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A COMPUTATIONAL FRAMEWORK FOR MODELING, SIMULATION AND OPTIMIZATION OF ENERGY SUPPLY CHAINS

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ABSTRACT

ENERGY Supply Chains (ESCs) are complex systems made up of a number of heterogeneous components/agents interacting with each other, the environment, its hazards and threats. The components/agents are structured in a hierarchical system, within which they operate and cooperate in a balanced transaction environment to realize the maximization of the benefits, under various environmental and safety constraints. ESCs significantly contribute to the sustainment of many industrial areas, such as biomass, oil and gas, chemical processing, sustainable and renewable energy, etc.

However, ESCs are challenged by multiple sources of uncertainties and risks. Uncertainties exist in supply and demand, propagate through the interactions over the whole ESC and influence the agents profits and the ESC operations. Due to the uncertainties, the risk of supply failure is difficult to predict. In such situation, ESCs must offer enhanced flexibility, innovative connectivity and communication, to guarantee an orderly and healthy supply management, so as to sustain the operation of the energy industry.

The objectives of the Ph.D. work are to develop a modeling framework for ESC process modeling simulation and optimization, which includes: 1. ESC modeling to identify, understand and analyze the complex interactions and for the evaluation of the resilience of ESCs. 2. ESCs efficient production planning optimization under multiple sources of uncertainty. 3. ESCs production planning considering risk of supply failure. 4. Solving the Many-objective Optimization Problem (MaOP) caused by the different agents for efficient production planning of ESCs.

With respect to the objective 1, an Agent-based Modeling(ABM) approach is proposed for modeling and simulating ESCs of the oil and gas industry, capturing the peculiarities of its diverse interacting elements, such as plants, refineries, storages, etc. Different disruption scenarios and recovery strategies are considered in the Agent-based ESC model for investigating the relevant factors influencing ESC resilience.

With respect to the objectives 2 and 3, a simulation-based Multi-Objective Optimization (MOO) framework for ESC production planning is developed. The ABM simulation is embedded into a Non-dominated Sorting Genetic Algorithm (NSGA-II) is then adopted for identifying the Pareto solutions. For ESCs with uncertainties and changing structures, the ESC total profit is maximized and the disequilibrium among the agents' profits is minimized. Moreover, considering disruption risks, the ESC total profit is maximized and ESC risk under uncertainties is minimized.

Furthermore, an improved Cooperative Co-evolutionary Particle Swarm Optimizer (CCPSO) is proposed to solve the Many-objective Optimization Problem (MaOP) in the agent-based ESC model. The variables are decomposed into different species based on agents relationships and allowed to evolve independently during the optimization process. Each species has its own repository to keep a historical record of the nondominated vectors in which the solutions are evaluated and updated by cooperating with other species. The effectiveness of CCPSO is proven by test functions and a case study.

KEYWORDS

Energy Supply Chain; Oil and Gas Supply Chain; Agent-based Modeling; Multi-objective Optimization; Uncertainty; Risk; Changing Structure; Monte Carlo Simulation; Non-dominated Sorting Genetic Algorithm; Many-objective Optimization Problems (MaOPs); Co-evolutionary Algorithm; Multi-objective Particle Swarm Optimization (MOPSO); Cooperative Co-evolutionary Particle Swarm Optimizer (CCPSO).

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LIST OF ACRONYMS

ABM	Agent-based Modeling
AHP	Analytic Hierarchy Process
CCGA	Cooperative Co-evolutionary Genetic Algorithm
CCPSO	Cooperative Co-evolutionary Particle Swarm Optimizer
CEA	Co-evolutionary Algorithm
CPSO	Cooperative Particle Swarm Optimizer
CVaR	Conditional Value at Risk
DEA	Data Envelopment Analysis
DES	Discrete Event Simulation
DS	Dynamic Simulation
EA	Evolutionary Algorithm
ESC	Energy Supply Chain
GA	Generation Algorithm
GIS	Geographical Information System
LP	Linear Programming
MaOP	Many-objective Optimization Problem
MC	Monte Carlo
MCDM	Multi-Criteria Decision Making
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
MOO	Multi-objective Optimization
MOP	Multi-objective Optimization Problem

MOPSO	Multi-objective Particle Swarm Optimization
NLP	Nonlinear Programming
NSGA-II	Non-dominated Sorting Genetic Algorithm
PSO	Particle Swarm Optimizer
VMI	Vendor Managed Inventory

SECTION I: GENERALITIES

This part of the dissertation introduces the context of the research, its relevance, the state-of-the-art methods, the challenges that are addressed and the research objectives. Furthermore, it briefly describes the developed methods and the applications carried out for their validation.

CHAPTER 1

Introduction

1.1 ESC

ESCs are complex systems made up of numerous components/agents interacting with each other, the environment and its hazards. An ESC may be view as an network of components/agents (e.g. retailer, refinery, storage, crude oil producer) and transportation (e.g. pipe line, crude oil tranker, truck) [1, 2]. ESCs management is a complex process because of many factors involved.

Energy companies in the ESC have to face uncertainties and risks. The demand, manufacturing and supply uncertainties involving the unknowns related to product characteristics are the major sources of uncertainties [3].

Along with these uncertainties, the considerations assigned to risk have grown. For example, new, unconventional sources of energy such as shale gas, tight oils, coal seam gas and oil sands are heavily influencing the energy market, while requiring the ESC to still offer reliable and high quality of service, but also to be more flexible and resilient. Yet, price volatility and increasing operating costs are causing energy companies to scrutinize the existing sourcing strategies and the costs associated with the VMI, consignments, etc. [4]. Moreover, the number of terroristic attacks impacting on supply chains has increased steadily over the past decade, reaching 3299 attacks in 2010 [5]. These attacks entail possibly disastrous consequences on societies, which nowadays depends on the effective functioning of complex network systems (e.g., power supply networks, transportation networks, etc.) [6, 7]. Setting measures for withstanding the attacks has also led to an increment in the operation costs of ESC. These considerations justify the increasing interest in analyzing the ESC risk which could be categorized into two types: disruption risks and operational risks [8, 9]. The disruption risks are related to circumstances such as natural disaster, terrorist attacks and labor strikes, while operation risks are caused by high uncertainty and unbalance between supply and demand [10, 11]. The risk is hard or even impossible to be predicted which makes the ESC disrupted and influences the ESC function [12].

Except for the influencing of uncertainties and risks, the structure of ESC is complex. The components/agents such as crude oil producers, refineries, storages in ESC are physically and functionally heterogeneous and organized in a hierarchy of subsystems, what happens to one individual will directly or indirectly affect others and spread through the whole ESC. For example, if the disruption happens on ESC, energy company may lose a drilling day waiting on mud system arrival, lose a week of production because of a treating chemical stock out, or miss a day of retail sales because the refinery production schedule was not balanced with demand. Secondly, the interaction between components/agents is complex and dynamic which is difficult to describe by traditional analytical methods [13].

According to the system and complexity's theories, we view an ESC as a complex system or in other words, it is a system in a complex system-of-system. Under such background, we focus our research on modeling and optimizing ESC which are important and significant issues and have been paid more and more attention but they are challenged by diverse factors.

1.2 Challenges in ESC

I. Uncertainty and risk challenge: The phenomena of uncertainties and risks needs to be addressed when designing ESC. Thus, there is a need to develop novel hybrid approaches combining the strengths of multiple techniques of optimization under uncertainties and risks [1].

II. Modeling challenge: This challenge arises from the need to accurately model materials and information flows in ESC [1]. Due to the complex features in ESC, identifying, understanding and analyzing the complex interactions between agents represent a challenge to ESC.

III. Optimization challenge: The efficient operation of energy companies' production planning is required. However, it is difficult and challengeable for ESC to get the production planning optimization in complex ESC environment.

III. Computation challenge: There are many agents (e.g. retailer, refinery, storage) whose variables and objectives are independent, so the MaOPs are caused in ESC which are difficult to be solved by traditional EA. It rises another challenge to ESC.

1.3 Research Objectives of The Thesis

In this context, considering the challenges mentioned above, we aim at solving the problem of modeling, analyzing, designing ESC in uncertain and risky environment. The research objectives focus on four of the most challenging problems:

I. Modeling to evaluate the resilience of the ESC

From the complexity of agents' interdependences, risk scenarios can originate in an unpredictable way, threatening the normal operation of the entire ESC and endangering its supply capability. New methodologies are, then, being developed for carrying out ESC risk and resilience analyses. In this study, we rely on ABM to build a multi-layer ESC modeling for analyzing its resilience. Every element in the ESC is simulated as an agent implementing basic functions like sending and receiving orders, and productions. We simulate different disruption scenarios and recovery strategies to investigate the essential factors influencing the resilience of the overall ESC.

II. Designing efficient energy companies' production planning

Energy production companies have to make planning decisions to satisfy the customers uncertain demands and to maximize their own profits. In this work, we propose a simulation-based MOO framework for the efficient management of the ESC sustaining production. The ESC agents interaction is uncertain and the ESC structure can dynamically change. ABM is used to model and simulate the agents actions and behavior, and the ESC transaction processes. The simulation is embedded into an NSGA-II optimization scheme for identifying the Pareto front of solutions for which the ESC total profit is maximized and the disequilibrium among the agents profits is minimized. Based on the Min-Max method, a single best compromised solution is identified. Finally, the MC simulations approach is used to operationalize the proposed ABM-MOO framework in presence of the uncertainty that affects the ESC.

For demonstration, we consider an oil and gas ESC modeling with five layers, including crude oil producers, storages, refineries, terminal storages and retailers. The results show that the proposed framework enables the optimization of the ESC planning, while taking into account multiple sources of uncertainty and the structure dynamics that challenge the ESC operation.

III. Optimizing the planning of ESCs considering the disruption risk

The planning of an ESC aims at maximizing the benefits of the ESC agents, while satisfying the demands of the customers [14, 15]. Demand variability and supply disruption, originating from the connectivity between supply and demand, can disturb the agents interactions and impair the agents management [16]. In this study, we propose a risk-based optimization approach for the management of ESC. We introduce a CVaR measure with the purpose of measuring and controlling the risk to the ESC management. The NSGA-II is performed to search for the solutions optimal with respect to the maximization of the ESC total profit and the minimization of the risk under uncertainties.

For demonstration, an application is carried out considering a specific oil&gas ESC modeling with five layers, including crude oil producers, storages, refineries, terminal storages and retailers. Results show that the optimization approach enables the trade-off between the ESC optimal planning and the source of risk that it is subjected to.

IV. Solving Many-objective Optimization Problems (MaOPs) in ESC

In ESCs, multiple agents proactively interact and cooperate in a coordinated production process, where each of them aims to grab the maximal own profits. In this study, we propose a cooperative co-evolutionary approach to solve such an ESC Many-objective Optimization Problem (MaOP) where the agents own profits are maximized. The autonomous behavior of the ESC agents and the interactive transaction processes are modelled in the context of ABM. A CCPSO algorithm is embedded into ABM for identifying the Pareto Front (PF). The effectiveness of the proposed approach is verified by the test functions.

For demonstration, we also illustrate the proposed approach by considering an oil and gas ESC model with five layers, including crude oil producers, storages, refineries, terminal storages and retailers. The results show that the proposed CCPSO enables the many-objective optimization for the efficient production planning of the ESC, whilst taking into account multiple sources of uncertainty and the structure dynamics challenging the ESC operation balance.

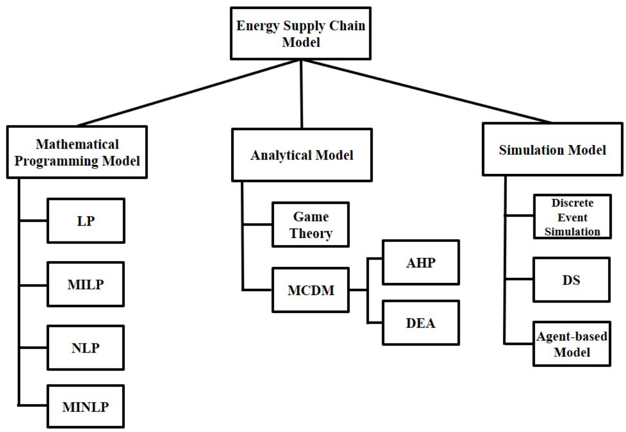

Figure 1.1: *ESC models*

1.4 State-of-the-Art Literature Review on ESC Models

A variety of models have been used to model and describe the characteristics of an ESC, and they can be identified into three categories based on model types, as shown in Figure 1.1.

Mathematical programming has been widely used to solve the problem of the optimal design of ESC networks. A variety of techniques have been applied in this context, like LP, MILP, NLP and MINLP, etc. For example, a simple LP model is presented for the optimal allocation of palm biomass supply chain [17]. Bittante et al. [18] have applied MILP to find the supply chain structure that minimizes costs associated with fuel procurement. Robertson et al. [19] have used NLP model to solve refinery production scheduling and unit operation optimization problems. In Ref.[20], a two-stage stochastic MINLP model combined with chance constraint is proposed to minimize the total cost of producing electricity from woody biomass in a four-level integrated bioenergy supply chain. Although applicable to the treatment of problems involving blending, continuous flow processing, production and distribution, strategic/tactical planning, etc., mathematical programming models are not flexible in dealing with the stochasticity, uncertainty and complexity of structure and interaction typically encountered in supply chains [21, 14].

Analytical models build on mathematical expressions and numerical models characterize the ESC behavior, and find solutions to ESC management problems by use of, for example, Game theory, MCDM (including DEA, AHP), etc.[22]. In Ref.[23], authors proposed a novel Game-theory-based stochastic model for optimizing decentralized supply chains under uncertainty. Optimization of renewable power sources has been tackled with a fuzzy MCDM technique based on cumulative prospect theory in Ref.[24]. A DEA model has been used to reduce the complexity of solving the proposed model in the literature [25]. In Ref.[26], AHP combined with a fuzzy set theory enhances the reliability of the sustainable results along different stages of petroleum refinery industry projects. Analytical modeling can be used to evaluate and improve the performance of an ESC, but has strong limitation in the description of realistically complex supply processes including stochastic and dynamic structures, uncertainty and partial information sharing [13].

Simulation models, e.g. DES and DS, have been developed to explore the behavior of agents in ESC, with the further goals of evaluation [27], analysis and optimization [28], risk management [29], and so on. For example, Windisch et al.[28] have applied DES to simulate the raw material planning in an energy wood supply chain. Becerra-Fernandez et al. [30] have proposed a DS model for assessing alternative security of supply policy along the natural gas value chain. The modeling benefits and the large computational capacities make simulation models increasingly attractive for the modeling of ESC realistic problems.

ABM provides another way to model and simulate ESC, also applicable to continuous processes [31, 32] and also applied to various types of supply chains. For example, Guo et al. [33] applied ABM to build an integrated system modeling framework for a resource-food-bioenergy nexus application. Raghu et al. [34] relied on ABM and GIS to assess the environmental impact on the forest biomass supply chain. Moncada et al. [35] developed a spatially explicit agent-based model to analyze the impact of different blend mandates and taxes levied on investment in processing capacity, and on production and consumption, of ethanol in the biofuel supply chain. In Ref.[36], the authors used ABM to analyze the evolution of biofuel production and production capacity.

These published researches confirm that ABM can be effectively used for modeling, simulating, assessing and analyzing ESC but, rarely it has been used in optimizing ESC operations. To the authors' knowledge, no study has yet attempted to solve ESC planning problems by using ABM within an optimization framework and also considering demand and supply uncertainties and structure dynamics at the same time. This is done here, thanks to the capability of ABM in dealing with complex production processes and service problems under uncertainty.

1.5 Overview of The Proposed Framework

1.5.1 Simulation-optimization framework

To the best of my knowledge, the hybrid simulation-optimization framework is first proposed by Subramanian, pekny and Reklaitis. They present the hybrid simulation-optimization framework to assess the uncertainty and control the risk in the pipeline [37]. Now, some researches have been done in this area.

For instance, Jung et al.[37] use a simulation-based optimization approach to determine the safety stock level and scheduling applications. Nikolopoulou and Ierapetritou [38] combine methematical progamming and simulation model to minimize the summation of production cost, transportation cost, inventory holding and shortage costs. Sahay and Ierapetritou propose a hybrid simulation-based optimization framework to solve the two-stage optimization problem [39].

In the hybrid simulation-based optimization, the method can be divided into phase: simulation phase and optimization phase. In the simulation phase, ABM is a good modeling to give a realistic representation of ESC. In the optimization phase, finding the high-quality solutions is the most important task [38]. This demand leads to various optimization algorithms applied in this field. The choice of optimization algorithm is important because it influences the effect and efficiency of the results [40]. Realistic ESC problems have multi-objective or even many-objective which contains more than three objectives. EA working with a population of solutions naturally offers a suited algorithm to solve such optimization problems [41, 42].

1.5.2 ABM

Although analytical model has been proven useful in many fields [38], it still has some limitation in describing some complex phenomenon from system perspective. ESC is a complex system which is dynamic, has complex structure and contains plenty of uncertainties, so traditional analytical model is confining in modeling ESC [13]. Overcoming these shortages of analytical model, ABM shows its advantage in modeling ESC.

Firstly, ABM is good at dealing with complex. Some systems are too complex for us to adequately model. However, Agent-based model is "bottom up" modeling approach which can model the complexity arising from individual actions and interactions [31, 43]. Secondly, ABM is easy to operate. ABM just needs to describe basic behaviors and interactions from individuals which are formalized by simple equations, (decision) rules such as if-then kind of rules or logical operation [44]. Moreover, it is easy to implement individual variations and random influences(stochasticity) in ABM [44]. Thirdly, ABM is observable. The Agent-based simulation approach is a method that allows to observe the behaviors through time and the dynamics of the supply chain from interactions [45].

Due to these advantages, at present, ABM is widely used in modeling supply chain. For example, ABM is used in Wu et al. [46] to investigate retail stockouts. In this literature, authors develop an Agent-based simulation model to understand the influence of different stockout length for different products and the response from the retailer and the manufacturers of the product. Fox et al. [47] rely on ABM to manage perturbation in the supply chain with complex cooperative work. Julka et al. [48] rely on ABM to model, monitor, and manage supply chains. Authors view elements in the supply chain as entities, flows and relationships. Entities are modeled as agents and flows are modeled as objects. The authors use two case studies to illustrate the framework. Finally, Gjerdrum et al. [49] develop a supply chain by applying ABM. In this literature, authors model every different role in the supply chain as an agent. All the agent types include customer, external logistics, warehouse, internal logistics, factory, spot market and transportation. In the experiment, authors investigate how optimal scheduling influence the behavior.

ABM offers possible way to control complex agents' behavior and their interaction in ESC. In this thesis, ABM is implemented in the software ANYLOGIC, which is exported as a jar file and then, imported and run in ECLIPSE.

1.5.3 Evolutionary algorithm

EAs are the algorithms that are based on the evolution of the species [50]. EAs use bio-inspired mechanisms, including mutation, crossover, selection and survival of the fittest to refine a set of solution candidates iteratively [51]. GA is one typical algorithm of EAs.

In GA, a set of candidate solutions represented as chromosomes is generated. By selection, crossover, mutation the GA iteratively eliminates poor solutions and the solutions with high fitness value have high probability to survive in the next generation. Consequently, GA is convergent to overall good solutions.

In the field of supply chain, many problems are solved by applying GA. For instance, Altiparmak et al. apply GA to solve a supply chain network design problem in order to minimize the total cost and the capacity utilization ratio in supply chain network and maximize the total customer demand (in %) [52]. Naso et al. propose a novel meta-heuristic approach based on GA to solve supply chain scheduling problem [53]. In literature [54], a heuristics based genetic algorithm is proposed by Kannan, Sasikumar and Devika to solve the optimum usage problem of secondary lead recovered from the spent lead-acid batteries for producing new battery. Yeh and Chuang use the multi-objective GA approach to solve the partner selection problem in green supply chain. GA is considered as a primary tool to solve many multi-objective problems in supply chain.

In spite of the liveliness of research applying GA in supply chain, only a few papers combine GA and AMB to solve problems in supply chain. Considering the good ability of ABM in dealing with complex problem under uncertainty. Simulation-based optimization combining GA and ABM offers a possible way to solve variety of problems in supply chain, more so in case of ESC [55].

1.5.4 CEA

CEA is similar to EA but CEA co-evolves sub-populations of individuals representing different parts of the global solution instead of evolving one population of similar individuals representing a global solution [56]. There are several advantages of CEA [57]: For example, decomposed problem allows calculating in parallel which speeds up the optimization process. Moreover, separated species help to maintain good solution diversity [58], increase the robustness against the modules' errors and failures and enhance the reusability in dynamic environments [59].

According to the relationship between sub-populations, CEA can be divided into two main types: the competitive CEA and the cooperative CEA [56]. In competitive CEA, individual competes with others so it usually contains the whole problem and variables but individual in cooperative CEA decomposes the problem and has partial variables.

In the competitive CEA, individuals in the populations compete among themselves, characterizing the classical predator-prey or an arms race co-evolution [60], and usually individuals contain the whole variables. The fitness of an individual is the result of a series of encounters with other individuals from other species [61, 56].

A variety of MaOPs have been solved by the competitive CEA. The competitive CEA is firstly proposed in Ref.[62], where two sub-populations are considered as the hosts and the parasites to evolve simultaneously and interact through their fitness function. The competitive CEA can be implemented in a predator-prey-like way, in order to imitate the competitive behavior between two sub-population, for example, a biogeography optimization in the constrained design of a brushless dc wheel motor [63]. Whereas, another way based on competitive fitness is adopted in the arms race forms of all-againts-all, bipartite, all versus best, tournament, k-random and so on [56, 64, 65, 66, 67].

For the cooperative CEA, the fitness of an individual is the performance collaborating with other individuals from other species[68, 69] in which individuals usually contain partial variables. Comparing with competitive CEA, the species in cooperative CEA has to cooperate with others to assemble the whole variables, and then, the fitness value can be calculated.

Potter and De Jong [69], for the first time, proposed a CCGA approach in which the decision variables are divided into the small size species, evolved independently, evaluated cooperatively. Bergh and Engelbrecht proposed two new cooperative PSO models: CPSO-S_k and CPSO-H_k, by applying Potter's co-evolutionary technique to the PSO [70]. It is proven that the PSO-based algorithms surpass the performances of the GA-based algorithms on the test problem [70]. Besides, some other researches are proposed to implement cooperative CEA architecture. For example, Antonio and Coello Coello [71] proposed an Indicator-based Cooperative Coevolutionary Multi-objective Evolutionary Algorithm (IBCCMOEA) which uses the CCGA framework and Differential Evolution (DE) as the main multi-objective optimizer. Tan, Yang and Goh [72] proposed a cooperative CEA for multiobjective optimization incorporated with features like archiving, dynamic sharing and extending operator. These studies show that cooperative CEAs have many different architectures which usually combine with GA or PSO and all of them are effective to deal with MOO problem or even MaOP.

The cooperative CEAs have also been applied to supply chains. For example, Gong et al. [73] proposed dynamic interval multi-objective cooperative co-evolutionary optimization framework to handle dynamic interval MOPs. Pedrasa, Spooner and MacGill [74] improved the formulation of the cooperative PSO to investigate the potential consumer value added by the coordinated Distributed Energy Resources (DER) scheduling. In Ref.[75], the authors proposed a Cooperative Co-evolutionary bare-bones PSO with Function Independent Decomposition (FID), for a multiperiod three-echelon a large-scale supply chain network design with uncertainties problem. The cooperative CEAs have been successfully applied to solve optimization problem in supply chain but rarely used in solving MaOP in

ESC.

Cooperative CEA highly fits the characteristics of ABM because ABM is made up of several individuals/agents with its own variables to be optimized and its own problem to be solved which need to cooperate to obtain the optimal objective, so cooperative CEA is more appropriate to used in solving MaOP in agent-based ESC modeling.

1.6 Case Studies

In this Ph.D. thesis, the studied field is the ESC. The ESC has some fundamental properties comparing with supply chain such as the network structure, organization made of people, information and resources moving. In order to build a comprehensible formulation for ESC problem, we take a petroleum supply chain as object of study which is organized in five layers: retailers, bottling & storage, refinery, port storage and crude oil producers. The framework of our Agent-based ESC model is shown in Figure 1.2.

Generally, we assume the total transaction days are 1000 days and every 30 days the agents make a deal. The variables (the supply and the demand) are sampled from Gaussian distributions when the agents make a deal and the beginning time is different for each agent, so the sampling size is about 30. Every agent makes decisions based on the oil production in hand and the order amount. The price fluctuations are not considered.

In the thesis, we assume the normal distribution in the supply and demand, which is a common assumption in the ESC modeling [76, 77, 78]. In the case study of Chapter 3, we optimize two objective functions which can be solved by NSGA-II effectively. When it comes to Many-objective Problem (MaOP) in the ESC, the problem of "curse of dimensionality" is easily caused, which is considered and solved in Chapter 5 by Co-evolutionary Algorithm (CEA). In Chapter 2, we consider 5 recovery strategies to help ESC to come back to be normal which are shown in Section 2.2. In Chapter 4, the recovery strategy is not considered in the case study. We assume that every disruption influences one transaction. After the transaction finishes, the disruption vanishes and the ESC come back to be normal.

The ESC modeling in this thesis features the following characteristics:

I. Make decisions by agent itself: In this model, customer agents try their best to get enough productions from suppliers. Simultaneously, supplier agents have right to choose the demanders who can bring them higher profit. Driven by these internal motivations, agents generate a series of behavior to realize their expectations. These behaviors are shown in Chapter 2. These behaviors define the internal rules and decision processes when

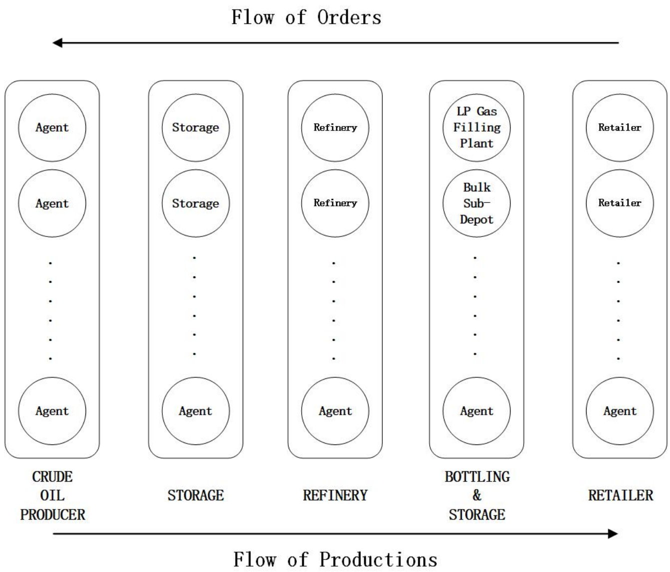

Figure 1.2: *The framework of our agent-based ESC modeling*

agents face other agents and variational environment. Meanwhile, by doing these behaviors, orders flow from retailers (layer1) to crude oil producers(layer5) and productions flow from crude oil producers (layer5) to retailers(layer1).

II. Uncertainty in demand and supply: We consider a set of customer agents who dynamically demand refined production and a set of supplier agents who dynamically supply crude oil. Because of the network structure of ESC and complex behaviors of agent, these uncertainties are easy to spread through the whole ESC, influence the agents' decision making and causally change the whole ESC structure.

III. Dynamic structure: An important aspect in ESC is that the ESC structure may change dynamically due to the interaction among agents. In ESC, every individual may take decisions independently at any time and these anonymous decisions cause the whole structure to change, which makes the ESC adaptive and dynamic. Therefore, the ESC structure dynamics must be considered when modeling ESC. In this modeling, every agent makes decisions by itself, based on the production amount of the supply and the demand. The supply and the demand are uncertain, so the agents decisions may be different in each transaction process, and thus, the structure changes from time to time.

Table 1.1: *The related factors considered in each chapter*

	Agent-based Modeling	Uncertainty	Structure Dynamic	Disruption Risk	Many-objective Problem	Optimization
Chapter 2	Yes	Yes	Yes	Yes	No	No
Chapter 3	Yes	Yes	Yes	No	No	Yes
Chapter 4	Yes	Yes	Yes	Yes	No	Yes
Chapter 5	Yes	Yes	Yes	No	Yes	Yes

1.7 Thesis Structure

In Chapter 2, we develop an agent-based ESC to investigate the resilience of the whole ESC under different disruptions. Based on the agent-based ESC modeling in Chapter 2, the research in Chapter 3, Chapter 4, and Chapter 5 have been done. Chapter 3 consider a multi-objective optimization problem under the uncertainty and the structure dynamic in the ESC. In Chapter 4, besides the uncertainty and the structure dynamic, the disruption risk is considered when optimize the ESC. Also based on Chapter 3, a many-objective optimization problem is solved in Chapter 5. The related factors we consider are shown in Table 1.1.

Figure 1.3 shows the structure of this PhD thesis. The following 4 Chapters (from 2 to 5) are dedicated to the deepening of the theoretical background of the exploited methods, to the description of the application and of the results provided by the developed methods, particularly focusing on the novelty and the original contributions introduced in this Ph.D. research work. Finally, in Chapter 6, some conclusions and remarks on the developed work are drawn, and the perspective regarding the possible future applications of the developed methods will be discussed. At the end of this Ph.D. thesis work, we also included a collection of the published/under review international journal papers to which the reader can refer to for further details.

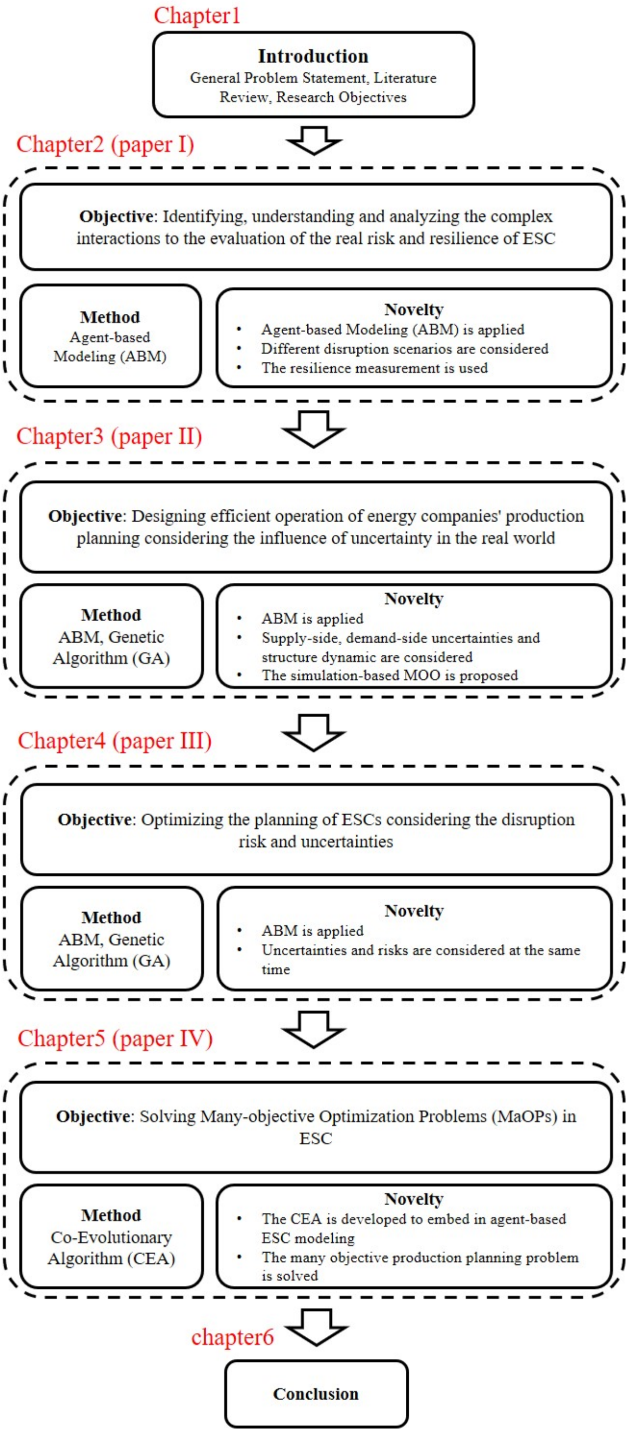

Figure 1.3: *The structure of the PhD thesis*

SECTION II: DETAILS OF THE DEVELOPED FRAMEWORK

This part is the main body of the thesis which includes 4 Chapters (from Chapter 2 to Chapter 5) and presents the original contributions of the research works.

CHAPTER 2

ABM for ESC Resilience Analysis

The objective of this work is to describe complex interaction between agents and assess the resilience of an ESC and for these we adopt an ABM framework, which allows modeling large interconnected systems. This capability comes from the fact that ABM is a bottom-up modeling approach, which focuses on modeling individual agents and their interactions, from which phenomena emerges, which are difficult to model by the traditional top-down modeling methods [43]. Every agent is defined by a set of behavioral functions, which give it intelligence to make decisions in response to its interactions with other agents and the environment. The simulation of the agents behaviours yields the overall system behavior.

2.1 The Proposed Method

In this study, we take an oil supply chain as object of study. The supply chain is considered organized in five layers: retailers, bottling & storage, refinery, port storage and crude oil producers. Every layer contains its agents, which are competitors. The structure of the ESC of the reference example is shown in Figure 2.1.
In this model, we consider bidirectional flows in the ESC: the orders flow

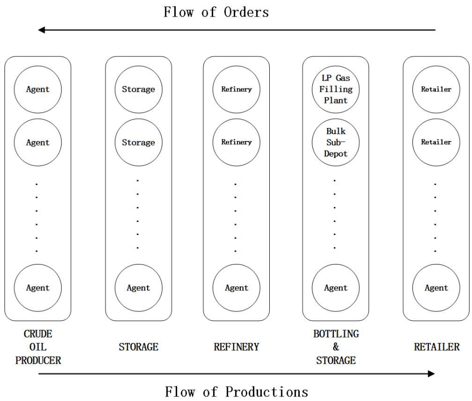

Figure 2.1: *ESC structure*

from the retailer (layer 1, on the right) to the producer (layer 5, on the left) in sequence, whereas the production, in turn, proceeds backward from the producers to the retailers. The basic idea of the negotiation strategy is that the demander sends orders to its preferred supplier. The supplier accepts or rejects the orders and, then, sends back its response. After a number of negotiation runs, the supply chain network sets up. The main parameters and variables are given below.

2.1.1 Modeling of agent uncertain behavior

We consider an ESC with L layers and each l-th layer consists of V_l agents, $a_{l,1}, a_{l,2}, ..., a_{l,v}, ..., a_{l,V_l}$ (Figure 2.2). In the ESC, the orders sent from Layer 1 flow layer-by-layer to the end layer L, whose V_L agents are suppliers that send supply decisions backward to the demanders.

An agent $a_{l,v}, v = 1, 2, ..., V_l$, in the l-th layer, is assigned with behaviors, which allow the agent to adaptively interact with the others. The details of the model are described in the following.

2.1.1.1 Sending Orders

The process of sending orders of an agent $a_{l,v}$ in the l-th layer (Figure 2.3) is as follows:

(a) $a_{l,v}$ chooses the supplier(s) $a_{l+1,v'}$ in the upper layer $l+1$.
(b) $a_{l,v}$ sends orders to $a_{l+1,v'}$.
(c) $a_{l,v}$ updates the list of alternative suppliers.

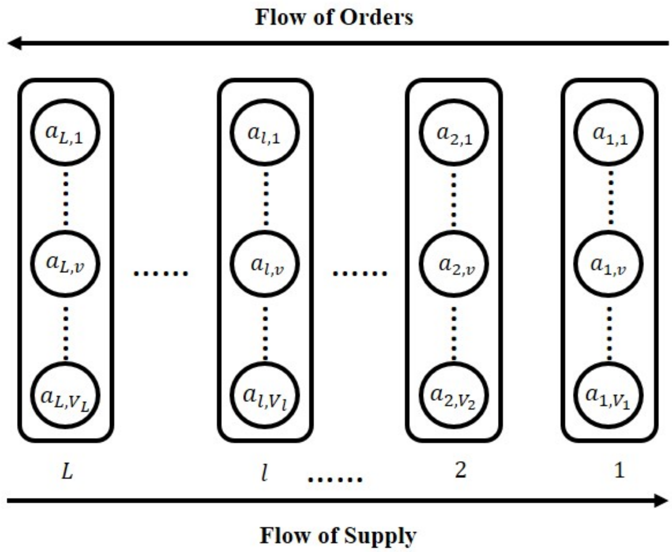

Figure 2.2: *The ABM-ESC model*

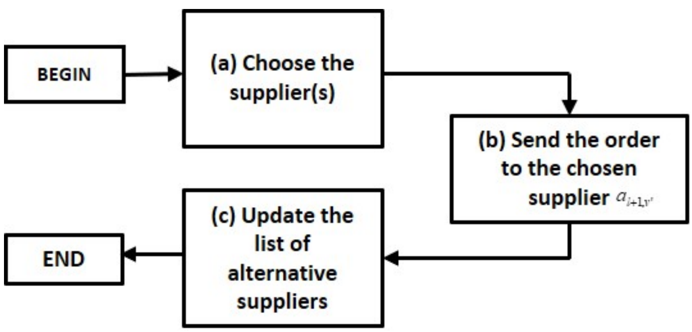

Figure 2.3: *The process of sending orders*

2.1.1.2 Receiving Orders and Choosing Demanders

The process of an agent $a_{l,v}$ receiving orders and choosing demander(s) is shown in Figure 2.4 and described as follows:
(a) $a_{l,v}$ receives the order from $a_{l-1,v''}$ in the lower layer $l-1$.
(b) $a_{l,v}$ checks whether the received order is empty:

- If yes, $a_{l,v}$ does not choose demanders.
- Otherwise, (c) $a_{l,v}$ checks whether it has available productions that satisfy the received orders.
  - If yes, (d) $a_{l,v}$ checks whether the received orders exceed the existing production limitation $U_{l,v}(t)$ defined as:

$$U_{l,v}(t) = S_{l,v}(t) - S^*_{l,v}(t) \tag{2.1}$$

    where $S_{l,v}$ is the storage of $a_{l,v}$ and $S^*_{l,v}$ is the back-up safety storage of $a_{l,v}$.
    * If yes, (e) $a_{l,v}$ refuses the order from $a_{l-1,v''}$ demanded with the lowest bid price, and returns to (d).
    * Otherwise, (f) the agent $a_{l,v}$ accepts the order and makes a contract with $a_{l-1,v''}$.
      Then, the existing oil production limitation of the agent $a_{l,v}$ (Eq.(2.2)) updates for the next time $t+1$:

$$U_{l,v}(t+1) = U_{l,v}(t) - \sum_{v'', v'' \in \{v_a\}} x^{l-1,v''}_{l,v}(t) \tag{2.2}$$

      where, $x^{l-1,v''}_{l,v}(t)$ is the amount of orders accepted by the agent $a_{l,v}$ which are sent by the agent $a_{l-1,v''}$
  - Otherwise, (g) $a_{l,v}$ sends a response back to the demander $a_{l-1,v''}$.

2.1.1.3 Response

One demander $a_{l,v}$ may negotiate with its supplier $a_{l+1,v'}$, in case of receiving a response from $a_{l+1,v'}$. This process is shown in Figure 2.5 and described as follows:
(a) The agent $a_{l,v}$ receives a response from the supplier $a_{l+1,v'}$.
(b) Check whether the order plan is satisfied:

- If yes, $a_{l,v}$ stops sending the order plan.

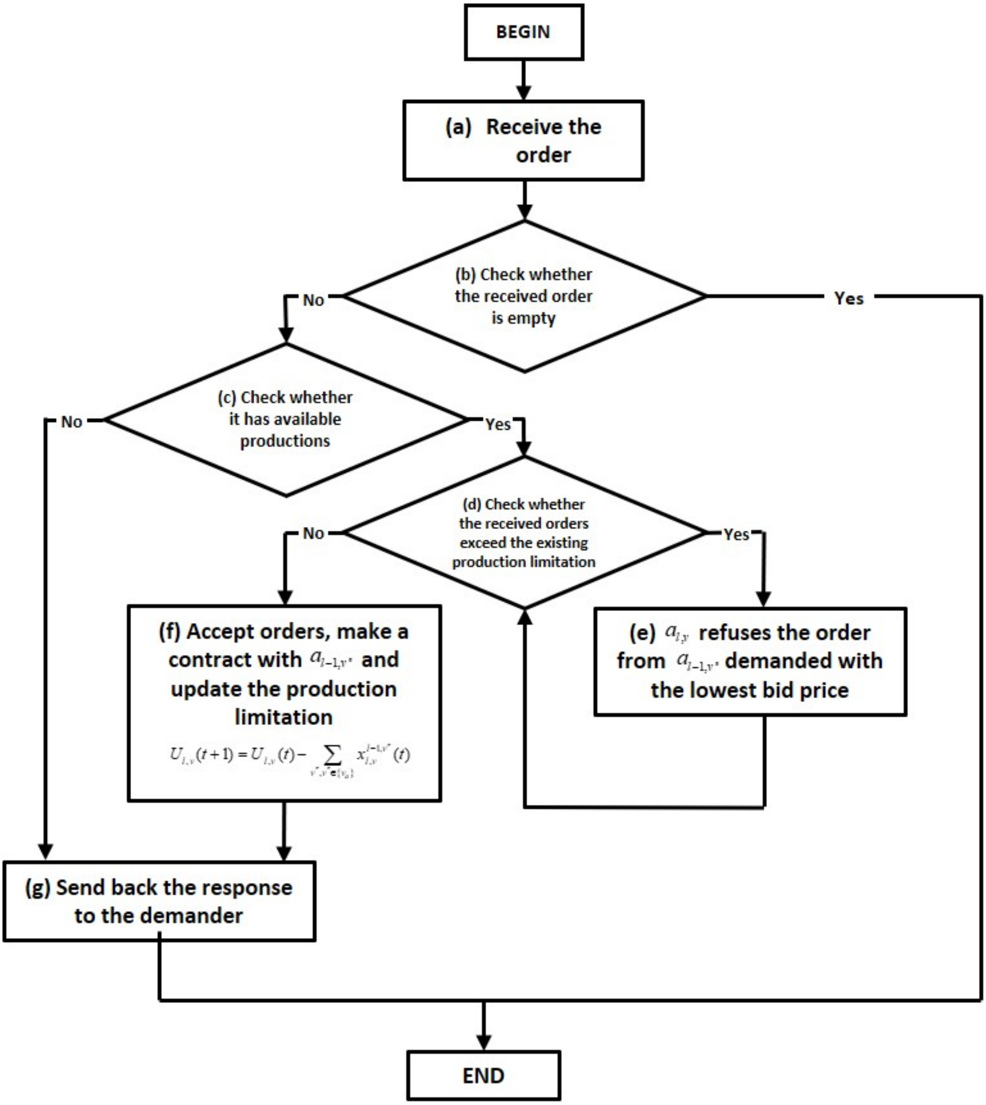

Figure 2.4: *The process of receiving orders and choosing demander(s)*

- Otherwise, (c) $a_{l,v}$ checks whether all the alternative suppliers have been considered:
  - If yes, the agent $a_{l,v}$ stops sending the order plan.
  - Otherwise, (d) the agent $a_{l,v}$ updates its demands,

$$y_{l,v}^{l+1,v'}(t+1) = y_{l,v}^{l+1,v'}(t) - \sum_{v',v' \in \{v_a\}} x_{l+1,v'}^{l,v}(t) \tag{2.3}$$

    where, $y_{l,v}^{l+1,v'}(t)$ is the amount of orders sent by the agent $a_{l,v}$ which are received by the agent $a_{l+1,v'}$ at time t, $x_{l+1,v'}^{l,v}(t)$ is the amount of orders accepted by the agent $a_{l+1,v'}$ which are sent by the agent $a_{l,v}$ at time t.

    And, (e) send orders (as discussed in Section 2.1.1.1) again.

2.1.1.4 Selling Production

An agent $a_{l,v}$ should sell productions after accepting an order plan. This process is shown in Figure 2.6 and defined as follows:

(a) $a_{l,v}$ checks whether it stores enough productions satisfying the accepted order plan:

- If yes, (b) sells the productions to the demander $a_{l-1,v''}$ and updates the set of accepted orders and the storage for the next time $t+1$ (Eq.(2.4)):

$$S_{l,v}(t+1) = S_{l,v}(t) - \sum_{v'',v'' \in \{v_a\}} z_{l,v}^{l-1,v''}(t) \tag{2.4}$$

  where $S_{l,v}$ is the production storage of $a_{l,v}$ and, $z_{l,v}^{l-1,v''}(t)$ is the amount of the production sold by $a_{l,v}$ to $a_{l-1,v''}$.

- Otherwise, (c) $a_{l,v}$ sells the productions to the demander who makes its income highest, and, then, updates the set of accepted orders and the storage $S_{l,v}(t+1)$.

  (d) Check whether the storage or the set of accepted orders is empty.

  - If not, repeat (c).
  - Otherwise, end.

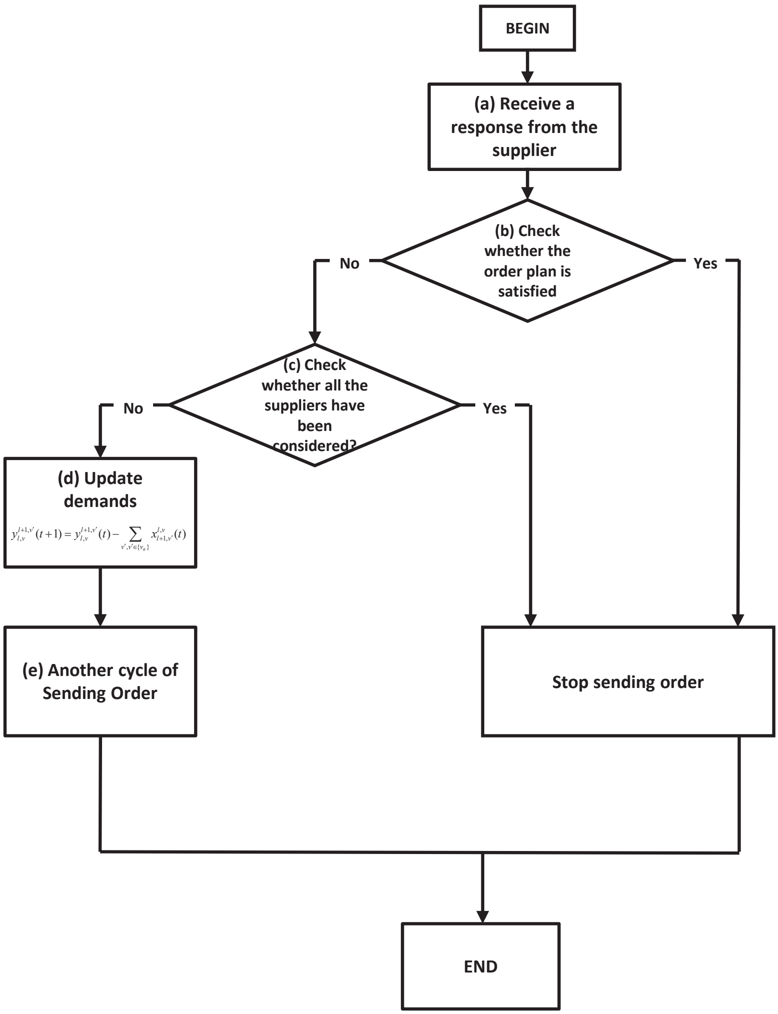

Figure 2.5: *The process of response*

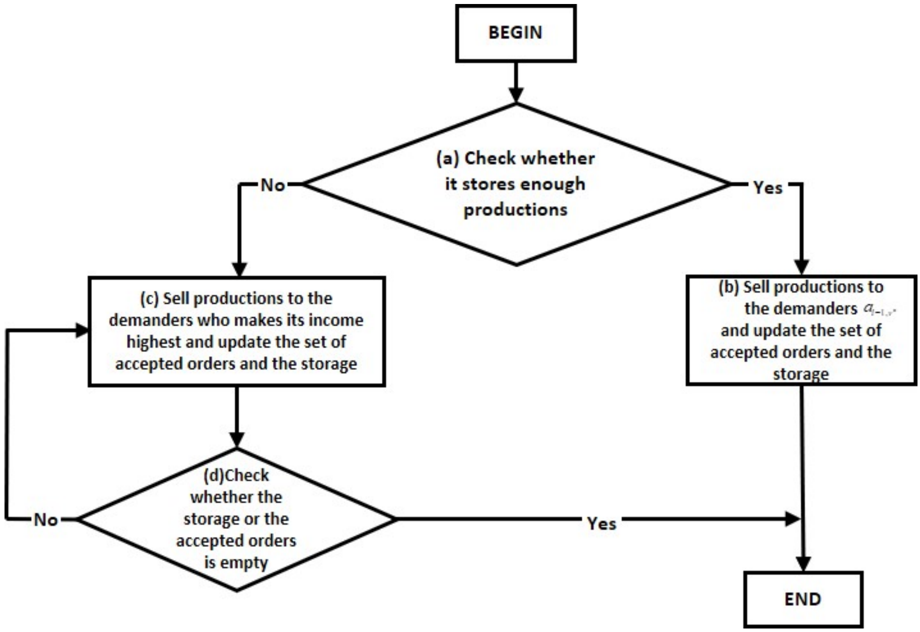

Figure 2.6: *The process of selling production*

2.1.1.5 Receiving Production

An agent $a_{l,v}$ receives the oil production from the upstream agents $a_{l+1,v'}$ and updates its storage $S_{l,v}(t+1)$ for the next time $t+1$:

$$S_{l,v}(t+1) = S_{l,v}(t) + w_{l,v}^{l+1,v'}(t) \cdot k_{l,v} \tag{2.5}$$

where $S_{l,v}$ is the production storage of $a_{l,v}$, $w_{l,v}^{l+1,v'}(t)$ is the amount of the oil production sent by the the agent $a_{l,v}$ which are received by the agent $a_{l+1,v'}$ time t, $k_{l,v}$ is the production capacity of $a_{l,v}$.

2.1.2 Resilience measurement

For simplicity, we consider a deterministic and static metric for measuring the resilience of the considered ESC ([79]), which is formally defined as:

$$RL = \int_{t_1}^{t_2} Q(t)dt \tag{2.6}$$

where t_1 and t_2 are the endpoints of the time interval under consideration and $Q(t)$ is the performance percentage:

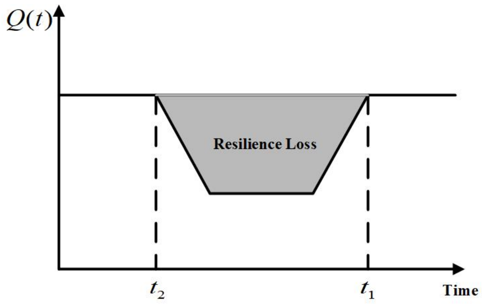

Figure 2.7: *Resilience loss*

$$Q(t) = 1 - \frac{\sum_{i=1}^{V} D'_{1,i}(t)}{\sum_{i=1}^{V} D_{1,i}(t)} \tag{2.7}$$

where D is the quantity of the total production that customers demand and $D'_{1,i}$ is the quantity of the total production delivered to the retailer after disruptions. In words, Eq. 2.6 denotes the shaded area in Figure 2.7. To estimate the ESC resilience, we apply MC simulations. We repeat simulating the ABM model for N times; in each trial, we insect a disruption and strategy. Then, we get resilience $RL_i (i = 1, 2, ..., N)$. We finally average the resilience values.

2.2 Case Study

According to the structure of the 5-layer ESC model, we assume that there are 5 agents in each layer. Every agent can implement the basic function like sending and receiving orders and production. The orders flow from the retailer agents to the producer agents, whereas the production flows from the producer agents to the retailer agents. In this case study, we consider several disruptions scenarios occurring in ESC. In order to investigate how these disruptions influence the resilience of the whole ESC, the following scenarios are considered.

Disruptions:
S1: an increase in demand (10%) for 15 transaction cycles
S2: an increase in demand (30%) for 15 transaction cycles
S3: a decrease in supply (10%) for 15 transaction cycles
S4: a decrease in supply (30%) for 15 transaction cycles

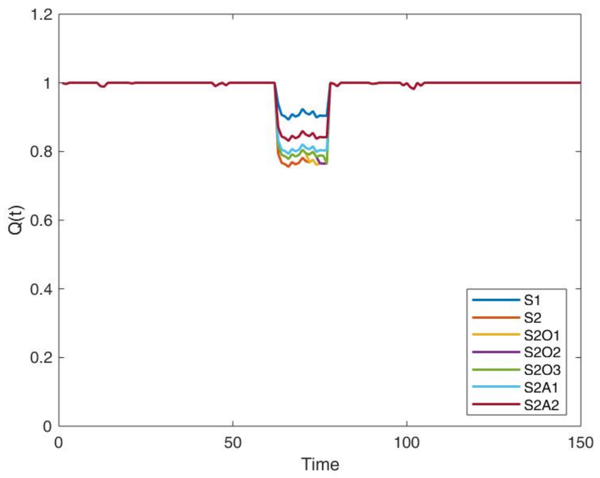

Figure 2.8: *The resilience loss in the scenario S1 and S2*

S5: a break in supply process

In the scenario S5, we assume that if the disruption happens, agent $a_{2,1}$ in Layer 2 cannot get oil production from upstream agents and thus, it cannot offer oil production for any downstream demanders.

To recover the ESC from disruption, we consider following strategies respectively: 1. The safety inventory. 2. The flexible production capacity. These strategies in detail are shown as follows.

Storage:
O1: Original storage
O2: Increasing storage 30%
O3: Increasing storage 50%

Supplier:
A1: Increase internal production capacity by 5% of existing capacity
A2: Increase internal production capacity by 10% of existing capacity

In each scenario, after the disruption happens, the retailers get less production than before, so there is a gap after the disruption happens which can be proven by comparing S1 and S2 in Figure 2.8 or S3 and S4 in Figure 2.9. However, if we take strategies, these strategies can effectively mitigate the influence of the disruption.

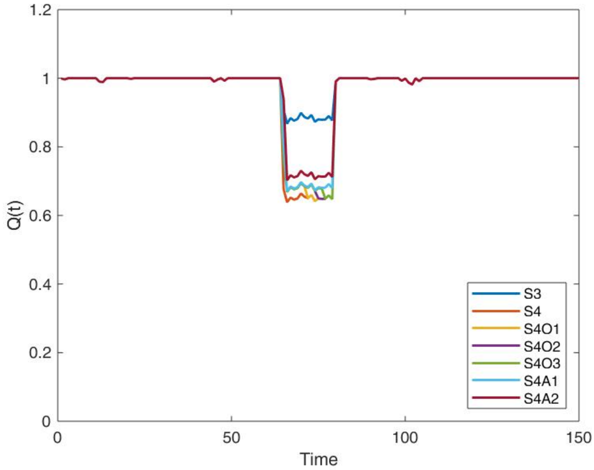

Figure 2.9: *The resilience loss in the scenario S3 and S4*

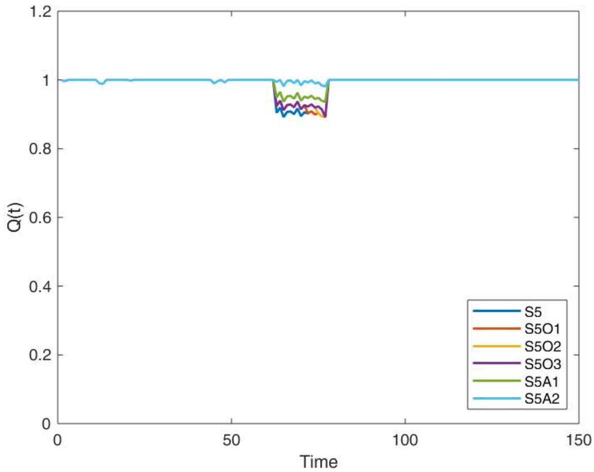

Figure 2.10: *The resilience loss in the scenario S5*

If we take the safety inventory (O1, O2 or O3) in the retailer storage as the mitigatory strategy, we assume that once the disruption happens, the agents take actions immediately, so in the beginning, the resilience loss gets smaller. After a while, the safety inventory is depleted, so the resilience loss becomes same as the resilience loss without taking any strategies. The total resilience loss gets smaller if the safety inventory is larger which can be demonstrated by comparing S2O1, S2O2 and S3O3 in Figure 2.8, S4O1, S4O2 and S4O3 in Figure 2.9 and S5O1, S5O2 and S5O3 in Figure 2.10.

If we take the flexible production capacity (A1 or A2) in the finery as the mitigatory strategy, we still assume that once the disruption happens, the agents take actions immediately, but we increase the production capacity until the disruption terminates. The results show that increasing production capacity can effectively decrease the resilience loss which are demonstrated by comparing S2A1 and S2A2 in Figure 2.8, S4A1 and S4A2 in Figure 2.9 and S5A1 and S5A2 in Figure 2.10.

The resilience loss for disruption impact under different scenarios and recovery strategies are represented in Table 2.1 and Table 2.2 in detail.

Table 2.1: *The resilience loss comparing with taking the safety inventory to mitigate the influence of disruption*

Scenario	No Strategy	O_1	O_2	O_3
S_1	1.372	1.126	1.044	0.990
S_2	3.476	3.269	3.199	3.153
S_3	1.740	1.473	1.383	1.323
S_4	5.224	4.953	4.863	4.803
S_5	1.483	1.302	1.242	1.202

Table 2.2: *The resilience loss comparing with taking the flexible production capacity to mitigate the influence of disruption*

Scenario	No Strategy	A_1	A_2
S_1	1.372	0.637	0.006
S_2	3.476	2.846	2.269
S_3	1.740	0.980	0.217
S_4	5.224	4.634	4.045
S_5	1.483	0.808	0.147

In this work, we simulate a basic ESC model within the Agent-based simulation framework. The main agents in ESC as retailers, bottling & storages, refineries, port storages and crude oil producers, which can communicate (sending and receiving orders) and interact (sending and receiving production) with each other. This ESC model is built for investigating the resilience of the whole ESC under different disruptions.

To this aim, we considered different scenarios and we used the resilience measurement to estimate the system resilience. It is notable that the more serious disruption will make more resilience loss. In addition, safety inventory and flexible production capacity are essential factors influencing the resilience of the ESC.

Based on this model, we know how disruption influence the resilience in the ESC. It also provides future scope for improvements. In the following, we plan to construct an Agent-based ESC model which has some specific difference from common supply chain and it is related to the energy system. How to design inter-system or/and inter-component dependencies and how to deal with their uncertainties will be more challenging. Finally, we desire to optimally design the ESCs with higher levels of resilience.

CHAPTER 3

A Simulation-based MOO Framework for ESCs

Energy production companies have to make planning decisions to satisfy the customers uncertain demands and to maximize their own profits. In this work, we propose a simulation-based MOO framework for the efficient management of the ESC sustaining production. The ESC agents interaction is uncertain and the ESC structure can dynamically change. ABM is used to model and simulate the agents actions and behavior, and the ESC transaction processes. The simulation is embedded into an NSGA-II optimization scheme for identifying the Pareto front of solutions for which the ESC total profit is maximized and the disequilibrium among the agents profits is minimized. Based on the Min-Max method, a single best compromised solution is identified. Finally, the MC simulations approach is used to operationalize the proposed ABM-MOO framework in presence of the uncertainty that affects the ESC.

For demonstration, we consider an oil and gas ESC model with five layers, including crude oil producers, storages, refineries, terminal storages and retailers. The results show that the proposed framework enables the optimization of the ESC planning, while taking into account multiple sources of uncertainty and the structure dynamics that challenge the ESC operation.

3.1 The Planning Problem of The ESC

ESC can be effectively described by ABM. ABM can provide logical rules to describe the agent behavior and interactions and allows simulating the ESC transaction processes in an uncertain, dynamic and time-dependent environment [31, 45, 48, 80, 81]. Thus, in our work, we apply ABM to the modeling, analysis and optimization of ESCs, taking into account both the demand and supply uncertainties, and the structure dynamics.

We consider an ESC with L layers and each l-th layer consists of V_l agents, $a_{l,1}, a_{l,2}, ..., a_{l,v}, ..., a_{l,V_l}$. In the ESC, the orders sent from Layer 1 flow layer-by-layer to the end layer L, whose V_L agents are suppliers that send supply decisions backward to the demanders.

An agent $a_{l,v}, v = 1, 2, ..., V_l$, in the l-th layer, is assigned with behaviors, which allow the agent to adaptively interact with the others. The details of the model are described in Chapter 2 Section 2.1.1.

In the aforementioned ESC, each agent $a_{l,v}$ needs to make decisions on the planning to satisfy its customers uncertain demands and to maximize the own profits. This is challenging due to the fact that the uncertainty originating from the production and purchase quantities (e.g., cost, price, demand, supply, etc.) influences the agents decisions associated with the interaction structure, which, in turn, affects the agents profits. The uncertainty propagates throughout the dynamic transaction process in the whole ESC, making it difficult to deal with production schedules and purchase orders.

To deal with this, we formulate a MOO problem in terms of the ESC total profit (that is expected to be maximized) and the agents own profits (for which the disequilibriums are supposed to be minimized).

Eq.(3.1) defines the ESC total profit P:

$$P = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{v=1}^{V_l} (A - B - C) - D \tag{3.1}$$

where A is related to the income from selling the oil production to the customer, expressed in Eq.(3.2).

$$A = \sum_{v''=1}^{V''_{l-1}} p_{l,v}^{l-1,v''} z_{l,v}^{l-1,v''}(t) \tag{3.2}$$

where $p_{l,v}^{l-1,v''}$ is the unit price of the agent $a_{l,v}$ when selling the oil production to the agent $a_{l-1,v''}$, $z_{l,v}^{l-1,v''}(t)$ is the production sent by the agent $a_{l,v}$, which is received by the agent $a_{l-1,v''}$ at time t.

B is the purchase cost, which includes the procurement cost plus the other costs e.g. the transportation cost, the labor cost and so forth.

$$B = \sum_{v'=1}^{V'} (p_{l+1,v'}^{l,v} + o_{l,v}^{l+1,v'}) w_{l,v,}^{l+1,v'}(t) \tag{3.3}$$

where $p_{l+1,v'}^{l,v}$ is the unit price of the agent $a_{l+1,v'}$ for selling the oil production to agent $a_{l,v}$, $o_{l,v}^{l+1,v'}$ is the unit price for the other cost, $w_{l,v,t}^{l+1,v'}$ is the amount of the oil production sent by the agent $a_{l+1,v'}$, which is received by the agent $a_{l,v}$.

The item C calculates the storage cost.

$$C = c_{l,v}^{S} S_{l,v}(t) \tag{3.4}$$

where $c_{l,v}^{S}$ is the agent $a_{l,v}$ storage unit cost, $S_{l,v,t}$ is the production storage of the agent $a_{l,v}$ at time t.

And, D is a penalty from the loss [82],

$$D = \sum_{t=1}^{T} r(t)\varepsilon_P \tag{3.5}$$

where $r(t)$ is equal to 1 when the agent suffers a loss after the oil production transaction at time t; otherwise, 0. ε_P is an arbitrary large number for the total profit.

On the other hand, the profits of the agents are expected to be different in a healthy ESC. It is of importance to measure and control the disequilibriums among the agents own profits, E, which is defined as the sum of the dispersion quantifying the deviation of the agents real profits from the expected values (F) and the penalty of loss in all the transaction cycles (G):

$$E = F + G \tag{3.6}$$

$$F = \sum_{l=1}^{L} \frac{\sigma_l^2}{|\mu_l|} \tag{3.7}$$

$$G = \sum_{t=1}^{T} r(t)\varepsilon_E \tag{3.8}$$

where σ_l is the standard deviation of the profits of the agents in the layer l, μ_l is the mean of the agents profits in the layer l, $r(t)$ is equal to 1 if the agent suffers a loss after the oil production transaction at time t; otherwise, 0. ε_E is an arbitrary large number for the disequilibrium.

Hence, the MOO problem can be formulated:

$$\max P(\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L}, p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}) \tag{3.9}$$

$$\min E(\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L}, p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}) \tag{3.10}$$

s.t.

$$\bar{y}_l^{\min} \leq \bar{y}_{l,v} \leq \bar{y}_l^{\max} \tag{3.11}$$

$$p_l^{\min} \leq p_{l,v}^{l-1,v''} \leq p_l^{\max} \tag{3.12}$$

The problem will be solved by maximizing the ESC total profit (3.9) and minimizing the disequilibrium (3.10), simultaneously. Eq.(3.11) and Eq.(3.12) are constraints defining the feasible regions for the average orders and the prices.

3.2 The ABM-MOO Framework

An ABM-MOO framework is originally proposed to obtain the non-dominant solutions of the Pareto fronts, which can maximize the total ESC profit P and minimize the disequilibrium among the agents profits E. To account for demand and supply uncertainties, MC simulations are used, as sketched in Figure 3.1, to operationalize the ABM-MOO framework. NSGA-II as a type of GA is easy and flexible to be applied to the optimization problem in our ESC. The general advantages of NSGA-II are list as follows [83]: 1. The non-dominated sorting techniques is used to get the optimal solution closely. 2. The crowding distance techniques is used to maintain diversity of the solutions. 3. The elitist techniques is used to preserve the best solution in the next generation. Specially, in our case, the number of decision variables is 39 which is difficult to be solved by derivative based methods but can be easily encoded and then optimized by NSGA-II.

The algorithm is summarized as follows:

Initialization

- Initialize the MC simulations.
- Set a total of $MG_{\max}$ runs of the MC loop.

Initialization of the ABM-MOO in each n-th MC run

- Set the transaction time $t = 0, 1, 2, ..., NT_{max}$, the GA population size NP, the maximum number of GA generations $NG_{\max}$, the crossover coefficient C_c and the mutation coefficient M_c.
- Generate $Q_{L,V_L}(t) \sim N(\mu_Q, \sigma_Q^2)$, where $Q_{L,V_L}(t)$ is the amount of productions which are produced by the agent a_{L,V_L} in the last layer at time t, μ_Q is the average value, σ_Q^2 is the variance.
- Set the NSGA-II generation index $k = 1$.
- Randomly generate the order and price decision matrices $POP_i^n(k) = \{[\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L}, p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}]_1^n, ..., [\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L}, p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}]_{NP}^n\}$ within the feasible space. They are coded into the chromosomes of the GA.
- Generate $y_{l,v}^{l+1,v'}(t) \sim N(\bar{y}_{l,v}, \sigma_y^2)$, where $y_{l,v}^{l+1,v'}(t)$ is the amount of orders sent by the agent $a_{l,v}$ which are received by the agent $a_{l+1,v'}$ at time t, $\bar{y}_{l,v}$ is the average value and σ_y^2 the variance.

Begin the NSGA-II loop

- Input all the generated values into the ABM ESC model, to simulate the transactions.
- Calculate the values of P and E, according to Eq.(3.1) and Eq.(3.6), respectively.
- Rank the chromosomes $POP_i^n(k)$ by running the fast non-dominated sorting algorithm.
- Rank the chromosome $POP_i^n(k)$ based on the crowding distance, aimed at finding the Euclidean distance between chromosomes in a front that maximizing P and minimizing E. It is worth pointing out that the chromosomes in the boundary are selected all the time, since they are assigned with infinite distance.
- Select the chromosome $POP_{i'}^n(k)$ by using a binary tournament selection with crowded-comparison-operator($\prec_\lambda$), where λ is a predefined tournament size.
- Apply the polynomial mutation [84, 85] and the simulated binary crossover operator [84, 86] to generate the offspring populations POP_i^n $(k + 1)$.

- Set $k = k + 1$ and check that the NSGA-II stopping criterion ($k > NG_{\max}$) is reached:
  - If yes, return the ranked Pareto-optimal $\{F_1^n, F_2^n, ..., F_{nd}^n\}$ where F_1^n is the best front and F_{nd}^n is the least good front, set $n = n + 1$.
  - Otherwise, begin a new NSGA-II cycle.
- Check whether the MC simulations stopping criterion reaches ($n > MG_{\max}$).
  - If yes, end ABM-MOO and get all the Pareto fronts.
  - Otherwise, begin a new MC simulations cycle.

Notice that a set of Pareto fronts can be identified from each MC run of the ABM-MOO framework and a best compromised solution can be identified among them by the Min-Max method [87, 88]. The Min-Max finds the highest value that one objective can be sure to get without knowing the strategy that would satisfy the other objective. Given Pareto front $H \equiv (P, E)$ the relative deviations of P and E are defined, respectively:

$$z_P = \frac{|P - P^{\min}|}{P^{\max} - P^{\min}} \tag{3.13}$$

where $P^{\min}$ and $P^{\max}$ are the minimum and maximum of the fitness values P, respectively.

$$z_E = \frac{|E - E^{\min}|}{E^{\max} - E^{\min}} \tag{3.14}$$

where $E^{\min}$ and $E^{\max}$ are the minimum and maximum of the fitness values E, respectively.

The best compromised solution is determined as

$$z_H = \min[\max\{z_P, z_E\}] \tag{3.15}$$

3.3 Case Study

For illustration, we consider an oil ESC which is structured in five layers, including retailers (Layer 1), terminal storage (Layer 2), refinery (Layer 3), storage (Layer 4) and crude oil producers (Layer 5). Three cooperative agents are modeled in Layer 1 (i.e., $a_{1,1}, a_{1,2}, a_{1,3}$), Layer 2 (i.e., $a_{2,1}, a_{2,2}, a_{2,3}$) and Layer 3 (i.e., $a_{3,1}, a_{3,2}, a_{3,3}$), respectively. Two agents

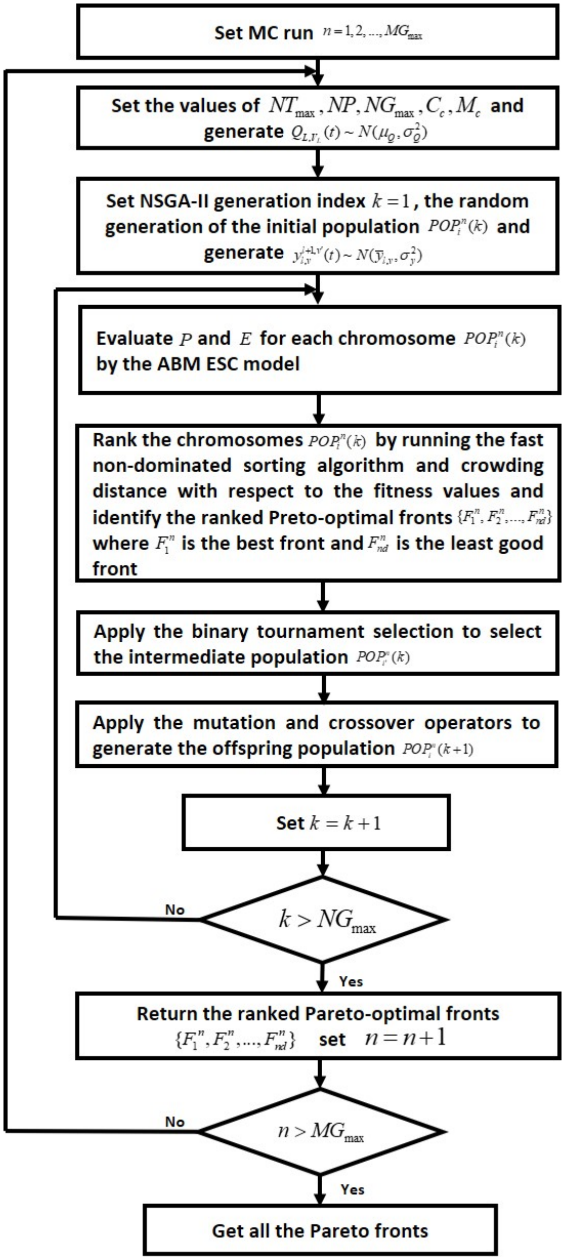

Figure 3.1: *The flowchart of the ABM-MOO framework*

Table 3.1: *The setting of the parameters for the ABM-MOO*

Symbol	Description	Value
NT_{max}	The total transaction time	1000(days)
MG_{max}	The number of MC simulations	100
NP	GA population size	200
NG_{max}	Maximum number of GA generations	100
C_c	Crossover coefficient	0.8
M_c	Mutation coefficient	0.8
μ_Q	The average value of $Q_{L,V_L}(t)$	362.5(ton)
σ_Q	The standard deviation value of $Q_{L,V_L}(t)$	2(ton)
σ_y	The standard deviation value of $y_{l,v}^{l+1,v'}(t)$	2(ton)
ε_P	An arbitrary large number for the total profit	100000
ε_E	An arbitrary large number for the uncertainty	1000
$k_{l,v}$	The production capacity of agent $a_{l,v}$	1 (if $l = 3$, 0.8)

Table 3.2: *The values of the orders and prices limitations*

	$l = 1$	$l = 2$	$l = 3$	$l = 4$
$\bar{y}_l^{\min}(ton)$	100	100	100	100
$\bar{y}_l^{\max}(ton)$	400	450	300	600
$p_l^{\min}(€/ton)$	40	25	15	10
$p_l^{\max}(€/ton)$	55	40	25	15

are modeled in Layer 4 (i.e., $a_{4,1}, a_{4,2}$) and Layer 5 (i.e., $a_{5,1}, a_{5,2}$), respectively.

Customer agents try to get enough productions from suppliers and, at the same time, supplier agents have to choose the demander(s) who can bring them the highest profits. Motivated by this, agents take relative behaviors to realize their expectations. These behaviors have been illustrated in Chapter 2 Section 2.1.1, and define the rules and decision processes of the agents interacting with other agents in an uncertain environment.

We apply the ABM-MOO framework to the ABM of the aforementioned oil ESC, for a total of $MG_{\max} = 100$ MC simulations runs, in a period of 1000 transaction days. Table 3.1 summarizes the main parameters set for the ABM-MOO algorithm. Table 3.2 lists the constraints as discussed in Eqs.3.11 and 3.12, and Table 3.3 lists the unit prices $o_{l,v}^{l+1,v'}$ for the other cost from $a_{l+1,v'}$ to $a_{l,v}$. The uncertain variables are distributed as Gaussian distributions.

Table 3.3: *The values of the unit prices $o_{l,v}^{l+1,v'}$ ($€/ton$) for the other cost from $a_{l+1,v'}$ to $a_{l,v}$*

Agent	Unit Price	Agent	Unit Price	Agent	Unit Price
$o_{1,1}^{2,1}$	3	$o_{2,1}^{3,1}$	9	$o_{3,1}^{4,1}$	2
$o_{1,1}^{2,2}$	3	$o_{2,1}^{3,2}$	2	$o_{3,1}^{4,2}$	4
$o_{1,1}^{2,3}$	5	$o_{2,1}^{3,3}$	6	$o_{3,2}^{4,1}$	4
$o_{1,2}^{2,1}$	22	$o_{2,2}^{3,1}$	5	$o_{3,2}^{4,2}$	3
$o_{1,2}^{2,2}$	15	$o_{2,2}^{3,2}$	4	$o_{3,3}^{4,1}$	3
$o_{1,2}^{2,3}$	2	$o_{2,2}^{3,3}$	5	$o_{3,3}^{4,2}$	4
$o_{1,3}^{2,1}$	5	$o_{2,3}^{3,1}$	11	$o_{4,1}^{5,1}$	2
$o_{1,3}^{2,2}$	5	$o_{2,3}^{3,2}$	10	$o_{4,1}^{5,2}$	3
$o_{1,3}^{2,3}$	4	$o_{2,3}^{3,3}$	5	$o_{4,2}^{5,1}$	4
				$o_{4,2}^{5,2}$	3

3.3.1 Sensitivity analysis

Based on the literature [89] and the literature [90], we have unformed sensitive analysis by using Sobol indices. In the Sobol indices, the higher the Sobol indices values, the more influential the respective model parameters are. The result is shown in Figure 3.2.

Regarding the objective total profit, the order amounts of the agents are more important than the prices of the agents. Based on Eq.(4.3) - Eq.(4.6) in the paper, the total profit can be written as:

$$\begin{aligned}
P &= P_1 + P_2 + P_3 + P_4 + P_5 \\
&\approx \sum_{t=1}^{T}\sum_{v=1}^{V} p_{1,v}^{0} z_{1,v}^{0}(t) - \sum_{t=1}^{T}\sum_{l=1}^{L-1}\sum_{v=1}^{V}\sum_{v'=1}^{V'} o_{l,v}^{l+1,v'} w_{l,v}^{l+1,v'}(t) - \sum_{t=1}^{T}\sum_{v=1}^{V} p_{6}^{5,v} w_{5,v}^{6}(t) \\
&- \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{v=1}^{V} c_{l,v}^{S} S_{l,v}(t)
\end{aligned} \tag{3.16}$$

where $p_{1,v}^{0}$ is the unit price of the agent $a_{1,v}$ by selling the oil production to the customers, $z_{1,v}^{0}(t)$ is the amount of the oil production sent by the agent $a_{1,v}$ which is received by the customers at time t, $o_{l,v}^{l+1,v'}$ is the unit price for the other cost, $w_{l,v}^{l+1,v'}(t)$ is the amount of the oil production sent by the the agent $a_{1+1,v'}$, which is received by the agent $a_{1,v}$ at time t, $p_{6}^{5,v}$ is the unit price of the crude oil production, $w_{5,v}^{6}(t)$ is the amount of the oil

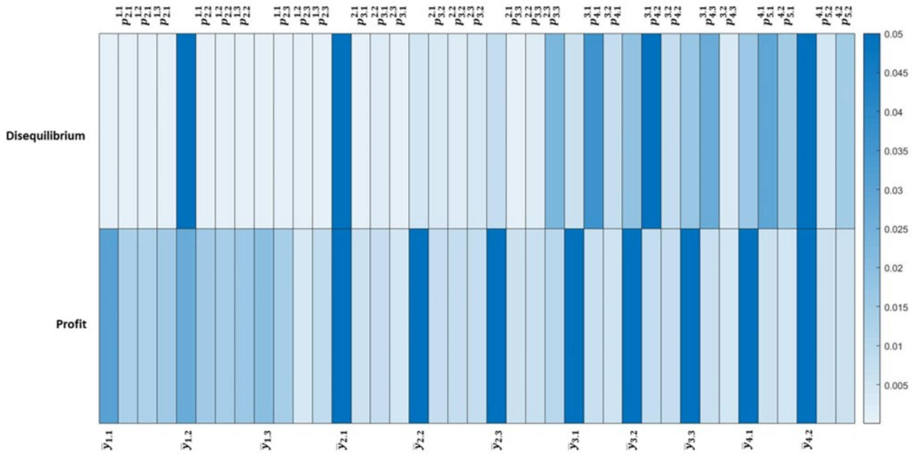

Figure 3.2: *Sensitivity for the profit and the disequilibrium*

production received by the agent $a_{5,v}$ at time t, $c^S_{l,v}$ is the agent $a_{l,v}$ storage unit cost and $S_{l,v}(t)$ is the storage of the agent $a_{l,v}$ at time t.

The Eq.(3.16) shows that the total profit is related to the order amount but has weak sensitivity on the price, because the price of one agent is the buying cost of others. The price influence is neutralized when calculating the total profit.

Figure 3.3 shows the sensitivity on the order amount for the total profit. The agents in the higher layer (up-stream) have higher sensitivity for the total profit, which makes sense because the oil supply chain model is a Make-to-Stock model. The down-stream agents profit strongly relies on the up-stream agents production amount in their hand. The agents in the higher layer have higher control on the total profit.

Every layer has at least one important variable sensitive to it regarding the objective of disequilibrium, $\bar{y}_{1,2}$ in layer 1, $\bar{y}_{2,1}$ in layer 2, $p^{3,1}_{4,2}$ in layer 3, $\bar{y}_{4,2}$ in layer 4 are most sensitive to the objective disequilibrium. In each layer, the influence of the order amount and the price on the disequilibrium is complicated and different from layer to layer. For example, $\bar{y}_{1,2}$ in layer 1 is sensitive because its cost is large if it buys the production from agent $a_{2,1}$ and agent $a_{2,2}$ in layer 2 which influences the equilibrium of the profit in layer 1.

3.3.2 Result of the Pareto front

As shown in Figure 3.4, the Pareto front is not continuous and broken into three pieces, mainly due to the fact that the model is complex, with discrete

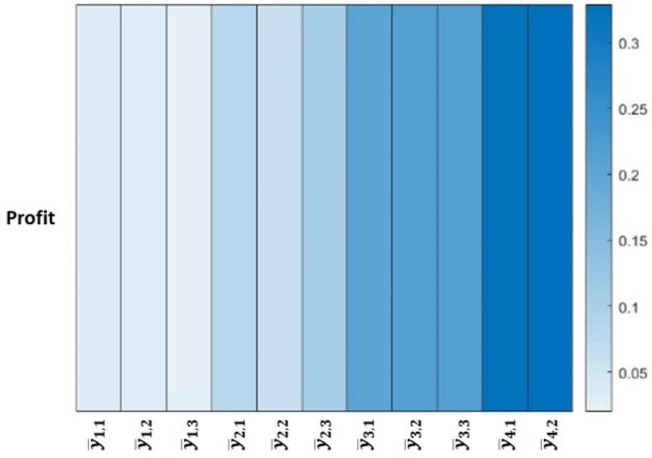

Figure 3.3: *Sensitivity on the order amounts for the profit*

and continuous values variables, whose combinations give rise to jumps in the objective function values.

The Pareto front shows that the ESC total profit increases when the disequilibrium among the agents profits tends to be large, which makes sense because some agents have price and cost advantages when they look for oil productions. Some agents can get more profit than others, which increases the total profit but also the disequilibrium among the agents profits.

According to Eq.(3.15) discussed in Section 3.2, the best compromised solution is identified by Min-Max method after substituting H_1, with P equal to €518440.3 and E equal to €1569.5.

Figure 3.4 shows that no single solution exists that simultaneously optimizes each objective and all solutions on the Pareto front are equally good but give different strategies to the ESC ABM and get different results for the total profit and the total disequilibrium. Some solutions (like H_3 in Figure 3.4) can get large total profit but at the expresses of a large disequilibrium. Some solutions (like H_2 in Figure 3.4) can get small disequilibrium but for small profit.

In order to show the agent own profits with the disequilibrium of each layer, three typical Pareto solutions (H_1, H_2 and H_3) are chosen to input into the original ESC ABM simulation again, where, H_1 is the best compromised solution identified, H_2 is the solution with the smallest values of both the ESC total profit and the disequilibrium, and H_3 is the solution with the highest values of both the ESC total profit and the disequilibrium. The

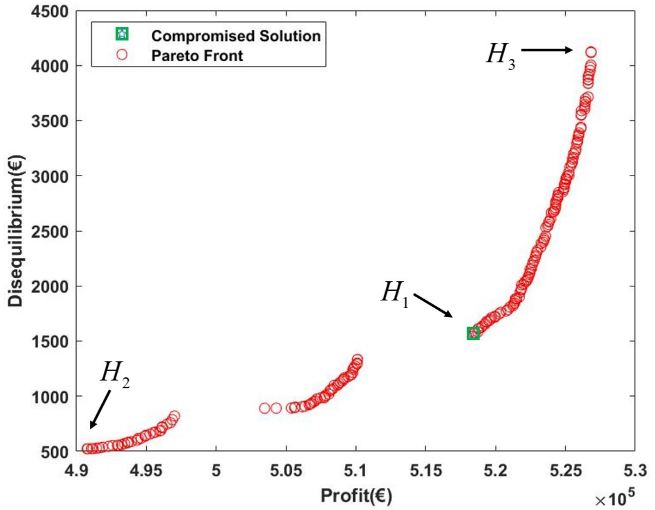

Figure 3.4: *The Pareto front*

values of decision variables getting H_1, H_2 and H_3 are shown in Figures 3.5 and 3.6.

3.3.2.1 Agent own profits obtained while re-inputting H_1 into the ESC ABM

Figure 3.7 shows the simulation results when the best compromised solution H_1 operationalizes the ESC ABM again. Figure 3.7(a)-(e) show the profits of the agents of different layers during the transaction processes. The results show that every agent in ESC gets a profit rather than a loss, due to the fact that the penalty terms Eq.(3.5) and Eq.(3.8) keep each agent from a profit loss.

In details, in Layer 1 (Figure 3.7(a)), we can find that Retailer 1 can get more profits, with an average of €3830, than Retailers 2 and 3 in the transaction processes after the initial phase, thanks to the relatively lower total cost giving higher opportunities to be accepted by the suppliers in Layer 2. This phenomenon is obvious in the intermediate Layer 2. As shown in Figure 3.7(b), Terminal Storage 1 beats Terminal Storage 2 and 3, profiting most in Layer 2. The difference among agents own profits weakens in Layer 3 and 4, as shown in Figure 3.7(c) and (d), respectively, due to the fact that the agents in the same layer are bidding with similar price levels and, thus, have equal chances to order productions from the agents in the upper layer and to sell productions to the agents in the lower layer. It should be noted that despite slight differences in the profits of

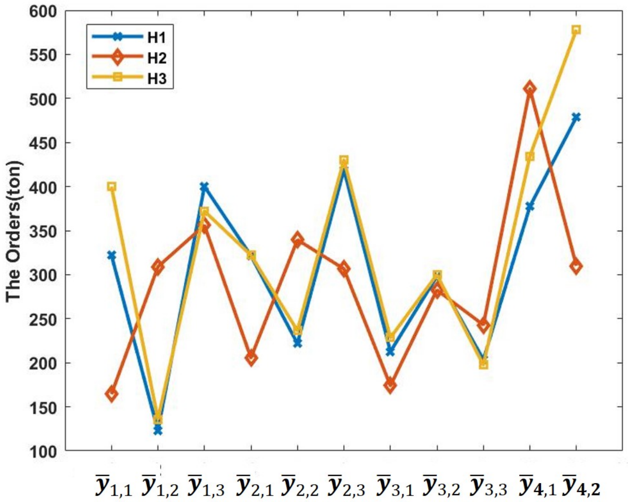

Figure 3.5: *The values of the orders (ton) sent by the agent $a_{l,v}$ for getting Pareto solutions H_1, H_2 and H_3*

the two crude oil producers in Layer5 (Figure 3.7(e)), both profits fluctuate severely during the transactions, because the supplier profits are mainly determined by the propagation of the demand and supply uncertainties in the supply chain network.

Figure 3.7(f) shows the disequilibrium for each layer. The results show that Layer 3 reaches the smallest value of the disequilibrium, equal to €90.8, followed by Layer 4 with value equal to €130.3. This makes sense because the agents in Layers 3 and 4 profit with slight difference, which makes their deviations from the expected profits small, equivalent to the results of Figures 3.7(c) and (d), respectively. In contrast, Layers 1 and 2 result in relatively large values of disequilibriums, equal to €643.7 and €478.4, respectively, mainly due to the imbalance of profits among agents in the layers. A value of €226.3 in Layer 5 proves that the propagation of uncertainty in the supply chain network can also result in a relative high probability of the imbalanced profits among agents.

3.3.2.2 Comparison of results obtained from the re-inputs of H_1, H_2 and H_3

We also re-input the Pareto solutions H_2 and H_3 into the ESC ABM, to operationalize the simulations of the transaction processes again. The agents profits of different layers obtained from the re-inputs of H_2 and H_3, respectively, show the same trends as the re-input of H_1. The simulation results

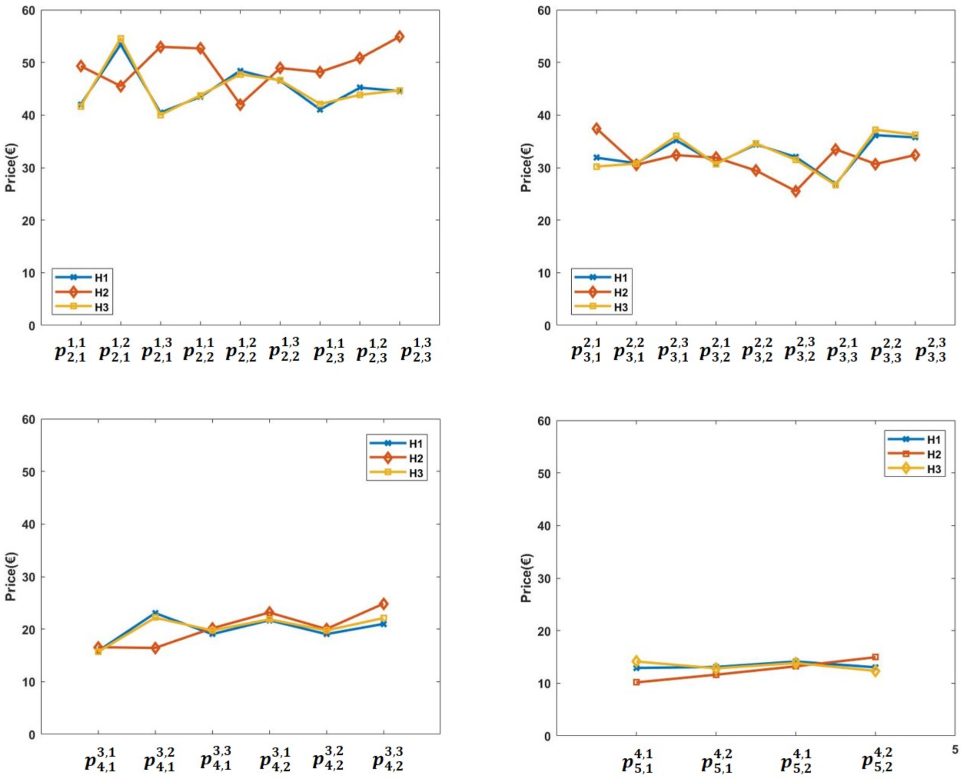

Figure 3.6: *The values of prices (€/ton) for getting H_1, H_2 and H_3*

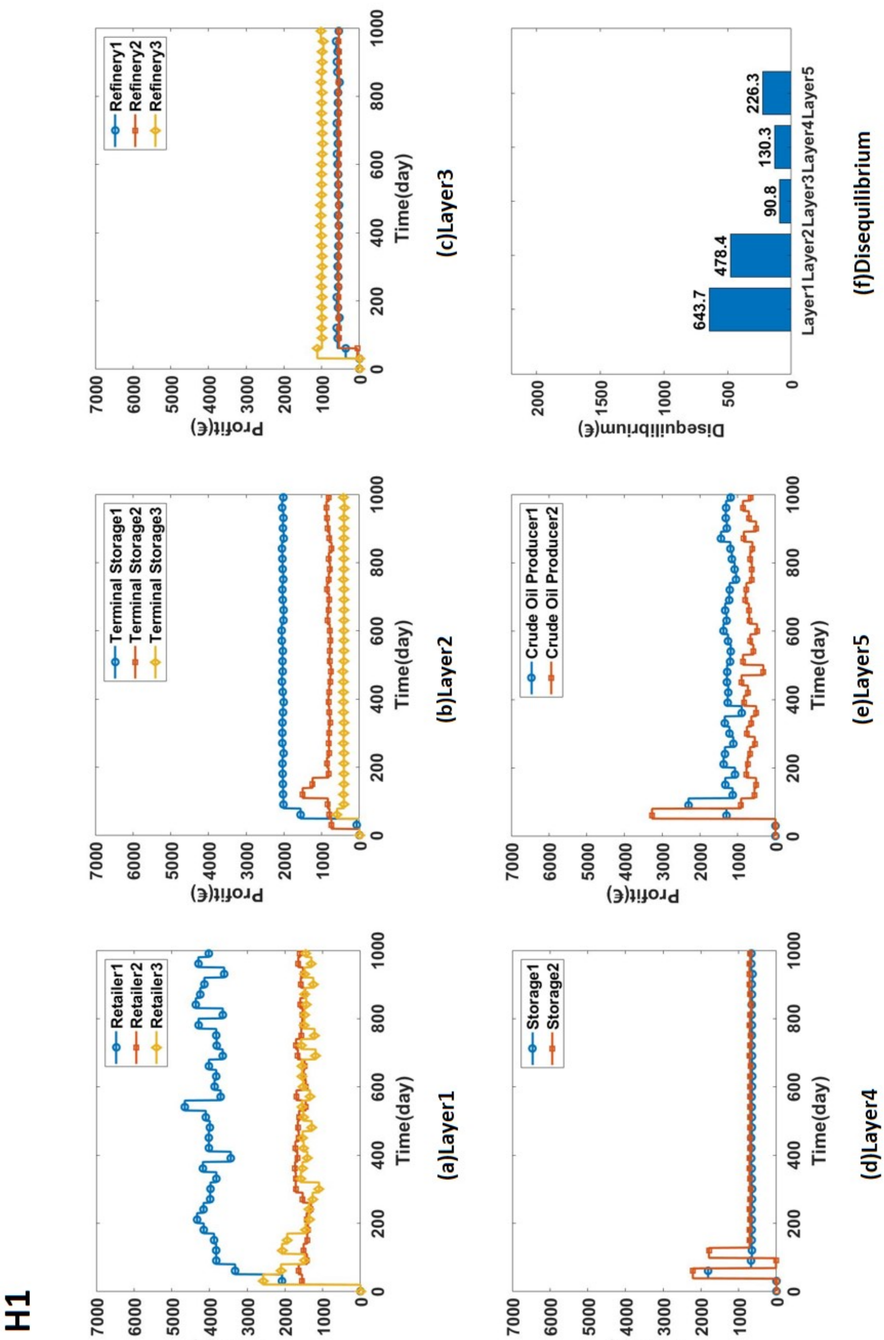

Figure 3.7: *The profit and the disequilibrium of the profit for each layer considering variables of* H_1

are attached in Figure 3.8 and Figure 3.9.

Furthermore, we compare the disequilibriums of each layers from the re-inputs of Pareto solutions into the ESC ABM, as shown in Figure 3.11. Despite the highest ESC total profit (€526831.4), the re-input of H_3 leads to the largest disequilibriums for all the layers, especially an extreme value equal to €2056.3 in the first layer, which can make the retailers own profits uncertain and less-foreseeable. In spite of the relatively large values of the disequilibriums of Layers 1 and 2, the re-input of the best compromise solution H_1 can achieve relatively small disequilibriums, equal to €90.8 for Layer 3, €130.3 for Layer 4, and €226.3 for Layer 5, which are very close to those obtained from the re-input of H_2 (which gives the smallest expected disequilibriums), equal to €36.1, €123.2 and €204.4, respectively. These results demonstrate that the re-input of the best compromise solution H_1 can be of use in solving the ESC planning problem while leveraging the ESC total profit with the disequilibrium of the ESC layers.

The results of Figures 3.10 and 3.11 show that the agents in a same layer can get close profits to decrease their disequilibrium, but sacrificing the maximization of their own profits at the same time. This is because the weak agents in the layer are constrained by the cost and the production amount, so the strong agents have to sacrifice their own profits in order to get similar profits as the weak agents and, eventually, to minimize their disequilibrium.

3.3.3 Results from the total MC runs

MC simulations are used to operationalize the proposed ABM-MOO framework, in presence of supply and demand uncertainties influencing the agents behaviors. Figure 3.12 shows the results of the Pareto fronts for different scenarios from a total of 100 MC runs. In each time, we generate 100 population size, and obtain 100 Pareto fronts (i.e., 10000 Pareto solutions). According to the equation:

$$\sqrt{n} = \frac{\lambda_\alpha s}{\phi} \tag{3.17}$$

in the literature [91], given a confidence level α, the sample size n is determined by the level of precision ϕ and the sample standard deviation s. Assuming s is fixed, an order of magnitude increasing in the level of precision ϕ requires an increasing of two orders of magnitude in the sample size n. Therefore, simply increasing n is not a valid and practical solution in our study due to the huge expense of the running time. In fact, here we get 100 Pareto fronts containing 10000 pareto solutions, which are enough for our study because we estimate that the sample standard deviation s in the profit equals to 12072. If we set the confidence level $\alpha = 0.1$, the level of precision $\phi = 197.98$, which is acceptable regarding to the order of magnitudes 10^5 in the profit.

The Pareto solutions are distributed roughly in three regions in Figure 3.12. This is meaningful because, as mentioned before, the ESC ABM considers a number of continuous and discrete design variables and various other design constraints, which consequently make the design space of ESC ABM system discontinuous and generate inherent non-linearities in the ESC ABM, whose concave section is dominated to produce the discontinuous Pareto front.

We calculate the mean values and the double-sided 95% confidence intervals of the ESC total profit and the ESC disequilibrium. The results show that the mean value of the expected ESC total profit (equal to €517084.5) and of the ESC disequilibrium (equal to €1835.4) are close to those of H_1 (equal to €518440.2 and €1569.5, respectively), demonstrating the effectiveness of selecting and re-inputting the best compromise solutions into the ESC ABM simulations.

Notice that we consider the MC simulations to control the demand and supply uncertainties and the dynamic structure in the proposed ABM-MOO framework. The estimates of the double-sided 95% confidence intervals can identify the range of the ESC total profit and the disequilibrium that their true values lie in. The ESC total profit is bounded within €493435.2 and €532110.5 with 95% level of confidence, which provides a range of values (€493435.2, €532110.5) that the expected ESC profit lies in, whereas, the disequilibrium is bounded between €516.5 and €3756.8, that suggests the ESC may operate in an uncertain way if the agents transact in an unbalanced and competitive environment.

In this work, we have proposed an ABM-MOO framework for optimal production planning in an ESC, where the agents interactive behavior is uncertain and the ESC structure dynamically changes. ABM is originally used to model and simulate the transaction processes by multiple behavioral and interactive agents, occurring in an ESC with ESC dynamic structure, and supply and demand uncertainties. An MOO problem is defined to drive the optimization of the production planning towards maximizing the ESC total profit, and at the same time, minimizing the disequilibrium among the agents profits. An MC sampling approach is deployed to operationalize the proposed ABM-MOO framework, with proper handling and controlling the uncertainty originating from multiple sources that can reduce the confidence in decision-making for optimal planning.

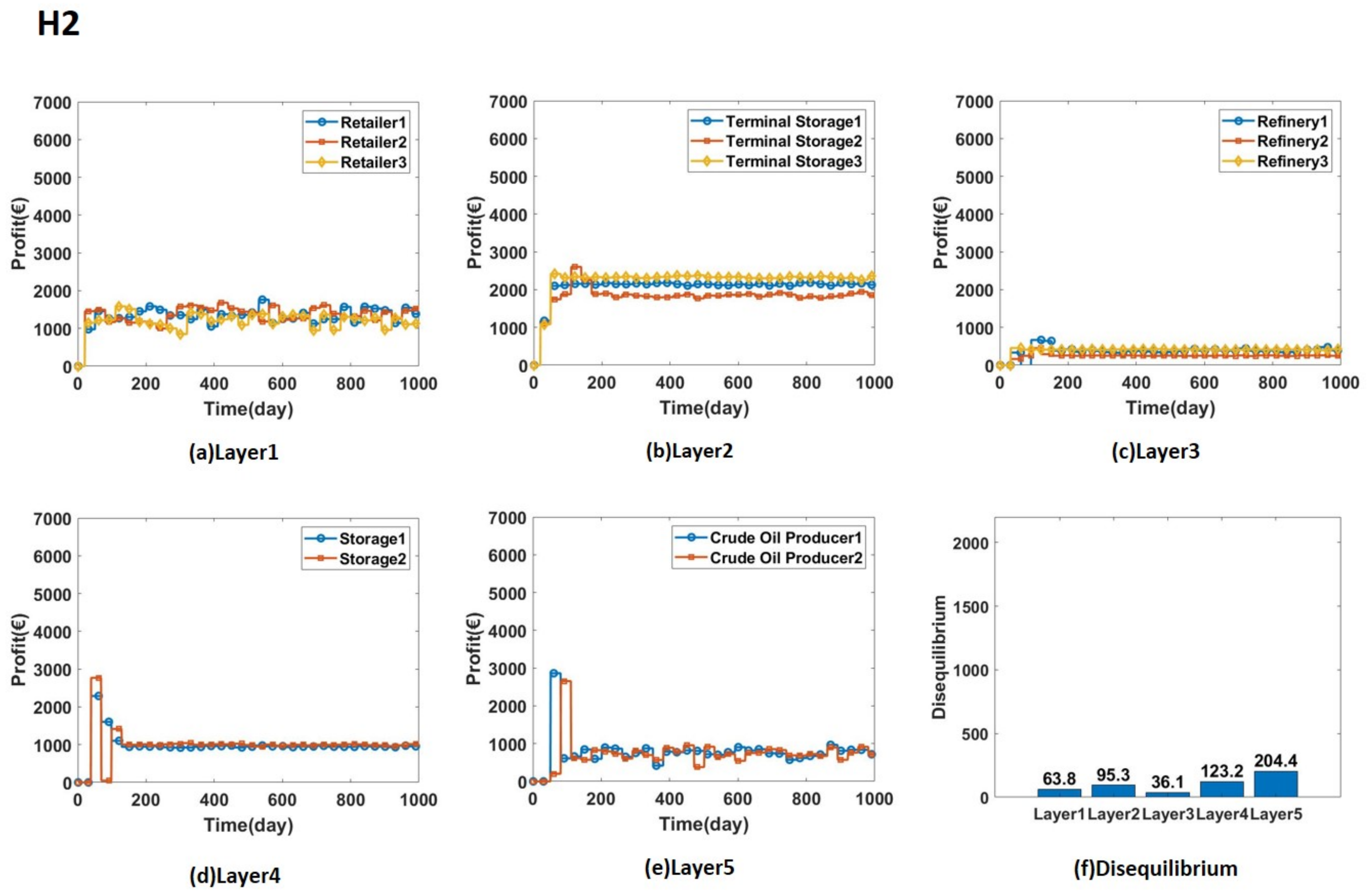

Figure 3.8: *The profit and the disequilibrium of the profit for each layer considering variables of H_2*

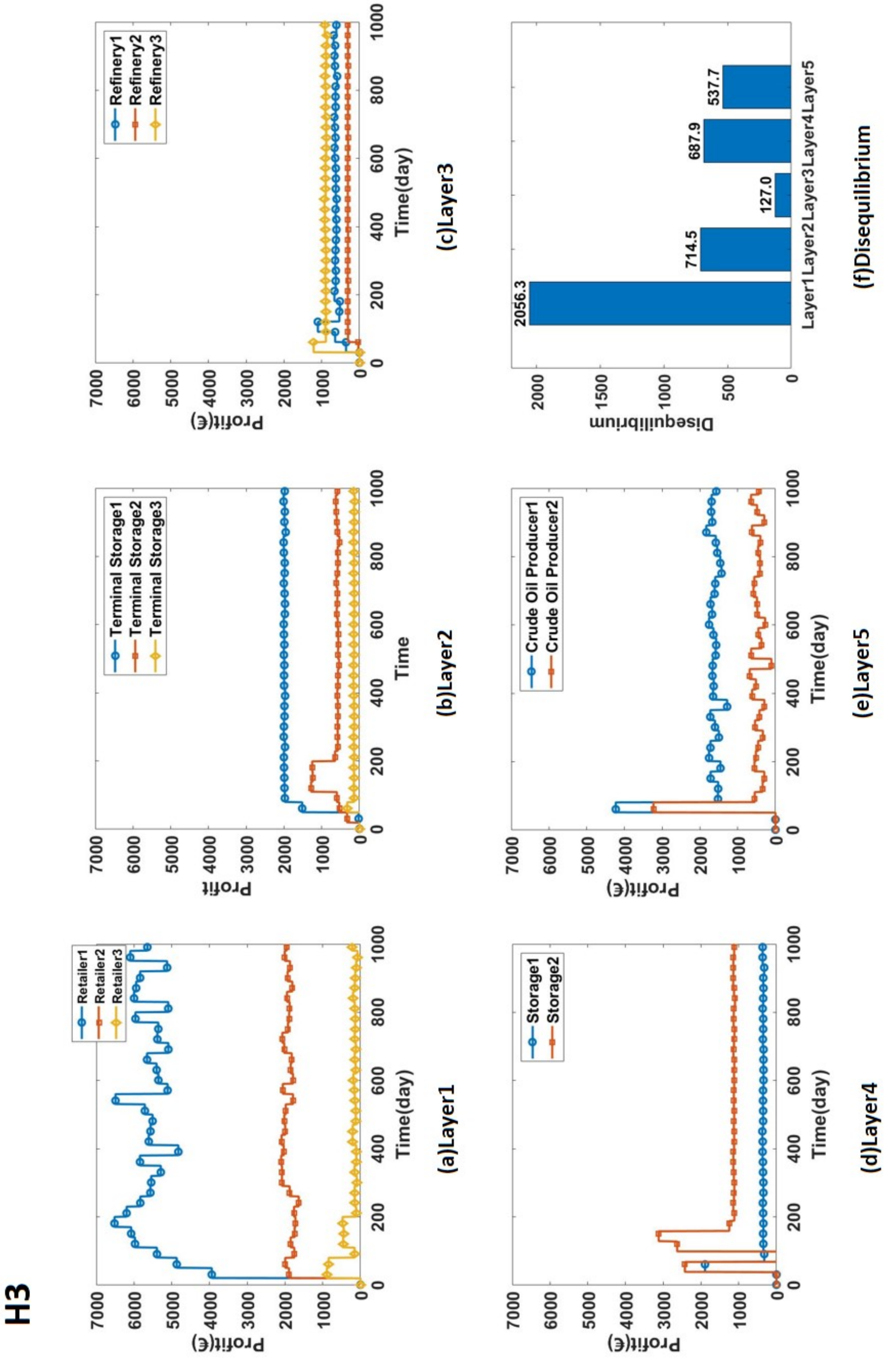

Figure 3.9: *The profit and the disequilibrium of the profit for each layer considering variables of H_3*

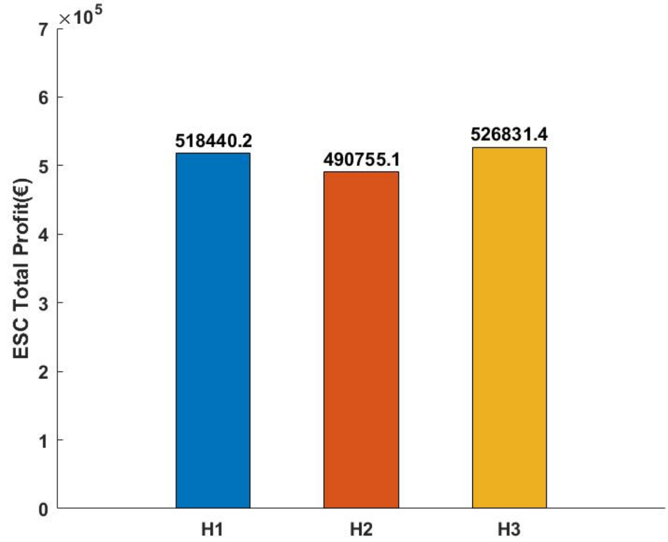

Figure 3.10: *The ESC total profits obtained from the re-inputs of H_1, H_2 and H_3*

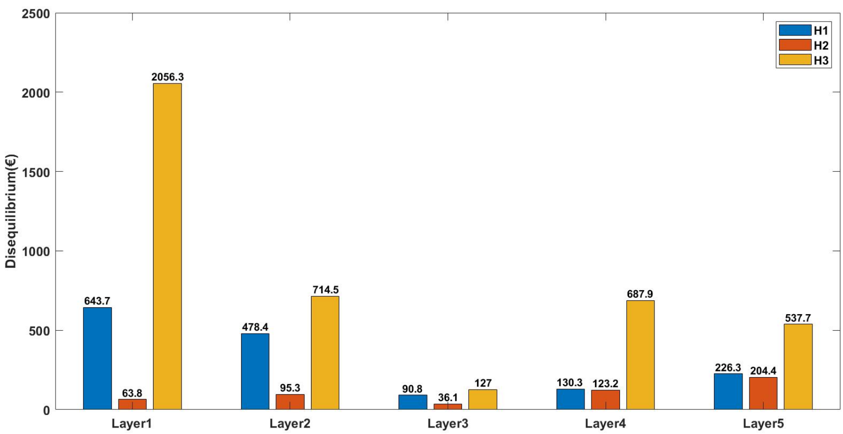

Figure 3.11: *The disequilibrium for each layer considering variables of H_1, H_2 and H_3*

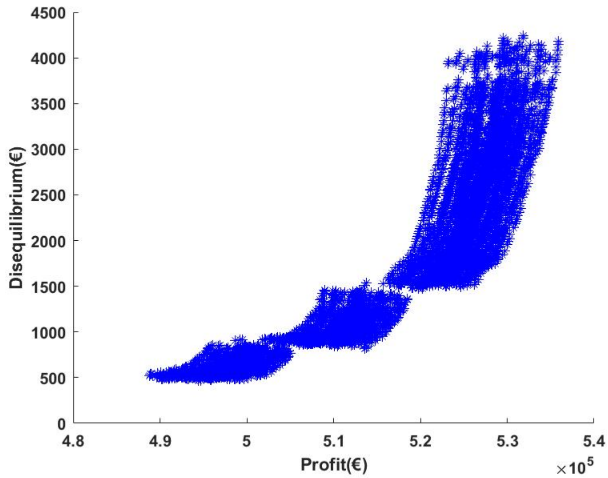

Figure 3.12: *Pareto fronts in MC simulations*

CHAPTER 4

ESCs Planning: Risk-based Optimization

The planning of an ESC aims at maximizing the benefits of the ESC agents, while satisfying the demands of the customers [14, 15]. Demand variability and supply disruption, originating from the connectivity between supply and demand, can disturb the agents interactions and impair the agents management [16]. In this study, we propose a risk-based optimization approach for the management of ESC. We introduce a CVaR measure with the purpose of measuring and controlling the risk to the ESC management. An MOO based by the NSGA-II is performed to search for the solution optimal with respect to the maximization of the ESC total profit and the minimization of the risk under uncertainties.

4.1 The Proposed Method

4.1.1 Uncertainty and risk assessment

In this study, we use the CVaR to measure the risk in the cost of supply [92, 93, 94, 95, 20, 96]. The definitions of VaR and CVaR are shown as follows:

$$VaR_\alpha(X) = \inf\{Z \in R : F_X(Z) > \alpha\} \tag{4.1}$$

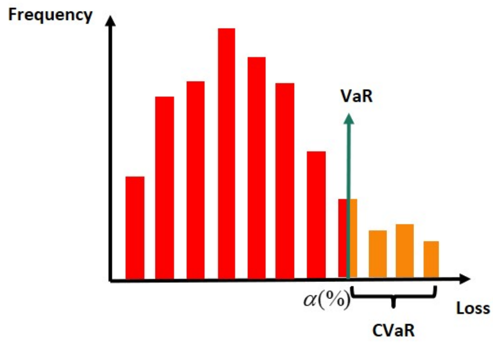

Figure 4.1: *Distribution of sending production loss*

where X is the loss, F_X is the discrete approximation of the probability distribution of the loss X, α is the α-percentile for the function F_X, Z is the smallest value of loss whose probability is greater than α.

$$CVaR_\alpha(X) = E(X|X \geq VaR_\alpha(X)) \tag{4.2}$$

where X is the loss and $E(X)$ is the expected value of X which is larger than $VaR_\alpha(X)$ defined in 4.1.

In order to understand the CVaR in a comprehensive view, we draw a graphical definition in Figure 4.1.

Figure 4.1 shows that VaR is the smallest value of the loss for a confidence level α of the probability distribution. Although the VaR has been widely used in measuring risk, it also presents some deficiencies [92].

CVaR is the expected value of the loss given that the loss is greater than or equal to the $VaR_\alpha(X)$. The definitions and properties of CVaR are given in detail in Ref.[97] and Ref.[98].

The ESC planning problem under risk and uncertainty is described in Section 4.1.2.

4.1.2 MOO problem formulation

In the ESC, every agent wants to maximize its profit. Here, we assume that the main income is from selling oil production and the main cost is in buying oil production.

Eq.(4.3) defines the ESC total profit P over a time horizon T:

$$P = \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{v=1}^{V_l} (A - B - C - D) \tag{4.3}$$

A is related to the income from selling the oil production to the customer, expressed as:

$$A = \sum_{v''=1}^{V''_{l-1}} p_{l,v}^{l-1,v''} z_{l,v}^{l-1,v''}(t) \tag{4.4}$$

where $p_{l,v}^{l-1,v''}$ is the unit price of the agent $a_{l,v}$ when selling the oil production to the agent $a_{l-1,v''}$, $z_{l,v}^{l-1,v''}(t)$ is the production sent by the agent $a_{l,v}$, which is received by the agent $a_{l-1,v''}$ at time t.

B is the purchase cost, which includes the procurement cost plus other costs like the transportation cost, the labor cost and so forth:

$$B = \sum_{v'=1}^{V'} (p_{l+1,v'}^{l,v} + o_{l,v}^{l+1,v'}) w_{l,v,}^{l+1,v'}(t) \tag{4.5}$$

where $p_{l+1,v'}^{l,v}$ is the unit price of the agent $a_{l+1,v'}$ for selling the oil production to agent $a_{l,v}$, $o_{l,v}^{l+1,v'}$ is the unit price for the other costs, $w_{l,v,t}^{l+1,v'}$ is the amount of the oil production sent by the agent $a_{l+1,v'}$ and which is received by the agent $a_{l,v}$.

The item C accounts for the storage cost:

$$C = c_{l,v}^{S} S_{l,v}(t) \tag{4.6}$$

where $c_{l,v}^{S}$ is the agent $a_{l,v}$ storage unit cost, $S_{l,v,t}$ is the production storage of the agent $a_{l,v}$ at time t.

Finally, D is the penalty for supply shortage:

$$D = \alpha_{l,v} \sum_{v''=1}^{V''_{l-1}} (x_{l,v}^{l-1,v''}(t) - z_{l,v}^{l-1,v''}(t)) \tag{4.7}$$

where $\alpha_{l,v}$ is the unit penalty cost, $x_{l,v}^{l-,v''}(t)$ is the amount of orders accepted by the agent $a_{l,v}$ which are sent by the agent, $z_{l,v}^{l-1,v''}(t)$ is the amount of oil production sent by the agent $a_{l,v}$, which are received by the agent $a_{l-1,v''}$ at time t.

Then, the total cost at time t could be defined as:

$$E(t) = \sum_{l=1}^{L} \sum_{v=1}^{V_l} (B + C + D) \tag{4.8}$$

The general MOO problem is, then, formulated as:

$$\begin{aligned}\max P(&\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L}, p_{2,1}^{1,1}, ...,\\ &p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}})\end{aligned} \tag{4.9}$$

$$\begin{aligned}\min CVaR(&\bar{y}_{1,1}, ..., \bar{y}_{l,v}, ..., \bar{y}_{L-1,V_L},\\ &p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}})\\ = CVaR_\alpha(&\sum_{l=1}^{L}\sum_{v=1}^{V_l} E_{l,v}(t))\end{aligned} \tag{4.10}$$

s.t.

$$\bar{y}_l^{\min} \leq \bar{y}_{l,v,t} \leq \bar{y}_l^{\max} \tag{4.11}$$

$$p_l^{\min} \leq p_{l,v}^{l-1,v''} \leq p_l^{\max} \tag{4.12}$$

Eq.4.9 maximizes the total profit and Eq.4.10 minimizes the risk, simultaneously. The constraint 4.11 and the constraint 4.12 give the feasible region for the average orders and the price.

4.2 The ABM-MOO Framework

GA is used to search a set of feasible solutions optimal with respect to the objective functions because its flexible and convenient capability to deal with complex problems [99]. In our case, there are 39 variables needing to be optimized which can be a problem for derivative based methods but can be easily encoded and then optimized by GA. These solutions (chromosomes, in GA terminology) are input in the simulation model. Figure 4.2 shows the framework of the hybrid simulation-based optimization process.

A set of Pareto solutions is, eventually, identified and a best-compromised solution can be chosen among them by the Min-Max method ([87, 88]). Given the Pareto solutions $H \equiv (P, CVaR)$ the relative deviations of P and CVaR are defined, respectively:

$$z_P = \frac{|P - P^{\min}|}{P^{\max} - P^{\min}} \tag{4.13}$$

where $P^{\min}$ and $P^{\max}$ are the minimum and maximum of the fitness values P, respectively.

$$z_{CVaR} = \frac{|CVaR - CVaR^{\min}|}{CVaR^{\max} - CVaR^{\min}} \tag{4.14}$$

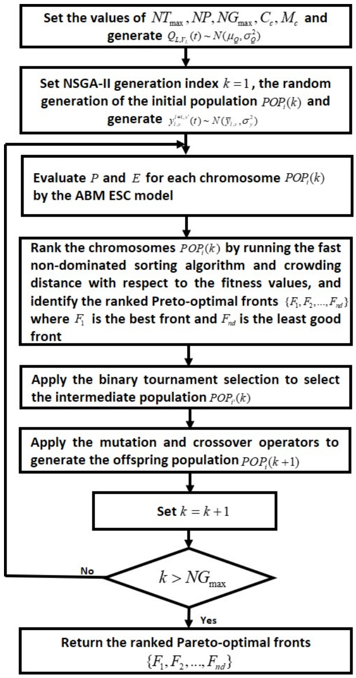

Figure 4.2: *The flowchart of the ABM-MOO framework*

where $CVaR^{\min}$ and $CVaR^{\max}$ are the minimum and maximum of the fitness values $CVaR$, respectively.

The best-compromised solution is determined as

$$z_H = \min[\max\{z_P, z_{CVaR}\}] \tag{4.15}$$

4.3 Case Study

An ESC ABM of five layers is considered. This includes retailers (Layer1), terminal storages (Layer2), refineries (Layer3), storages (Layer4) and crude oil producers (Layer5). In Layer1, Layer2 and Layer3, there are 3 agents respectively. In Layer4 and Layer5, there are 2 agents in each layer. In this ESC, we assume that there is 10% probability that the refinery 3 is disrupted. When it is disrupted, it is not able to send oil production to down stream demanders. The recovery strategy is not considered in this case study. We assume that every disruption influences one transaction. After the transaction finishes, the disruption vanishes and the ESC come back to be normal.

Figure 4.3 shows the Pareto front which reflects that the CVaR increases

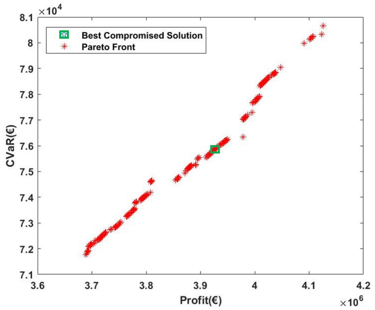

Figure 4.3: *The Pareto front with the best-compromised solution*

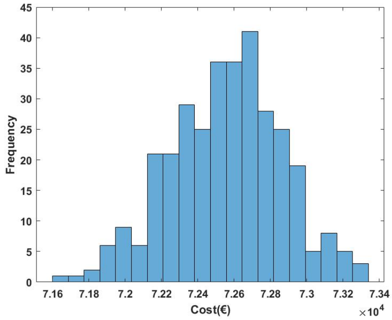

Figure 4.4: *The cost frequency distribution under the ESC normal state*

when the ESC total profit tends to be large. Then increasing CVaR means increasing risk: if the agents want to get more profit they have to face larger risk which makes sense because high profit are always accompanied by high risk. According to Eq.(4.15) discussed in Section 4.2, the best compromised solution is identified, and the total profit P equals to €3924956.04 and $CVaR$ equals to €75851.93.

Figure 4.4 shows the cost frequency distribution in the normal state which is optimized in the literature ([15]). Figure 4.5 shows the cost frequency distribution with disruption risks if we do not take any measure to control them. Figure 4.6 shows the cost frequency distribution with disruption risk if the ESC is optimized.

Figure 4.4 shows that if the ESC is without disruption risk, the cost is distributed in the range from €7.16×10^4 to €7.34×10^4 which is a relatively concentrated range. Comparing Figure 4.4 with Figure 4.5 and Figure4.6, the range of the cost distribution increases, because the disruption risks cause the refinery storage cost and shortage penalty to increase. On the other hand, after the disruption happens, some oil production has to be

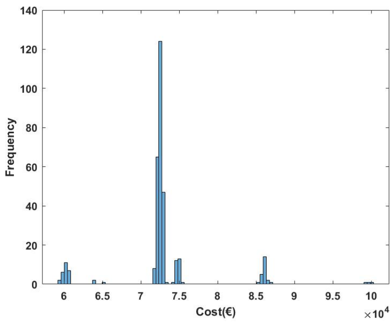

Figure 4.5: *The cost frequency distribution with the ESC disruption risk*

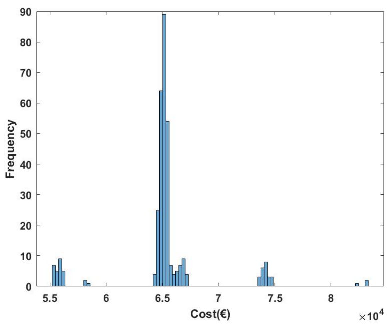

Figure 4.6: *The cost frequency distribution with the ESC disruption risk after optimization*

stored in Refinery 3. When the ESC goes back to normal, Refinery 3 does not need to order new oil production from up stream storage, so the procurement cost is decreasing, which further increases the range of the cost distribution. In Figure 4.5, the $CVaR_{95\%}$ of the cost is €88650. In Figure 4.6, the $CVaR_{95\%}$ of the cost is €75851.93. Comparing Figure 4.5 with Figure 4.6, the proposed ABM-MOO framework is effective to decrease the CVaR related to the risk disruption.

The objective of this study is to manage the production planning problem in ESCs, where the agent interaction behavior is uncertain and the ESC faces disruption risk. In order to address this problem, we propose a simulation-based MOO framework which enables decision making on planning production, including the price and the amount of purchased oil production. Firstly, we use ABM to model and simulate the agent behaviors and the ESC transaction processes. Secondly, we use NSGA-II to get the optimal solutions that maximize the ESC total profit and minimize the disruption risk. An oil ESC model with five layers, including crude oil producers, storages, refineries, terminal storages and retailers is presented to demonstrate the methodology.

CHAPTER 5

A Cooperative Co-evolutionary Approach for Many-objective Optimization in ESCs

In ESCs, multiple agents proactively interact and cooperate in a coordinated production process, where each of them aims to grab the maximal own profits. In this study, we propose a cooperative co-evolutionary approach to solve such an ESC MaOP where the agents own profits are maximized. The autonomous behavior of the ESC agents and the interactive transaction processes are modelled in the context of ABM. A CCPSO algorithm is embedded into ABM for identifying the Pareto Front (PF). The effectiveness of the proposed approach is verified by the test functions.

For demonstration, we illustrate the proposed approach by considering an oil and gas ESC model with five layers, including crude oil producers, storages, refineries, terminal storages and retailers. The results show that the proposed CCPSO enables the many-objective optimization for the efficient production planning of the ESC, whilst taking into account multiple sources of uncertainty and the structure dynamics challenging the ESC operation balance.

5.1 The ESC MaOP

In chapter 3 and chpater 4, the optimization problem is the Multi-objective Optimization Problem (MOP) containing less than three objective functions. In chapter 5, the optimization problem is an ESC Many-objective Optimization Problem (MaOP), which contains more than three objective functions.

EAs can flexibly adjust to MOP thanks to its capabilities to address the uncertainty in supply and demand conveniently and limit the computational burden. However, they are deteriorative and suffer from the curse of dimensionality, when solving a Many-objective Optimization Problem (MaOP) where the number of objectives becomes more than three [100, 101]. By contrast, Co-Evolutionary Algorithm (CEA) releases the evolutionary pressure of EAs converging the various individuals to a same niche, but coevolves sub-populations of individuals that represent different parts of the global solution making it possible to solve MaOPs. CEA can be used to obtain Pareto solutions for MaOP by decomposing problem into subproblems, and solving each subproblem with a subpopulation, evolved by an individual Evolutionary Algorithm (EA). CEA allows calculating decomposed problems in parallel, which speeds up the optimization process [59]. On the other hand, separated species help to maintain good solution diversity, increase the robustness against the modules' errors and failures, and, thus, enhance the reusability in dynamic environments [58, 59].

Cooperative CEA highly fits the characteristics of ABM because ABM is made up of several individuals/agents with its own variables to be optimized and its own problem to be solved which need to cooperate to obtain the optimal objective, so cooperative CEA is more appropriate to used in solving MaOP in agent-based ESC modelling.

ESC can be effectively described by ABM. ABM can provide logical rules to describe the agent behavior and interactions and allows simulating the ESC transaction processes in an uncertain, dynamic and time-dependent environment [45, 48, 80, 81, 31]. Thus, in our work, we apply ABM to the modeling, analysis and optimization of ESCs, taking into account both the demand and supply uncertainties, and the structure dynamics.

We consider an ESC with L layers and each l-th layer consists of V_l agents, $a_{l,1}, a_{l,2}, ..., a_{l,v}, ..., a_{l,V_l}$. In the ESC, the orders sent from Layer 1 flow layer-by-layer to the end layer L, whose V_L agents are suppliers that send supply decisions backward to the demanders.

An agent $a_{l,v}, v = 1, 2, ..., V_l$, in the l-th layer, is assigned with behaviors, which allow the agent to adaptively interact with the others. The details of the model are described in Chapter 2 Section 2.1.1.

In an ESC, each agent $a_{l,v}$ makes decisions on the planning to satisfy its customers uncertain demands and to maximize the own profits. To deal with this, a MaOP is formulated with the aim of maximizing the profit.

Eq.(5.1) defines the profit P for each agent $a_{l,v}$:

$$P_{l,v} = \sum_{t=1}^{T} A_{l,v} - B_{l,v} - C_{l,v} \tag{5.1}$$

where $A_{l,v}$ is related to the income from selling the oil production to the customer, expressed in Eq.(5.2).

$$A_{l,v} = \sum_{v''=1}^{V''_{l-1}} p_{l,v}^{l-1,v''} z_{l,v}^{l-1,v''}(t) \tag{5.2}$$

where $p_{l,v}^{l-1,v''}$ is the unit price of the agent $a_{l,v}$ when selling the oil production to the agent $a_{l-1,v''}$, $z_{l,v}^{l-1,v''}(t)$ is the production sent by the agent $a_{l,v}$, which is received by the agent $a_{l-1,v''}$ at time t.

$B_{l,v}$ is the purchase cost, which includes the procurement cost plus the other costs e.g. the transportation cost, the labor cost and so forth.

$$B_{l,v} = \sum_{v'=1}^{V'} (p_{l+1,v'}^{l,v} + o_{l,v}^{l+1,v'}) w_{l,v,}^{l+1,v'}(t) \tag{5.3}$$

where $p_{l+1,v'}^{l,v}$ is the unit price of the agent $a_{l+1,v'}$ for selling the oil production to agent $a_{l,v}$, $o_{l,v}^{l+1,v'}$ is the unit price for the other cost, $w_{l,v,t}^{l+1,v'}$ is the amount of the oil production sent by the agent $a_{l+1,v'}$, which is received by the agent $a_{l,v}$.

The item C calculates the storage cost.

$$C_{l,v} = c_{l,v}^{S} S_{l,v}(t) \tag{5.4}$$

where $c_{l,v}^{S}$ is the agent $a_{l,v}$ storage unit cost, $S_{l,v,t}$ is the production storage of the agent $a_{l,v}$ at time t.

Hence, the MaOP problem is solved by:

$$\max P_{l,v}(\bar{y}_{l,v}, p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}) \tag{5.5}$$

s.t.

$$\bar{y}_l^{\min} \leq \bar{y}_{l,v} \leq \bar{y}_l^{\max} \tag{5.6}$$

$$p_l^{\min} \leq p_{l,v}^{l-1,v''} \leq p_l^{\max} \tag{5.7}$$

where $P_{l,v}$ is the profit for the agent $a_{l,v}$, $\bar{y}_{l,v}$ is the amount of average orders sent by the agent $a_{l,v}$, $p_{l,v}^{l-1,v''}$ is the unit price of the agent $a_{l,v}$ by selling the oil production to the agent $a_{l-1,v''}$, $\bar{y}_l^{\min}$ is the minimum for the average orders, $\bar{y}_l^{\max}$ is the maximum for the average orders, $p_l^{\min}$ is the minimum for the unit price, $p_l^{\max}$is the maximum for the unit price. Eq.(5.6) and Eq.(5.7) are constraints defining the feasible regions for the average orders and the prices.

5.2 The Agent-based CEA

5.2.1 The agent-based cooperative CEA

In order to embed CA into ABM appropriately, we address the following issues of problem: the decomposition, the interdependencies between subcomponents, and the maintenance of selection pressure.

5.2.1.1 Decomposition

Each agent in ESC has its own decision variables. These variables are put into species based on their owner-member relationship. For example, the variables x_1, x_2, x_3 are decided by the agent 1, so they are assigned to species 1. Each agent has a group of sub-populations representing variable(s) which it uses to interact with other agents to get the fitness value(s).

5.2.1.2 Interdependencies Between Subcomponents

In CEAs, the agent has to cooperate with other agents to assemble the complete solution. The fitness value of an individual is evaluated based on their interactions with others. If it has good cooperation with others, the subpopulation gets good fitness value.

5.2.1.3 Maintenance of Selection Pressure

In our CCPSO, to allow PSO to deal with MaOP, we consider the MOPSO framework which contains a external repository to record the nondominated variables [102] which is also updated, recorded and used by each agent when cooperating. On one hand, in order to make MOPSO suit for the ABM, we synthesize the co-evolutionary into original MOPSO. On the other hand, to overcome the loss of sufficient selection pressure caused by the Pareto-ranking approach and the decomposition approach [103, 104, 105], the balanceable fitness estimation (BFE) method is used [103]. For each particle $H_i^j = [\bar{y}_{l,v}, p_{2,1}^{1,1}, ..., p_{l,v}^{l-1,v''}, ..., p_{L,V_L}^{L-1,V_{L-1}}]$, its BFE($D(p_i^j)$) is defined as:

$$D(H_i^j) = \alpha \times Cd(H_i^j) + \beta \times Cv(H_i^j) \tag{5.8}$$

where H_i^j indicates the i-th particles current position in the j-th swarm. $Cd(H_i^j)$ and $Cv(H_i^j)$ denote the normalized diversity and convergence distance of the particle H_i^j. α and β are two factors to tune the impacts of the diversity and convergence distances, respectively.

The speed of particle is defined as:

$$v_i^j = w \times v_i^j + c_1 \times r_1 \times (pbest_i^j - H_i^j) + c_2 \times r_2 \times (R_h^j - H_i^j) \tag{5.9}$$

where v_i^j is the i-th particles speed in the j-th swarm, w is the inertia weight, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are random numbers in [0, 1], $pbest_i^j$ is the personal-best particle position, H_i^j is the i-th particles current position in the j-th swarm, R_h^j is the h-th particle's position in the j-th external repository.

Then, the position of particle updates as:

$$H_i^j = H_i^j + v_i^j \tag{5.10}$$

where H_i^j is the i-th particles current position in the j-th swarm, v_i^j is the i-th particles speed in the j-th swarm.

The pseudocode of CCPSO is described in Algorithm 1.

5.2.2 Test problem

To show the effectiveness of the proposed CCPSO, the test problems ZDT2 and DTLZ2 are used. The variables number and the objectives number of ZDT2 and DTLZ2 are shown in Table 5.1. In order to show the effectiveness of our CCPSO, we compare it with the original MOPSO framework which is a preliminary approach without using the co-evolutionary framework. The parameter settings of CCPSO and MOPSO for the test problem ZDT2 and DTLZ2 are shown in Table 5.2 and Table 5.3 respectively.

Figure 5.1 shows the Pareto front for the test problem ZDT2. In this test, the small generation number 50 is used. MOPSO is close to the true Pareto front but CCPSO shows its more efficient capability to get close to the true Pareto front comparing with MOPSO.

Algorithm 1 Cooperative Co-evolutionary Particle Swarm Optimization (CCPSO)

Set m swarms and in jth swarm, there are n_j particles;
Initial the particles in each swarm $S^j = [H_1^j; H_2^j; ...; H_i^j; ...; H_{n_j}^j]$ and the external repository $R^j = null$;
Randomly initialize position H_i^j and speed $v_i^j = 0$ for each particle in each swarm;
Randomly set $PBEST^j = [pbest_1^j; pbest_2^j; ...; pbest_i^j; ...; pbest_{n_j}^j]$;
Assemble the complete solutions for particle H_i^j in each swarm:
    $G^1 = [S^1, PBEST^2, ..., PBEST^j, ...PBEST^m]$;
    $G^2 = [PBEST^1, S^2, ..., PBEST^j, ...PBEST^m]$;
    ......;
Evaluate the objective value $F^j = [f_1^j, f_2^j, ...f_i^j, ..., f_{n_j}^j]$ for particles in each swarm;
Assemble all the solutions and corresponding objective values:
    $G = [G^1; G^2; ...; G^m]$; $F = [F^1; F^2; ...; F^m]$;
Put non-dominated solutions into R^1,R^2,...R^m;
while $(t < T)$ **do**
    Select out leader h;
    Update the speed v_i^j and the position H_i^j for particles in each swarm based on Eq.5.9 and Eq.5.10;
    Use mutation operator for particles in each swarm respectively;
    Check boundaries for particles in each swarm respectively;
    Assemble the complete solutions:
        $G^1 = [S^1, R_h^2, ..., R_h^j, ...R_h^m]$;
        $G^2 = [R_h^1, S^2, ..., R_h^j, ...R_h^m]$;
        ......;
    Evaluate the objective values $F^j = [f_1^j, f_2^j, ...f_i^j, ..., f_{n_j}^j]$ for particles in each swarm;
    Assemble all the solutions and corresponding objective values:
        $G = [G^1; G^2; ...; G^m]$; $F = [F^1; F^2; ...; F^m]$;
    Select out good particles based on BFE:
        $R = updateArchive(R_f, R_s, F, S)$
    Update particles position in the R;
    Update the best position for each particle;
    if $pbest_i^j$ cannot dominate H_i^j **then**
        $pbest_i^j = H_i^j$;
    end if
end while

Test problem DTLZ2 is a MaOP with 10 objectives. We draw the objective values in the parallel coordinates (Figure 5.2) and each vertical axis indicates an objective value. It shows that CCPSO has an better convergence, with its Pareto solutions ranging from 0 to 1 in contrast to the MOPSO's Pareto solutions ranging from 0 to 3 [106].

The CCPSO applied co-evolutionary framework which helps to avoid the weakness of the MOPSO [68, 70]. In co-evolutionary framework, the various swarms have their own evolutionary directions instead of evolving in one direction which improved efficiency of evolution. The test problems also demonstrate such perspective that the proposed CCPSO is effective and efficient to deal with MOP or even MaOP.

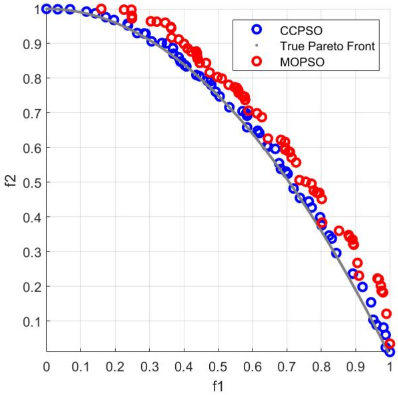

Figure 5.1: *The Pareto front of CCPSO and MOPSO for ZDT2*

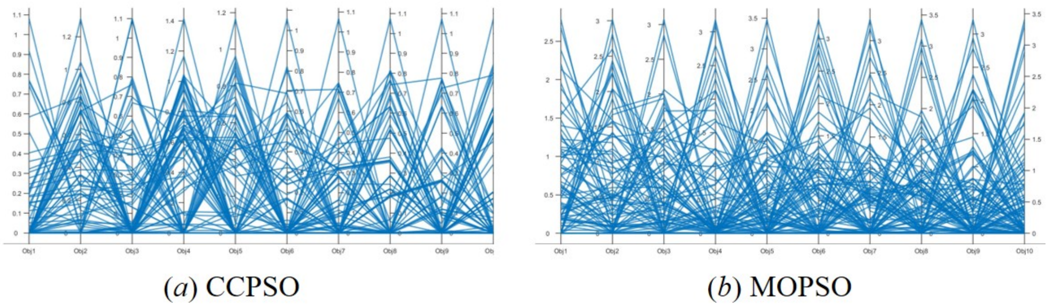

Figure 5.2: *The Pareto optimal solutions of CCPSO and MOPSO for DTLZ2*

Table 5.1: *The variable number and the objective number of ZDT2 and DTLZ2*

	The variable number	The objective number
ZDT2	30	2
DTLZ2	19	10

Table 5.2: *The parameter settings of CCPSO and MOPSO for ZDT2*

	CCPSO	MOPSO
Generation Number	50	50
Swarm Number	5	-
Total Particles	100	100
Particles in Each Swarm	20	-
Total Variable Number	30	30
Variables in Each Swarm	6	-

5.2.3 CCPSO in agent-based ESC modeling

An ABM-MOO framework is originally proposed to obtain the non-dominant solutions of the Pareto front, which can maximize each agent's ESC profit $P_{l,v}$. The overall framework is shown in Figure 5.3. CCPSO is used to search a set of feasible solutions optimal with respect to the objective functions. These solutions are input in the simulation agent-based ESC modeling. After several iterations, the Pareto front is obtained.

5.3 Case Study

For illustration, we consider an oil ESC which is structured in five layers, including retailers (Layer 1), terminal storage (Layer 2), refinery (Layer 3), storage (Layer 4) and crude oil producers (Layer 5). Three cooperative agents are modeled in Layer 1 (i.e., $a_{1,1}, a_{1,2}, a_{1,3}$), Layer 2 (i.e., $a_{2,1}, a_{2,2}, a_{2,3}$) and Layer 3, respectively. Two agents are modeled in Layer 4 and Layer 5, respectively.

Customer agents try to get enough productions from suppliers and, at the

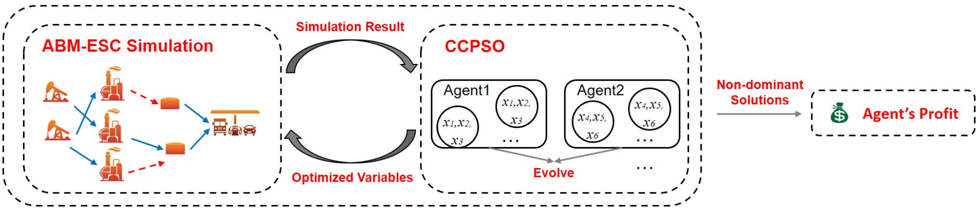

Figure 5.3: *The framework for MaOP in agent-based ESC modeling*

Table 5.3: *The parameter settings of CCPSO and MOPSO for DTLZ2*

	CCPSO	MOPSO
Generation Number	200	200
Swarm Number	5	-
Total Particles	150	150
Particles in Each Swarm	30	-
Total Variable Number	19	19
Variables in Each Swarm	4 or 3	-

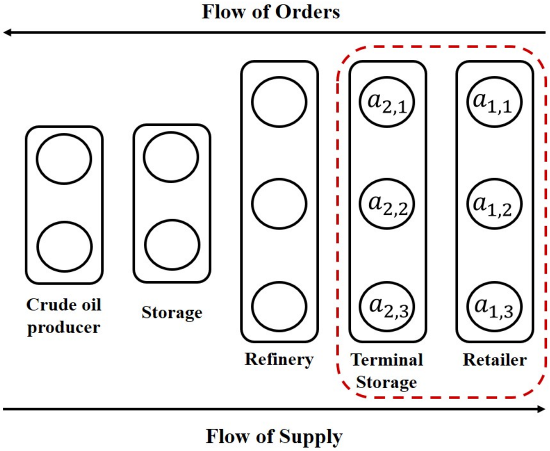

Figure 5.4: *The framework for MaOP in agent-based ESC modeling case study*

same time, supplier agents have to choose the demander(s) who can bring them the highest profits. Motivated by this, agents take relative behaviors to realize their expectations. These behaviors have been illustrated in Chapter 2 Section 2.1.1, and define the rules and decision processes of the agents interacting with other agents in an uncertain environment.

We optimize the price and the amount of production orders between the retailers (Layer 1) and the terminal storages (Layer 2) by applying the proposed CCPSO. There are 6 agents in Layer 1 and Layer 2, so 6 objectives maximizing the agent profit are generated. Figure 5.4 shows the framework for MaOP in agent-based ESC modeling case study and the agents optimized are shown in the red box.

5.3.1 Evaluation indicators

There are many indicators can be used to evaluate the algorithm performance regarding the results such as Generational Distance (GD) [107], Di-

Table 5.4: *The setting of the parameters for the ABM-MOO*

Symbol	Description	Value
NT_{max}	The total transaction time	1000(days)
NG_{max}	Maximum number of generations	200
μ_Q	The average value of $Q_{L,V_L}(t)$	362.5(ton)
σ_Q	The standard deviation value of $Q_{L,V_L}(t)$	2(ton)
σ_y	The standard deviation value of $y_{l,v}^{l+1,v'}(t)$	2(ton)
$k_{l,v}$	The production capacity of agent $a_{l,v}$	1 (if $l=3$, 0.8)
M	Swarms number	3
TN	Total particles	90
N	Particles in each swarm	30
T_v	Total variables	12
w	Inertia coefficient	0.4
c_1	Personal confidence factor	2
c_2	Swarm confidence factor	2

Table 5.5: *The values of the orders and prices limitations*

	$\bar{y}_l^{\min}(ton)$	$\bar{y}_l^{\min}(ton)$	$p_l^{\min}(€/ton)$	$p_l^{\max}(€/ton)$
$l=1$	100	250	40	55

versity Measure [108], Inverted Generational Distance (IGD) [109] etc., but some of them need the reference solutions set. In the case research, the ideal solutions are unavailable, so we select Hypervolume (HV) to evaluate the algorithm performance to prove the reliability of the results which integrates the convergence and diversity performance. When evaluate the quality of the results, a larger HV value indicates a better approximation of the true Pareto Front regarding both convergence and diversity.

5.3.2 Parameter settings

We apply the ABM-MOO framework to the ABM of the aforementioned oil ESC, in a period of 1000 transaction days. Table 5.4 summarizes the main parameters set for the ABM-MOO algorithm. Table 5.5 lists the constraints, and Table 5.6 lists the unit prices $o_{1,v}^{2,v'}$ for the other cost from $a_{2,v'}$ to $a_{1,v}$. The uncertain variables are distributed as Gaussian distributions.

5.3.3 Result and performance of the Pareto front

Utilizing the method proposed in Section 5.2, we get the Pareto front for the MaOP in the ESC which is shown in Figure 5.5. We draw the Pareto front in a parallel coordinates in which each vertical axis indicates an objec-

Table 5.6: *The values of the unit prices $o_{l,v}^{l+1,v'}$ (€/ton) for the other cost from $a_{l+1,v'}$ to $a_{l,v}$*

Agent	Unit Price	Agent	Unit Price	Agent	Unit Price
$o_{1,1}^{2,1}$	3	$o_{1,2}^{2,1}$	22	$o_{1,3}^{2,1}$	5
$o_{1,1}^{2,2}$	3	$o_{1,2}^{2,2}$	15	$o_{1,3}^{2,2}$	5
$o_{1,1}^{2,3}$	5	$o_{1,2}^{2,3}$	2	$o_{1,3}^{2,3}$	4

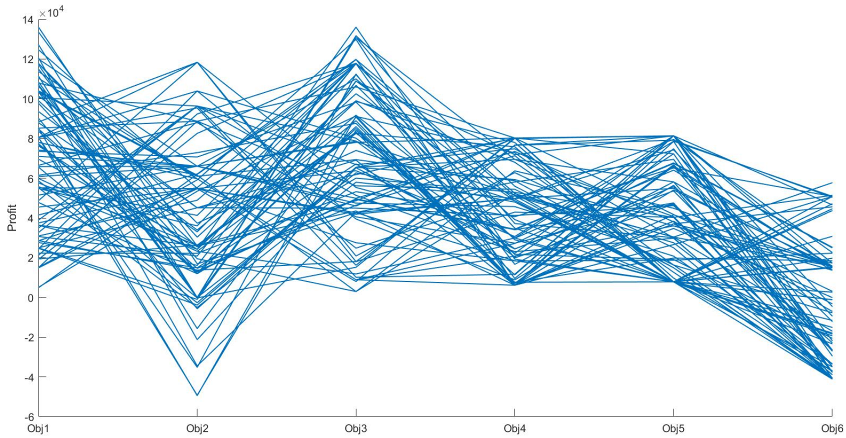

Figure 5.5: *The Pareto optimal solutions*

tive value. In Figure 5.5, we can see the objectives distributing in different ranges which makes sense because some agents have price and cost advantages when they look for oil productions. Some agents can get more profit than others, so different agent has different ranges for profit.

In order to evaluates the algorithm performance to test the reliability of optimized results, the HV result is shown in Figure 5.6. With an increase in the number of generations, the HV increases which illustrates the diversity gets increasing. In addition, the HV value goes stable since about 50 generations. It means that the Pareto solutions set has been converged.

In this work, we have proposed a CCPSO for the optimal production planning in an ESC, where the agents interactive behavior is uncertain and the ESC structure dynamically changes. ABM is originally used to model and simulate the transaction processes by multiple behavioral and interactive agents. An MaOP problem is defined to drive the optimization of the production planning towards maximizing each agent profit. The test problem is used to prove the effectiveness and efficiency of the proposed

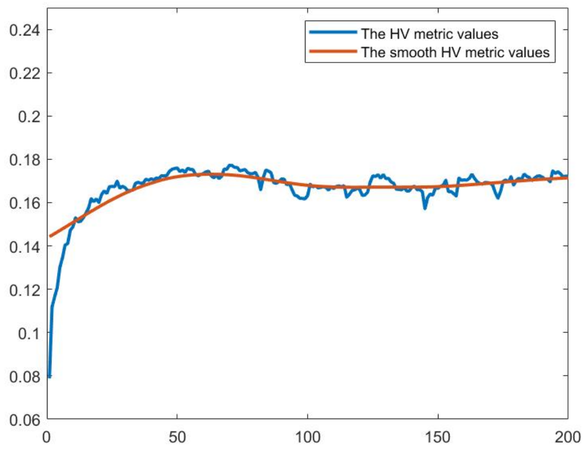

Figure 5.6: *The HV metric values*

CCPSO. An oil ESC with five layers is considered to illustrate the framework combining ABM and CCPSO. The results of the case study show that the CCPSO is effective to address the MaOP for the ESC planning problem.

CHAPTER 6

Conclusions and Perspectives

In the Ph.D. thesis, the studied field is ESC which has some fundamental particular properties of complex system. Based on the system and complexity's theories, we view ESC as a complex system or in other words, it is a system in a complex system-of-system. In this research work, we have tackled the problem of modeling, analyzing, designing ESC in uncertain and risky environment.

For the research limitation, because we combine the simulation module and the optimization module, when we run the optimization algorithm for one iteration, it needs to run the simulation once, which is burdensome from the completed time point of view.

The developed computational methods have been shown able to: 1. Identify, understand and analyze the complex interactions to the evaluation of the resilience of ESC. 2. Design efficient production planning in ESC under multiple sources of uncertainty. 3. Optimize the production planning considering the ESC risk. 4. Solve MaOPs caused by different agents for efficient production planning in ESC.

In the thesis, we mainly use two optimization algorithms to implement the computation framework for optimization: EA and CEA. In EA, we use NSGA-II to optimize the ESC. NSGA-II is traditional and widely used

Table 6.1: *Original contributions of this Ph.D. work*

Research I: ABM for ESC resilience analysis	
Proposed method	ABM
Originalities	a) An ESC modeling within the Agent-based simulation framework is built. b) Different scenarios and a resilience metric are used for investigating the resilience of the whole ESC.
Research II: A simulation-based MOO framework for ESCs	
Proposed method	ABM, NSGA-II
Originalities	a) ABM is adopted to model and simulate an ESC with multiple behavioral and interactive agents. b) MOO is originally embedded within the ABM model. c) MC is used to operationalize the proposed ABM-MOO framework, in a way to properly handle and control the uncertainty originating from multiple sources.
Research III: ESCs planning risk-based optimization	
Proposed method	ABM, NSGA-II, CVaR
Originalities	a) CVaR is used with the purpose of measuring and controlling the risk to the ESC management. b) An MOO based by the NSGA-II is performed to search for the solution optimal with respect to the maximization of the ESC total profit and the minimization of the risk under uncertainties.
Research IV: A cooperative co-evolutionary approach for many-objective optimization in ESCs	
Proposed method	ABM, CCPSO
Originalities	a) The CCPSO is developed to embed in agent-based ESC modeling. b) The ESC production planning MaOP is solved by the proposed CCPSO algorithm.

algorithm in the optimization. Like most EA, NSGA-II is flexible and convenient to be used in optimizing ESC but it is inefficient to deal with MaOP in ESC. CEA has higher efficiency when solving MaOP due to the characteristic of the parallel computing, the mechanism of maintaining good solution diversity, which is more appropriate to be used to deal with MaOP in ESC.

6.1 Original contributions of this PhD work

The proposed methods in this Ph.D. work, the originalities with respect to the four research objectives are summarized in Table 6.1.

6.2 Perspectives

Various research directions can be taken to extend the work developed in this thesis. Regarding the research objectives, important issues to be addressed are reported in Table 6.2:

Table 6.2: *Perspectives of this Ph.D. work*

Future Research I: An ESC design considering disruption and revival policies	
Proposed method	ABM, EA
Description	Considering possible risks, the ESC is optimized under the environment that the recovery policies are applied during the disruption period.
Future Research II: Game between agents in ESC	
Proposed method	ABM, Game Theory
Description	Game theory has become an important analyzing tool in ESC with multiple agents. In this work, we plan to rely on Game theory to find an optimal balance between pricing, supplier relations etc. in the ESC.

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SECTION IV: PUBLICATIONS AND MANUSCRIPTS

This part lists all the papers related with this PhD work. Four papers which introduce the core techniques of this PhD work are attached in this Section.

Journal papers
Paper I: **Chen, SY.**, Wang, W. and Zio, E., *A simulation-based multi-objective optimization framework for energy supply chains.* (submitted to Computers & Chemical Engineering)
Paper II: **Chen, SY.**, Wang, W. and Zio, E., *A cooperative co-evolutionary approach for many-objective optimization in energy supply chains.* (in preparation)

Conference papers
Paper I: **Chen, SY.**, Compare, M. and Zio, E., *Agent-based modeling for energy supply chain resilience analysis.* European Safety and Reliability Conference 2019. (published)
Paper II: **Chen, SY.**, Wang, W. and Zio, E., *Energy supply chains planning risk-based optimization.* European Safety and Reliability Conference 2020. (published)

PAPER I

AGENT-BASED MODELING FOR ENERGY SUPPLY CHAIN RESILIENCE ANALYSIS

Chen, SY., Compare, M. and Zio, E.

PAPER II

A SIMULATION-BASED MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK FOR ENERGY SUPPLY CHAINS

Chen, SY., Wang, W. and Zio, E.,

PAPER III

ENERGY SUPPLY CHAINS PLANNING RISK-BASED OPTIMIZATION

Chen, SY., Wang, W. and Zio, E.,

PAPER IV

A COOPERATIVE CO-EVOLUTIONARY APPROACH FOR MANY-OBJECTIVE OPTIMIZATION IN ENERGY SUPPLY CHAINS

Chen, SY., Wang, W. and Zio, E.,