i} \end{aligned} \tag{9}$$

$$\sum_{i=1}^{N} y_{i,j} \leq 1 \,; \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}}$$
$$\sum_{i}^{N} x_{i,j} \leq 1 \,; \; \forall \mathrm{j} \in \mathrm{J}_{\mathbf{C}} \tag{10}$$
$$\sum_{j=1}^{J} Q_{i,j} = \sum_{k=1}^{K} X_{i,k}, \; \forall \mathrm{i} \tag{11}$$
$$\sum_{\boldsymbol{j}} Q_{i,j} \leq \sum_{\boldsymbol{k}} D_{i,k}, \; \forall \mathrm{i} \tag{12}$$
$$X_{\boldsymbol{i},\boldsymbol{k}} \leq D_{i,k}, \; \forall \mathrm{i}, \mathrm{k} \tag{13}$$
$$y_{i,j} = 0, \; \forall \mathrm{j} \in \mathrm{J}_{\mathbf{I}}; \; \forall \mathrm{i} \tag{14}$$
$$x_{i,j} = 0, \; \forall \mathrm{j} \notin \mathrm{J}_{\mathbf{C}}; \; \forall \mathrm{i} \tag{15}$$
$$Q_{i,j} \geq 0, X_{i,k} \geq 0, \; \forall \mathrm{i}, \mathrm{j}, \mathrm{k} \tag{16}$$
$$z_{i,j}, y_{i,j}, x_{i,j} \; \textit{are binary} \tag{17}$$

The objective function (2) maximizes the mean value of the profit function for each scenario, and (3) maximizes the robustness as defined previously in 3.3. Constraints (4) and (5) define the factories state z_{ij}. Constraint (6) means that a new factory cannot be closed before it is implemented first. The linearization of this constraint is as follows:

$$x_{i,j} \leq \sum_{p=1}^{i} y_{p,j}, \; \forall \mathrm{i}, \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}} \tag{6'}$$

Constraint (7) ensures the assumption made about the closing of a newly implemented factory, which can only occur after two periods; here follows its linearization:

$$\sum_{p=i}^{i+2} x_{p,j} \leq 1 - y_{i,j},$$
$$x_{N-1,j} + x_{N,j} \leq 1 - y_{N-1,j} \tag{7'}$$
$$x_{N,j} \leq 1 - y_{N,j}, \; \forall \mathrm{j} \in \mathrm{J}_{\mathbf{E}}, \forall \mathrm{i}$$

Constraint (8) prevents the opening and the closure of factories in the same period. The linearized form of these constraints is the following:

$$\sum_{j \in \mathrm{J_E}} y_{i,j} \leq E(1 - \sum_{j' \in \mathrm{J_C}} x_{i,j'}), \tag{8'}$$

Where E is the cardinality of the set J_E. Besides, Constraint (9) ensures that open factories produce at most up to their capacity, and newly opened factories do not produce anything during the first period of implementation. Constraint (10) imposes that each eventual factory can be opened at most once; similarly, each factory from the J_c can be closed at most once. In addition, Constraint (11) ensures the assumption made about no stocking is allowed between periods made in [3.4]. Constraints (12) and (13) impose the total production to be less than the total demand, and the sales to a market k should be less than the market demand, respectively.

Moreover, Constraint (14) defines the decision variable y for the set of first factories, and Constraint (15) defines the decision variable x likewise for the complement of the set J_c. Finally, Constraints (16) and (17) defines the nature of the decision variables.

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Chapter 4. Solution Approach

The Non-dominated Sorting Genetic Algorithm (NSGA II) was designed by Deb et al., in 2000, as an improvement of a previous algorithm developed by the same authors called NSGA. It belongs to the multi-objective evolutionary algorithms category, popular for generating Pareto optimal solutions, which is the reason this GA was chosen for this problem. NSGA II procedure is characterized by three major features that make this algorithm fast, efficient and popular, namely the use of an elitism principle, the emphasis on the best non-dominated solutions, and the explicit diversity preserving mechanism (Deb et al., 2002).

The problem defined in the previous Chapter is adapted to be optimized with NSGA II. It was decided not to use a deterministic solution approach to solve the given problem because it is difficult to include the EMA approach within the optimization process. In the following sections, the problem adaptation will be discussed in more detail.

4.1 Problem simplification

To simplify the problem, the number of decision variables were reduced by implementing two rules to calculate $Q_{i,j}$ and $X_{i,k}$, namely the quantity produced by each factory and the quantity sold to each market.

In Algorithm 1, the rule used to calculate $Q_{i,j}$ distinguishes between two situations. The first situation is when the total demand is greater than the available capacity.

In this case, all open factories produce up to their capacity to meet the demand as much as possible.

The second case is when the total demand is less than the available capacity, in which case factories are sorted by their production costs. If the capacity of the factory with the smallest production cost is less than the total demand, the factory produces up to its capacity. Similarly, the next factory in the sorted set will produce up to its capacity, and so on. This procedure is continued until the capacity of a factory is greater than the remaining demand. This factory will produce the remaining quantity while the other factories from the sorted set produce nothing, considering the assumption –made in 3.4- of no stocking between periods.

Given the factories states z_{ij}, their capacities Cp_j, the demand $D_{i,k}$, and the production costs $C_{prod,j}$, the quantities produced by each factory are calculated by the following algorithm.

Algorithm 1. Calculation of $Q_{i,j}$
Initialization: Q=0 For each period i: { $d = \sum_{k=1}^{K} D_{i,k}$;   if ($\sum_{j=1}^{J} Cp_j z_{ij} \leq d$) then   for j in J do: { $Q_{i,j} = Cp_j z_{ij}$}   else   j=0;   fact_sorted=sort_open_fact_by_Cprod();   while {$d \geq 0$}   {   index=fact_sorted[j]   if ($d > Cp_{index}$) then

```
                    Q_{i,index} = Cp_{index};
                    d = d − Cp(index);
                    j=j+1
            else
                    Q_{i,index} = d;
                    d = 0
            end if
            }
   end if;
}
```

This rule optimizes the robustness regardless of its impact on the profit. In other words, such a rule can induce a decrease in profit, as it is not always profitable to meet the demand. However, it will always aim to increase robustness as it implies that the company will produce as much product as it can to meet the demand.

Similarly, the second rule to calculate $X_{i,k}$ distinguishes between two situations; whether the supply can satisfy all the demand or not. In the first case, the company sells its products to all markets. In the second case, markets are sorted by their "profitability." Indeed, the difference between the selling price and transportation costs and tariffs ($P_{i,k}$ - $C_{t,k}$ - $f_{i,k}$) is a good indicator to determine how much the company will gain from selling its product to that market, as it can be deducted from the objective function (1). Again, the company sells to the markets with the highest "profitability" in priority until the remaining production is less than the market demand. It is assumed that the market accepts to buy a portion of its demand, i.e., the remaining production and no fees are induced by a future shortage. The company sells nothing to the remaining markets.
Algorithm 2 shows the implementation of the second rule to calculate the quantity sold to each market.

Algorithm 2. Calculation of $X_{i,k}$

```
Initialization: X=0
For each period i:
{
   d = Σ_{k=1}^{K} D_{i,k};
   Q = Σ_{j=1}^{J} Q_{i,j};
   if (Q = d) then
          for k in K do:
                    {
                    X_{i,k} = D_{i,k}}
   else
          k=0;
          market_sorted=sort_market();
          while {Q >0}
          {
             index=market_sorted[k]
             if (Q > D_{i,index} then
                    X_{i,index} = D_{i,index};
                    Q = Q − D_{i,index};
                    k=k+1
             else
                    X_{i,index} = Q;
                    Q = 0
             end if
             }
   end if;
}
```

This rule optimizes the profit without diminishing the robustness index. Concretely, such rule can induce an increase in the profit, as it is always more profitable to sell to the market with the highest (Market_Price-Transport_cost-Tariffs) value. However, it will not change the robustness index as the amount of the demand met remain unchanged.

It can be noticed that Constraints (9), (11), (12), (13) and (16) were all verified in the calculation process described above. However, the calculation of the quantity sold to each market $X_{i,k}$ using this rule prevents the company from choosing whether to sell to the new foreign market or not. In other words, it strips the company of its third option.

4.2 Solution representation

To simplify the problem, the decision variables used in the optimization process are the periods of opening and closing each factory from J_c. The chromosome, or the solution representation, consists of two lists: one list for the opening periods and the second for the closing periods for each factory. If a factory is not opened during the time horizon, the gene corresponding to that factory will take the value 0, and the same thing applies for the closing periods.

Factory j ∈ J	1	2	3	4	5
Opening Period	0	5	4	4	0
Closing period	0	0	9	0	0

Figure 4.1 Solution representation example

This representation implicitly implies that Constraint (10) holds true because there are one closing period and one opening period for each factory. Also, we chose to take into account Constraints (6), (14), (15) and (17) while generating the solutions, for the sake of simplicity. The next section will discuss the handling of the remaining constraints.

4.3 Constraint handling

The constraint-handling approach for the NSGA II (Deb et al., 2002) in multi-objective optimization problems uses the constrained-domination notion, based on the overall constraint violation value: a solution i constrained- dominates j if:

1) i is feasible and j is not.
2) i and j are infeasible but i has a smaller overall constraint violation.
3) i and j are feasible and i dominates j.

This means that between the infeasible solutions, it is the constraint violation that determines which solution dominates. The only constraints allowed to be violated are Constraints (7) and (8). The constraint violation is then calculated as the number of times the opening and the closing of two factories happens simultaneously, plus the number of times it was decided to close a factory before two periods passed from its opening.

It was decided not to include the performance criteria in the constraints because it was found computationally inefficient, and were calculated within the second objective function.

Chapter 5. Computational experiments

In this section, we describe and analyze the numerical experiments built in Python 3.6, and conducted with an Intel Core(TM) i5-8250U CPU 1.6 GHz with 8 GB of RAM in Windows 10.

5.1 Data description

A 10-year time horizon and a year staging interval were chosen for all the experiments. The alternatives that the company can choose from, namely the set of possible factories, with their respective production costs, opening, and closing costs and capacities, are resumed in the following table:

Table 5.1 Factories data

Factory number	1	2	3	4	5	6	7	8	9
Production costs ($)	13	11	8.5	9	9.5	10	10	11	11.5
Opening costs ($)	0	0	155000	135000	95000	80000	72000	55000	45000
Closing costs ($)	0	40000	80000	60000	50000	30000	25000	20000	15000
Unit capacity	950	1200	1400	1000	750	600	500	400	250

Except for the factories number 1 and 2, all the factories do not exist initially but can be opened, and all factories except the factory number 1 can be closed.

The used data is artificial but consistent to some extent. For instance, the production costs decrease with the factory capacity due to economies of scale. Also, the preexisting factories have higher production costs because of age. Closing and opening costs are proportional to the capacity as well.

Regarding markets, three markets were adopted: local 'L,' foreign with uncertain tariffs 'F,' and new foreign with uncertain demand 'N.' The following table resumes their characteristics.

Table 5.2 Markets data

Market number	1	2	3
Market type	L	F	N
Transportation costs ($)	2	6	10
Selling price ($)	20	25	30

One crucial assumption here is that all costs and selling prices, in particular, are fixed over the time horizon. Assuming that the selling prices are fixed over the time horizon is, of course, unrealistic since the price depends on the demand and the supply, and evolves with time especially in a 10 years space, but was chosen to simplify the problem. One possible way to overcome it is to select a cost function as an objective rather than the profit function.

The discount rate used to calculate the capital costs present value is equal to 0.06.

5.2 Scenarios

As mentioned in 3.3.1, a scenario consists of a combination of uncertain variables states. Here, the uncertain variables are the demand of the new foreign markets and the tariffs of the primary foreign market.

For the new market demand variable, three states were identified: low, average and high demand. The following table resumes the ranges for each state.

Table 5.3 Upper and lower bounds of the foreign market demand for each state

Demand	Lower bound	Upper bound
High	1000	1500
Average	650	999
Low	100	649

For the tariffs variable in the primary foreign market, 27 situations were identified. The tariffs are assumed to be changing over the time horizon and can take three states: null, low and high. The study starts with the initial situation where no tariffs are yet imposed. After the first period, tariffs take different values every three periods. For instance, in the three first periods, tariffs can stay low, then go up high for the next three periods, and stay high for the last three periods. Since tariffs can take three values (null, low and high), and can vary three times over nine periods, - the first period being the initial state, - it results in 27 situations: (3 states*3 states*3 states). Hence, 81 scenarios are identified in total (3*27).

Genetic operators' parameters

To generate the population offspring and to preserve diversity, a single-point crossover method with a 1.0 crossover probability was chosen as the genetic operator for both solution lists. A mutation probability of 0.9 was chosen for both lists as well. A series of tests were conducted before choosing these probabilities.

5.3 Results and discussion

The optimization process lasted about one hour and twenty minutes. Figure 3 shows the Pareto front of the solutions given by the NSGA II algorithm.

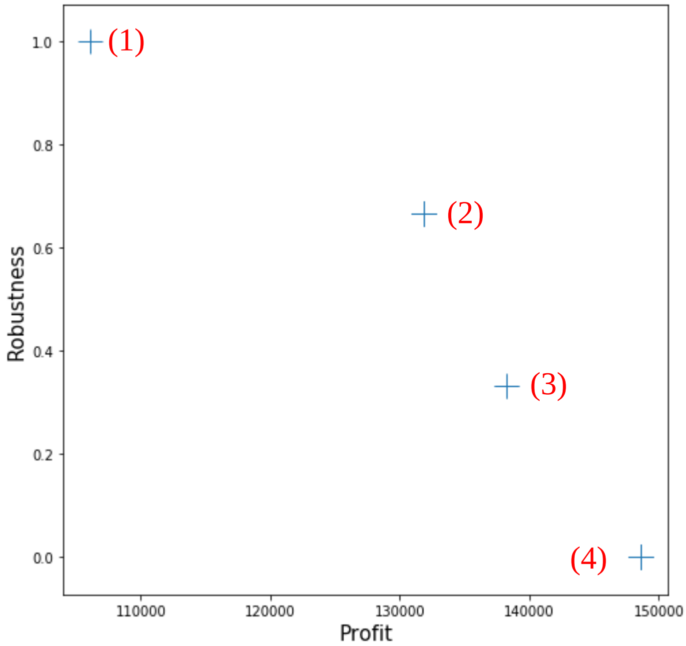

Figure 5.1 Pareto-Front Solutions

Four solutions and three significant jumps in robustness can be observed in Figure 5.1. The latter shows that the robustness index and the profit evolve in opposite directions, as it can be intuitively predicted. The two solutions in the extremes (robustness $= \{0,\ 1\}$) depict two extreme situations. Solution (4) with a null robustness index refers to the initial situation, namely the company keeps the two initial factories opened with no further changes. Solution (1), depicts the situation where the company chooses to open the factory with the highest capacity, factory 3, in the 1st period. Solution (2) consists of opening factory 5 in the 1st period, and Solution (3) consists of opening the factory number 6 in the 1st period. Solution (2) can be considered better than Solution (3) because the difference in the profit function between the two solutions is relatively insignificant (about \$16000), but the robustness index of (2) is greater by 0.33 than that of (3). The company can choose among these four solutions based on its strategy, its vision and its economic health.

All four solutions did not include the closing options. The relatively high closing costs can explain this result. The closing option aims at setting a more general problem. Indeed, even though it seems unlikely that a company makes such big decision like closing a factory in a relatively short period, this option was considered to account for other scenarios that a company can think of or is likely to face.

We investigated the effect of using only one state of demand at once: we run the program three times, having 27 scenarios each time with different tariffs states and a single demand state; the following results were obtained:

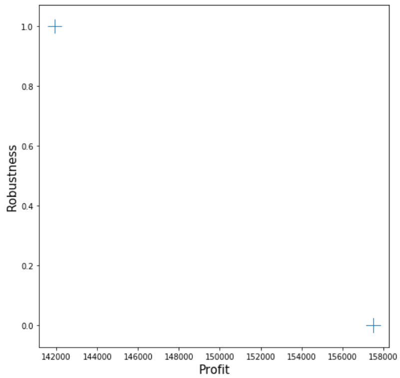

Figure 5.2 Pareto Front for the low demand case

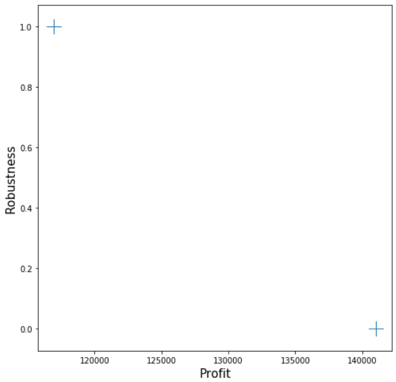

Figure 5.2 Pareto Front for the average demand state

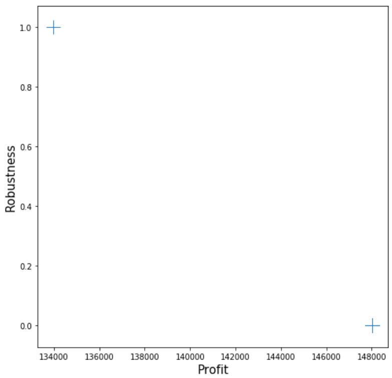

Figure 5.3 Pareto Front for the high demand state

Each run lasted about 42 minutes. In this experiment, the solutions that optimize the profit function are similar to those found in the first experiment: the decision of no factory opening always optimizes the profit function. For low demand, the solution that optimizes the robustness index consists of opening factory 9 in the 1st period. For average demand, the solution consists of opening factory 5 from the 1st period while high demand solution consists of opening factory 4 in the 1st period and factory 9 in the 2nd period. Only the average demand situation results in a similar solution of the first experiment (Solution (3)). Finding only two solutions for each situation can be explained by the lack of enough appropriate capacities options to be investigated. Furthermore, the two rules (cf. 4.1) implemented to simplify the problem may impact these results. The use of artificial data can also explain this finding because the resulted profits are in the same range as opening and closing factories, which limits our discussion.

Chapter 6. Conclusion

A new strategic facility allocation problem was presented. Using the deep uncertainty approach, the optimization problem was investigated over a set of identified multiple scenarios. In the following sections, the limitations and future research directions are discussed.

6.1 Discussion and limitations

The present paper contains many limitations. First, it is not realistic that a company strategy is based only on the profit. Other factors, such as the market evolution and technological advancements, should be taken into account when making long term strategies. In addition to other unrealistic assumptions, it is assumed that there was a constant selling price over a long period, despite the price ratio being driven by market supply and demand forces. Besides, the performance metrics chosen may not be the most adequate in assessing the performance of a company. Future studies can investigate which metrics to choose to represent the definition of robust decisions of a company.

6.2 Recommendations for future research

One potential improvement of this paper is the consideration of more options such as outsourcing services, temporary workers, or any other solution to extend the company capacity. The approach can be more adaptive depending on the results of each period. Moreover, rather than considering merely the profit function and robustness index as objectives, one can add social impact as a third objective. Indeed, since the problem implies the closure of manufacturing sites and the loss of jobs in one hand, and the opening of factories and the creation of jobs in the other hand, it would be interesting to investigate the social impact of such decisions. The Pareto front, in this case, could include more solutions and more conclusions could be derived.

In addition, there is an interest in applying the deep uncertainty approach in other fields, when such uncertainty is identified. The stochastic optimization and other probabilistic approaches were heavily used in many optimization problems, but not the EMA approach. The biggest challenge is to identify the scenarios and the uncertain variables and their ranges, as they depend on the study case under investigation.

Future research can focus on improving the limitations discussed above in general, and include more realistic features of long-term strategic decision making in particular. More expansion options can be added, and performance metrics definition should be reviewed.

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국문초록

관세 및 수요변동 등 기업이 직면할 수 있는 광범위한 불확실성은 장기적 전략 수립을 어렵게 한다.

이러한 유형의 불확실성은 주로 수자원 계획과 같은 분야에서 다양한 접근방식을 사용하여 수많은 연구에서 평가되으며, 본 연구에서는 전략적 할당문제에 불확실성 요소를 고려하였다. 본 논문에서, 이러한 불확실성을 고려하여 기업의 공장 규모 및 운용기간등을 결정하는 설비 할당 결정문제(Facility allocation problem)을 제안한다. 또한 전략적 문제에 대한 불확실성 접근법의 유효성을 확인하고, NSGA ii 를 사용하여, 사례 연구에 대한 Pareto front solution 찾았으며, 여러가지 새로운 시각과 통찰력을 제공한다.

주요어: Facility allocation problems, Multi-objective Optimization, Deep uncertainty, Genetic algorithm, Robust decision-making

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