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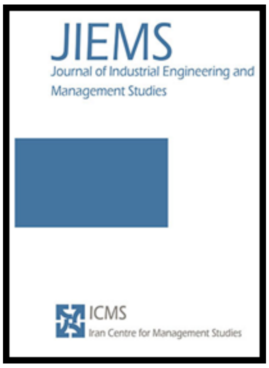

Agent-based simulation-optimization model for a bi-objective stochastic multi-period supply chain design problem

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Abstract
During the last decade, many researchers have been attracted to study the role of uncertainties in their supply chain designs. Two important uncertainties of a supply chain are demand uncertainty and supply disruption. The basic concept of the proposed model of this paper is based on the newsvendor problem. The model consists of many retailers and many suppliers as two types of autonomous agents that interact with each other considering demand and supply uncertainties. To cope with the uncertainties, retailers have three choices: a forward contract, an option contract, and purchasing from the spot market. Retailers maybe risk sensitive or risk neutral. A new simulation optimization approach is developed to find the best behavior of a risk sensitive retailer in contrast with the other risk neutral retailers during the multiple contract periods. In this model two objectives are defined to find the best behavior of the risk sensitive retailer: the maximization of the profit and the service level. In order to optimize the agent based simulation, an NSGA-II approach is used. The proposed simulation based NSGA-II is further developed in two directions: the one is different realization numbers of the uncertain parameters, and the other is preference points. Under the different preference points and different number of realizations, Pareto optimal solutions are discovered by the collaboration of the agents. Results of the numerical studies showed that adopting more risk averse policies during the contract periods will result in a larger service level and smaller profit rather than adopting more risk taking policies.

Keywords: stochastic supply chain; newsvendor problem; agent based modeling; simulation optimization; NSGA-II.

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1. Introduction

Decision making in a stochastic condition plays an important role in the retail markets which deal with the daily demands of customers. On the other hand, many researchers in the recent years have been attracted to develop more stochastic supply chain models instead of deterministic ones. Demand uncertainty and supplier disruption are two important uncertainties of the supply chain which associate with the operational risk and natural disaster risk respectively. The aim of risk management is to minimize uncertainties. Multi-sourcing is a common approach to hedge against the supplier disruption (Ray & Jenamani, 2016). To hedge

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against the demand uncertainty, Merzifonluoglu (2015) suggested option contracts and buying from spot market. Decision making in the supply chain management with demand and supply uncertainties is a challenging process. One of the powerful techniques that could help decision makers in the uncertain situations is simulation. Based on Oliveira et al. (2016), there is a growing trend regarding the use of the simulation to analyze the SCM. They also explained about the combination of the optimization methods with agent based simulation as a trend. Nevertheless, simulation has been recognized as an efficient approach to analyze the complex problems. Uncertainties is the main source of complexity in the SCM.

In a basic supply chain with two echelons, usually two types of uncertainties are more important. The uncertainty of the supplier and retailer sides of the supply chain is usually derived from the demands of the customers and disruption of the suppliers (respectively). One of the basic decision making problems in the SCM considering demand uncertainty is the newsvendor problem (NVP). A basic form of the NVP consists of a buyer and a seller in which the buyer has to decide on the amount of order from the seller before the realization of the demand. Many extensions have been suggested to develop the NVP. Developing the basic NVP with multiple uncertain suppliers, multiple periods and multiple retailers are some of the recent extensions. There are a little investigation of NVP with unreliable suppliers (Merzifonluoglu & Feng, 2014). On the other hand, as discussed by Qin et al. (2011), considering multiple periods and supplier capacity constraints are two important NVP extensions. The basic concept of the proposed model of this paper is based on the newsvendor problem.

In this paper, the supply chain is modeled as an agent based network consisting of multiple retailers and suppliers interact with each other and their environment. The aggregate behavior of the system arises from the cooperative behavior of the individual agents. Agent-based modeling is recognized as a bottom-up approach among different approaches of simulation modeling (Chiacchio et al., 2014). Indeed, it facilitates simulation optimization loop of the associated optimization of behavioral parameters (Humann & Madni, 2014). Agent-based models are stochastic, but methods such as dynamic programming could not easily use for its optimization. On the other hand, a large number of states in an agent-based model makes it hard to define a finite Markov decision process. In addition to the mathematical programming (e.g. dynamic programming), usually two types of optimization approaches are used in cooperation with the simulation procedures: 1- reinforcement learning, 2- metaheuristics. In reinforcement learning algorithms, all possible actions and related rewards must be predetermined (Avci & Selim, 2017). Metaheuristic algorithms are widely used as a simulation optimization approach in the supply chain management. In the recent years, as explained by Avci and Selim (2017), multi objective approaches have been applied in more researches. Among different multi-objective evolutionary algorithms, the Non Dominated Sorting Genetic Algorithm (NSGA-II) is one of the most important algorithms. As discussed by Deb et al. (2002), less computational complexity and better elitism approach are the most important benefits of the NSGA-II. Adding the preference points of the decision makers, resulted in a reference point based genetic algorithm (R-NSGA-II) which was proposed by Deb and Sundar (2006) and Siegmund et al. (2012). The R-NSGA-II could find a preferred set of solutions near the reference points. In addition, a simulation estimation approach is used to calculate the objective functions by applying a solution to a sampling of the stochastic parameters.

Thus, in this paper, the multi agent approach is used to model and to simulate the stochastic supply chain and an NSGA-II is used to optimize the multi-agent simulation procedure. The combined algorithm is called Sim-NSGA-II. In the next sections we will explain how we set the reference points in our algorithm. It is extended in two directions: 1- Multiple realizations of the stochastic parameters, 2- Multiple preference points.

The main contribution of this paper is to develop the multi-period newsvendor problem in order to consider the risk sensitive behavior of the buyers; and to develop a new simulation-optimization algorithm based on the reference point NSGA-II.
The remainder of the paper is organized as follows. In the section 2, a review of the related works is presented. In the section 3, the stochastic supply chain problem is described. In the section 4, the simulation optimization approach is explained. In the section 5, a numerical example is solved by the proposed simulation optimization approach. Finally, the conclusions are presented in the section 6.

2. Literature review

This paper surveys the decision making problem in the multi period supply chain with uncertain customer demand and supplier disruption. There are some models in the literature focused on the decision making in the uncertain supply chain. Ma et al. (2019) developed a multi-period closed loop supply chain network and solved it using the mathematical programming.
One of the most important problems regarding demand uncertainty in the supply chain is the NVP. In addition, multi agent simulation based optimization is the solution approach which is used to analyze the stochastic supply chain. Hence, in this section, related works of the NVP are reviewed in the first part and in the second part, utilization of the simulation optimization in the stochastic supply chain is reviewed.

2.1. NVP extensions

There are many extensions regarding the NVP in the literature. Developing the basic NVP to multiple unreliable suppliers in one of the important extensions of the NVP. As explained by Merzifonluoglu and Feng (2014), several papers have been surveyed the NVP with single and dual sourcing in an uncertain situation. The first paper that considers many uncertain suppliers in the NVP context is a work presented by Agrawal and Nahmias (1997). Afterward, especially in the recent years, several researchers developed the NVP with multiple uncertain suppliers in different directions. Merzifonluoglu and Feng (2014) developed a mathematical model for the NVP with multiple unreliable and capacitated suppliers. They proposed an exact algorithm and a heuristic algorithm to solve the problem. Ray and Jenamani (2013) developed a mathematical model for a stochastic single period two echelon supply chain with many capacitated and unreliable suppliers. Because of the complexity of the problem, they used a simulation optimization approach (using genetic algorithm and discrete event simulation) to solve their problem. They also asserted that sourcing decision under disruption needs the application of the simulation. In addition, they proposed the extension of the NVP to multiple periods and the development of contracts between buyer and supplier under disruption risk. We adopted these suggestions in our model. Merzifonluoglu (2015) developed the work of Merzifonluoglu and Feng (2014) and proposed a single period NVP considering contract options and spot market purchasing. She assumed that a retailer could order from a primary supplier and reserve a certain capacity in the secondary supplier before demand realization. After the realization of the demand, the retailer could order from the reserved secondary supplier or buy from the spot market. Our model assumptions are generally based on this paper, but we extended the decision making process and disruption events to multiple periods. Details of the model are presented in the next section. Additionally Ray and Jenamani (2016) developed their previous works and proposed a heuristic approach to solve the problem in the small scale sizes.
Developing the basic NVP to multiple periods is the second extension. The literature of the multi-period NVP generally could be divided into two categories: 1- the estimation of the demand distribution such as Bouakiz and Sobel (1992), Bensoussan et al. (2007); 2- developing

a model to consider customer demand and supplier capacities such as Wang et al. (2010), Nagarajan and Rajagopalan (2008), Zhang and Yang (2016). The main focus of the first category is on mathematical programming and monte-carlo simulation as common approaches to estimate the distribution of the demand. The second category focuses on the development of a model to consider multiple periods. In this regard, Kim et al. (2015) developed a multi-period NVP with a distributer and many retailers, in spite of the related papers of NVP with many uncertain suppliers and only one retailer. We combined these assumptions and developed a many to many relationship between suppliers and retailers.

Based on the above explanations, our model is a multi-period NVP with many retailers and many uncertain suppliers. In the next part of this section the related papers of the solution approach are reviewed.

2.2. Multi agent supply chain simulation based optimization

Multi agent modeling and simulation is widely used in the SCM (Li and Liu (2012), J. Li et al. (2010)). Muraveva et al. (2021) developed a set of hybrid simulation models to optimize the main parameters of intermodal terminals using any logic software in order to making decision about strategic facility planning problem. As discussed by Oliveira et al. (2016), simulation optimization is a research trend in the SCM. Optimization of the simulation in the supply chain could be divided into two major categories: 1- reinforcement learning, 2- metaheuristics. In this paper we used an evolutionary algorithm in cooperation with a multi agent simulation procedure. Juan et al. (2015) reviewed the application of the metaheuristics to deal with stochastic optimization problems which are named simheuristics. They addressed the need for the application of agent based simulation in simheuristic algorithms. Based on their review, a few papers in the literature surveyed the agent based simheuristic. For example, Kasaie and Kelton (2013) proposed an agent-based simulation with response-surface optimization in a healthcare problem.

Additionally there are several papers in the literature which used evolutionary algorithms to optimize the other types of simulation procedure. NSGA-II is a popular non-domination based genetic algorithm to solve multi-objective supply chain optimization problems. Goli et al. (2019) and Tirkolaee et al. (2020) used NSGA-II to optimize the decision in the supply chain management. Basirati et al. (2019) studied a many-to-many hub location-routing problem. They developed a bi-objective optimization model and solved it using imperialist competitive algorithm and NSGA-II.

However, in order to get optimal solution from a simulation model a hybrid simulation optimization algorithm is required. Rabe et al. (2021) investigated a multi-period facility location problem by using a hybrid model consisting system dynamics, optimization algorithms and monte carlo simulation to solve the problem. In the multi-objective problems NSGA-II is usually used as the optimization algorithm. Koo et al. (2008), Brintrup (2010), Sadeghi et al. (2014) and Avci and Selim (2017) used NSGA-II algorithm as an evolutionary algorithm to optimize the simulation procedure. The combination of other metaheuristic algorithms such as PSO, GA and electromagnetism are used in the literature as the multi objective optimization part of their approaches: Kuo and Han (2011) and Devika et al. (2016).

The main related literature was introduced in the above three sections. Table 1 summarizes the main features of the previous related works comparing the model presented in this paper.

Table 1. The comparison of the proposed NVP with regard to the related literature

	Multi-objective	Multi-period	Capacity consideration	Supplier disruption	hedging contracts	Risk analysis	approach
Ray and Jenamani (2016)				*		*	Heuristic method.
Ray and Jenamani (2013)			*	*		*	Simulation-optimization.
Merzifonluoglu (2015)				*	*	*	SAA & optimization
Merzifonluoglu and Feng (2014)			*	*			Heuristic method
Bouakiz and Sobel (1992)		*				*	Mathematical programming
Kim et al. (2015)		*	*				Heuristic algorithm
Our paper	*	*	*	*	*	*	Simulation-optimization.

To the best of our knowledge, the application of these novelties in the model (discussed in section 2-1) and solution approach (explained in section 2-2), has not been addressed in the literature. Details of the model and solution approach are presented in the subsequent sections.

3. Problem description

In this paper a stochastic supply chain is developed using four types of the agents: customers, retailers, suppliers, spot market. Customers order daily random normal demands. The model is developed for a certain amount of contract periods. Each contract period consists of a certain amount of time units. Figure 1 represents the time based decision making in the proposed multi objective NVP.

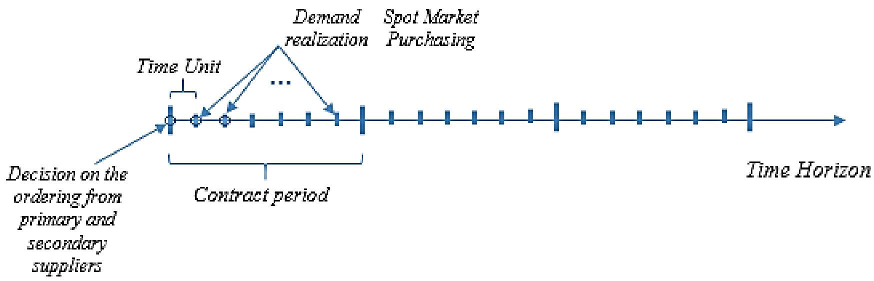


Figure 1. Time based decision making of a retailer

Before demand realization and at the beginning of each contract period, retailers decide on the amount of order from the suppliers. Each supplier in each time unit, as a primary supplier could sign a forward contract with a retailer and as a secondary supplier could sign an option contract with another retailer. The capacities of the primary and secondary suppliers are fixed but supplier disruptions may decrease these fixed capacities. Hence, to satisfy the customer demands, retailers have two options. After demand realization, in each time unit of a contract period, each retailer could order from its secondary supplier and if it is not sufficient, the retailer could order from the spot market. Spot market have infinite capacity but the spot market price is correlated with the excess demand. A simplified agent based system consists of a customer agent, a retailer agent, a supplier agent and a spot market agent is depicted in the following figure.

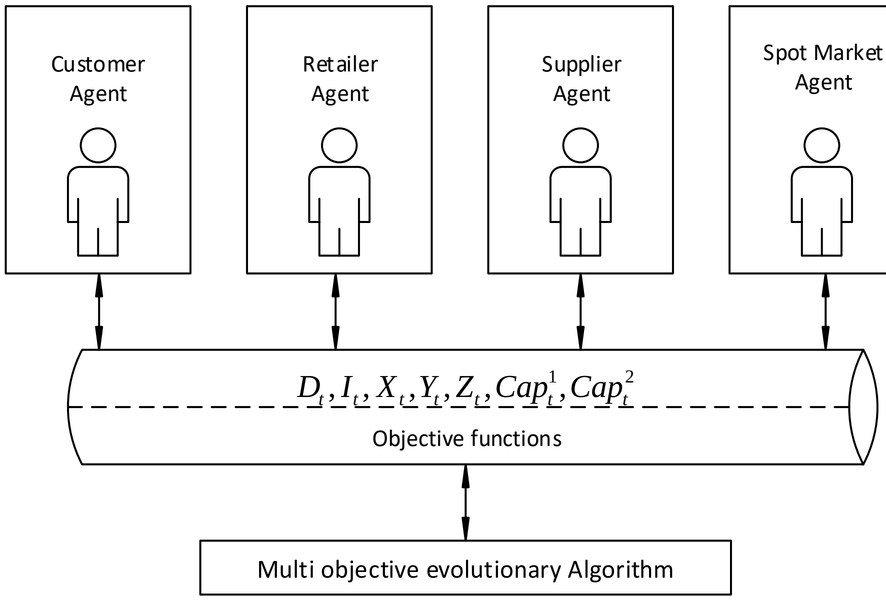


Figure 2. The overall agent based system

$D_t, I_t, X_t, Y_t, Z_t, Cap_t^1$ and Cap_t^2 respectively denote: the demand of the customer at time t, Inventory position of the retailer at time t, Ordering amount of the retailer at time t from primary supplier, Amount of ordering from secondary supplier at time t, Amount of ordering from the spot market at time t, A fixed capacity dedicated to the retailer by the supplier during the contract period, A fixed capacity of the supplier which could be reserved by the retailer at the beginning of a contract period.

As mentioned before, our problem consists of many suppliers and many retailers which are introduced by two indices i and j respectively. We assumed that there is a risk sensitive retailer and other retailers are risk neutral. The goal is to find the best decision of the risk sensitive retailer interacting with other risk neutral retailers in an uncertain supply chain with demand uncertainty and supplier disruption.

Because of the uncertainty of demand, risk neutral retailer i place an order from primary supplier based on $N(\mu_i, \sigma_i)$, and risk sensitive retailer place an order based on $N((1 \pm \alpha_{i,t})\mu_i, (1-\alpha_{i,t})\sigma_i)$. In other words, $\alpha_{i,t}$ is the coefficient of the risk. For the risk neutral retailers $\alpha_{i,t} = 0$. We defined certain amounts of $\alpha_{i,t}$ in this paper: $\alpha_{i,t} \in \{-0.6, -0.4, -0.2, 0.2, 0.4, 0.6\}$

Following figure shows the procedure of decision making of the retailers -risk sensitive and risk neutrals- regarding the forward contract.

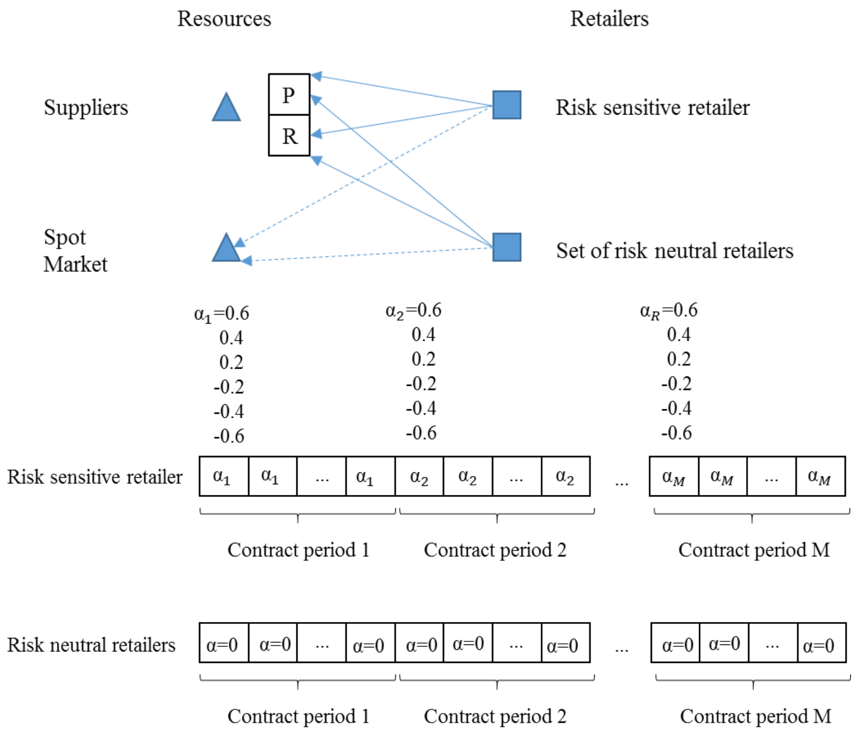


Figure 3. Simplified schematic view of the problem (Up: main agents of the system, Down: procedure of decision making for two types of the retailers)

The risk sensitive retailer, uses a wider or tighter distribution than demand. For example suppose that demand follows a normal distribution with mean 100 and standard deviation 20. Results of the numerical simulation showed that a retailer with extremely risk averse behavior (α=0.6) approximately in %95 of time, orders above the realized demand and a retailer with extremely risk taking behavior (α=-0.6) in %95 of time, orders under the realized demand. The risk attitude of the retailer toward the uncertain demand is as follows:

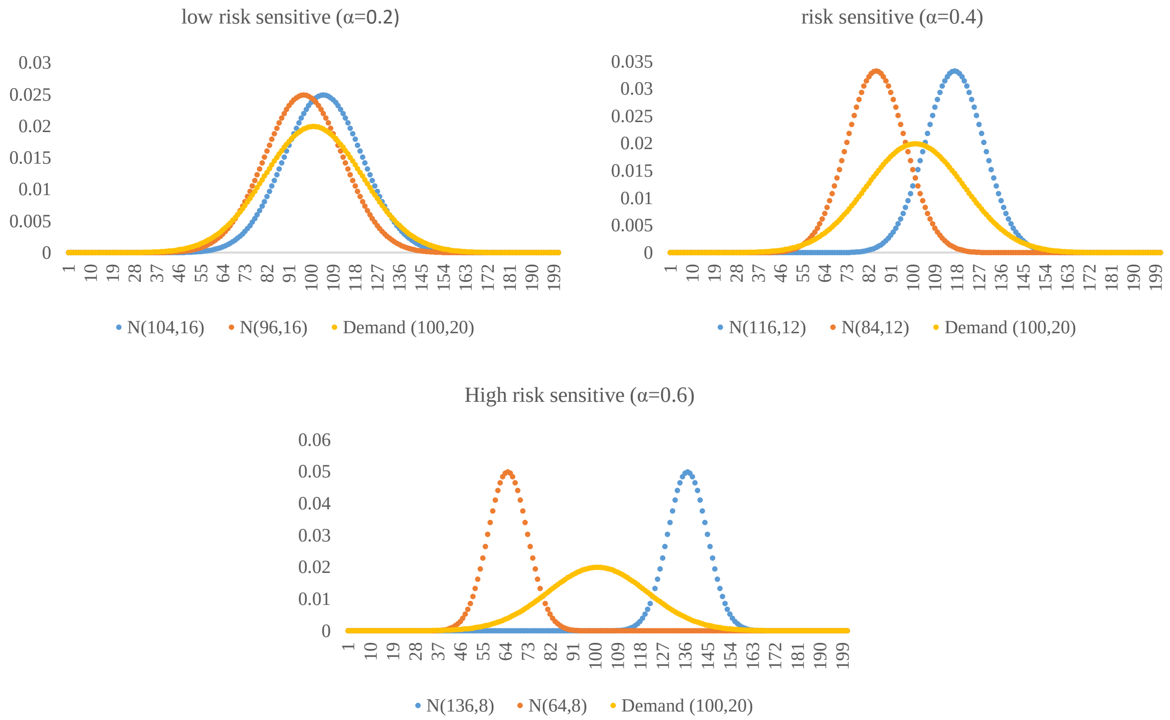


Figure 4. Different risk attitude of the risk sensitive retailer

A simple numerical analysis (using many random numbers) shows that the probabilities of ordering greater than demand in different cases (figure 4) are as follows:

Table 1. The probability of ordering greater than demand in different cases

	$\alpha=-0.6$	$\alpha=-0.4$	$\alpha=-0.2$	$\alpha=0.2$	$\alpha=0.4$	$\alpha=0.6$
Pr(demand<order)	0.054	0.253	0.437	0.557	0.763	0.952

Additionally, the behavior of the risk sensitive retailer affects the amount of the reserved capacity. In other words, the risk averse retailer prefers to order more from the primary supplier and less from secondary supplier. The following table shows the relation between α and β (a percentage of $Cap^2_{i,j}$ which a retailer reserves in the secondary supplier).

Table 2. Relation between α and β

	$\alpha=-0.6$	$\alpha=-0.4$	$\alpha=-0.2$	$\alpha=0.2$	$\alpha=0.4$	$\alpha=0.6$
β	1	0.8	0.6	0.4	0.2	0

Capacities of suppliers, as a result of the disruption, are uncertain. Following formulas show the mechanism of updating capacities of suppliers. $\pi_{j,t}$ denotes the percentage of the capacity of the supplier j loses as a result of happening a disruption event at time t

$$Cap^1_{i,j,t}=(1-\pi_{j,t})Cap^1_{i,j};\forall i,j,t \quad (1)$$

$$Cap^2_{i,j,t}=(1-\pi_{j,t})Cap^2_{i,j};\forall i,j,t \quad (2)$$

Let define $\eta_{i,t}$ as the amount of order of retailer i from primary suppliers which is satisfied,

$$\eta_{i,t}=\sum_j \min(x_{i,j,t},Cap^1_{i,j,t});\forall i,t \quad (3)$$

In the case that $x_{i,j,t}<Cap^1_{i,j,t}$, suppliers add the remained capacity to its capacity as a secondary supplier ($Cap^2_{i,j,t}$).

Let define $\iota_{i,t}=\left(D_{i,t}-\eta_{i,t}-I_{i,t-1}\right)^+$ as the unsatisfied amount of order of retailer i at time t from primary supplier ($(\mathrm{X})^+$ is equal to $\max(x,0)$). Therefore, if $\iota_{i,t}$=0, then $\sum_j y_{i,j,t}=0$.

$$0\le\sum_j y_{i,j,t}\le M\iota_{i,t};\forall i,t \quad (4)$$

Let define $\kappa_{i,t}$ as the amount of excess order of retailer i from secondary suppliers which is satisfied:

$$\kappa_{i,t}=\sum_j \min(\iota_{i,t},\beta_{i,t}Cap^2_{i,j,t}+\sum_i (Cap^1_{i,j,t}-x_{i,j,t})^+);\forall i,t \quad (5)$$

Let define $\tau_{i,t}=\left(D_{i,t}-\iota_{i,t}-\kappa_{i,t}\right)^+$ be unsatisfied order of retailer i which is unsatisfied at time t (after receiving products from primary and secondary suppliers). Thus if $\tau_{i,t}$=0 then $z_{i,t}=0$.

$$0\le z_{i,t}\le M\tau_{i,t};\forall i,t \quad (6)$$

It is assumed that retailers will compare the cost of shortage with the cost of purchasing from spot market and then decide on the amount of order from spot market, indeed considering $\xi\in[0,1]$, retailers examine different values for ξ (0.1, 0.2, …, 1). Therefore shortage would be: $\varsigma_{i,t}=(1-\xi)\times(\tau_{i,t}-z_{i,t})^+$.

The equation of inventory balance is as follows:

$$I_{i,t}=I_{i,t-1}+\eta_{i,t}+\kappa_{i,t}+z_{i,t}-\varsigma_{i,t};\forall i,t \quad (7)$$

The objective functions are maximizing the profit and service level of the risk sensitive retailer. We define i^* as the index of the risk sensitive retailer. The objective function is considered as the maximization of the profit of retailer i^*. Thus the profit function is as follows (consists of selling revenue and costs: holding cost, shortage cost, cost of purchasing and cost of reserving the capacity):

$$\psi_{i^*} = \sum_t pD_{i^*,t} - \sum_t \sum_j \beta_{i^*,t} Cap^2_{i^*,j} f_j - \sum_t \sum_j c^1_j x_{i^*,j,t} - \sum_t \sum_t c^2_j y_{i^*,j,t} - \sum_t \varsigma_{i^*,t}\theta - \sum_t \omega z_{i^*,t} - \sum_t hI_{i^*,t} \quad (8)$$

In which p denotes the revenue of selling product to the customers, f_j Cost of capacity reservation in supplier j (as a secondary supplier), c^1_j, c^2_j are costs of ordering from (primary/ secondary) supplier j, h denotes the holding cost paid by retailers per product, θ denotes the shortage cost of retailers per product, ω is the spot market price (correlated with the amount of excess demand not satisfied from primary and secondary suppliers).

To calculating service level, the following formula is needed to count time units with positive inventory ($\delta_{i^*,t}$ is a binary variable).

$$-M(1-\delta_{i^*,t}) \le I_{i^*,t} < M(\delta_{i^*,t}) \quad (9)$$

The service level could be calculated using the following formula.

$$\phi_{i^*} = \frac{\sum_{t=1}^{T} \delta_{i^*,t}}{T} \quad (10)$$

In the next section, the simulation optimization approach is explained.

4. Simulation optimization approach: Sim-NSGA-II

Simheuristic is an important category of the simulation optimization approaches. In this paper a multi-agent simulation and an NSGA-II (Sim-NSGA-II) are used together to find the Pareto front of the problem. The following sections represent details of the simulation and optimization parts of the Sim-NSGA-II. In addition, two extensions on the simulation and optimization parts are introduced in the following sections.

4.1. Simulation procedure

Simulation modeling is an efficient approach to artificially reproduce the interactions of a complex system (Nance & Sargent, 2002). The simulation is suitable for analyzing the effect of different decisions on the system in a stochastic condition. But the simulation could not find the best possible decision in that stochastic condition by its own. Hence, optimization tools are used to achieve this purpose. In a complex system with many decision variables metaheuristics are widely used to find a near optimal solution. The combination of a meta-heuristic algorithm with a simulation procedure is called a simheuristic algorithm (Juan et al., 2015). The simulation procedure is modeled using a multi-agent structure introduced in the previous sections. Netlogo 5.3 is used to model the agent based system. Following figure shows the proposed simulation procedure of the multi-period NVP.

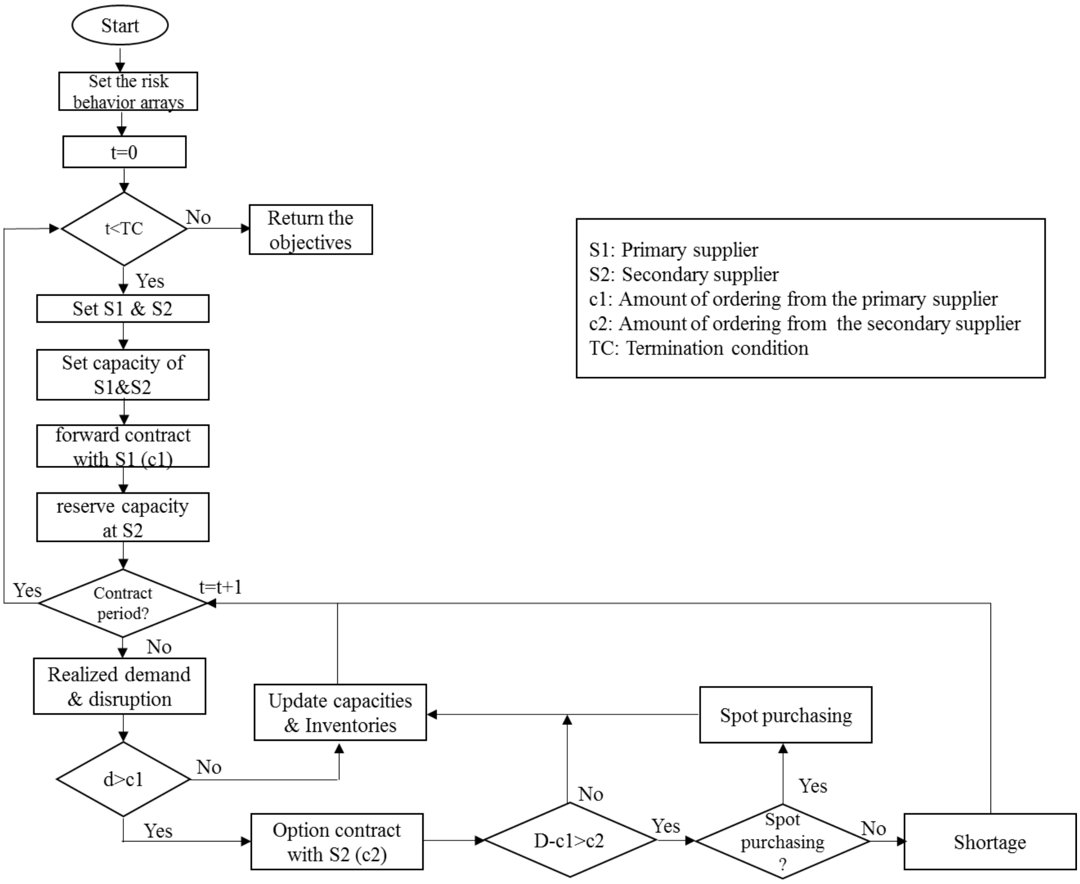


Figure 5. The simulation procedure

Following figure shows a summary of the interactions between agents in the form of different programming classes.

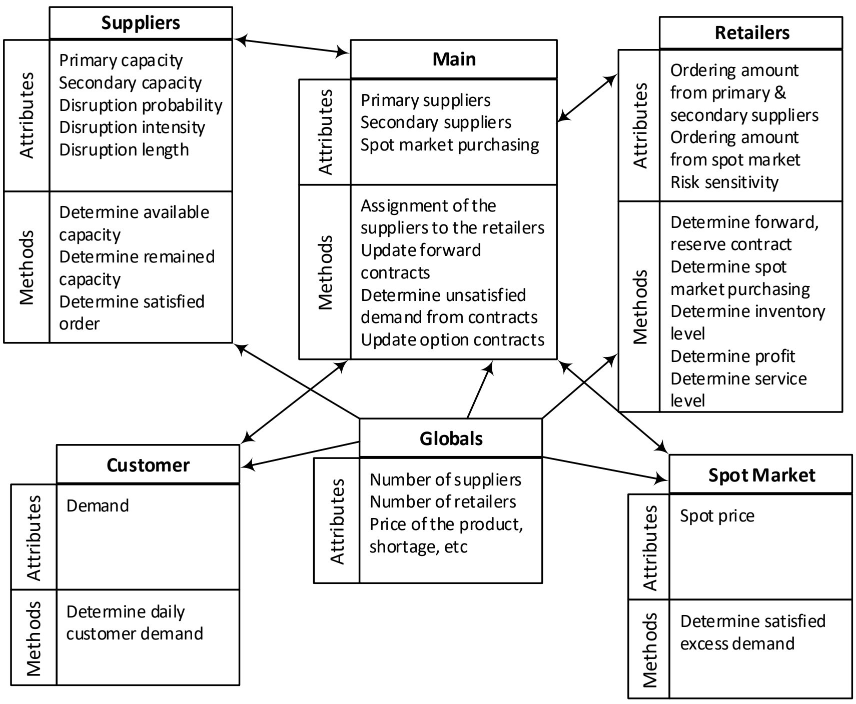


Figure 6. Interactions between different programming classes

4.1.1. Simulation-based estimation

According to Liu et al. (2017) we used R realizations of the simulation procedure. Hence, in this paper, objective functions are estimated using the results of R realizations of the uncertain parameters (such as demand, disruption etc.). In the Simulation Optimization algorithm, a same set of realizations is used in each iteration toward the optimal solution. R realizations of the simulation are used to estimate the objective functions. Thus, if $F_1(x, y, z, \varepsilon)$, $F_2(x, y, z, \varepsilon)$ denote two objective functions, the optimization algorithm tries to optimize following statistics in each iteration:

$$\overline{F_1} = \frac{\sum_{j=1}^{R} F_1(\mathrm{x}, \mathrm{y}, \mathrm{z}, \varepsilon_j)}{R} , \overline{F_2} = \frac{\sum_{j=1}^{R} F_2(\mathrm{x}, \mathrm{y}, \mathrm{z}, \varepsilon_j)}{R}$$

In the following section, the optimization algorithm is explained.

4.2. Optimization algorithm

As mentioned in the previous sections, R-NSGA-II as a reference point multi-objective evolutionary algorithm is used to optimize the simulation procedure. To obtain the reference points, we use an NSGA-II algorithm. The NSGA-II is one of the most important meta-heuristic tools for the multi-objective evolutionary optimization. Originally, the NSGA II developed from the NSGA which presented by Srinivas and Deb (1994). The algorithm forms the combined population by merging the initial population and offspring population. The NSGA-II algorithm is implemented using R script language. The simulation optimization algorithm is implemented by using R-Netlogo package which empowers us to transmit data between R and Netlogo packages. Then, the new population is sorted into a number of fronts using non-dominated sorting approach (Deb et al., 2000). The NSGA-II used in this paper is as follow:

Inputs: *Parameters (Population size, MaxIteration, number of elites, tournament size, Length of the contract periods)*
Output: *Pareto fronts*

1. **Set** initial values for decision chromosome ($\alpha_{i,t}$) with “n” genes *// Where “n” is the length of the contract periods*
2. **While** *iter<MaxIteration* **do**
3. **For** *all retailers*
4. Contracting ⟵ decision chromosome *// Based on the Fig. 5 contracting decisions will be made*
5. **End**
6. Calculate the objective functions based on the Contracting
7. ►Non-dominated sorting algorithm
8. **For** *all chromosomes in the population*
9. Calculate i_{rank} *// Non-dominated sorting of the decision chromosome*
10. Calculate $i_{distance}$ *//* $i \prec_n j$ *if* $(i_{rank} \prec j_{rank})$ *or* $((i_{rank} = j_{rank})$ *and* $(i_{distance} \succ j_{distance}))$
11. Tournament selection *// According to the ordered rank index and crowding distance*
12. **End**
13. Apply binary Crossover on the selected chromosomes
14. Apply polynomial mutation on the selected chromosomes
15. ►Non-dominated sorting algorithm *// Sorting the new pool of solutions*
16. ►Elite chromosome selection
17. **While** pool_size < number of elites
18. Select a number of individuals from the population

```
            Determine p ∈ [0,1)
            If p > p_0
            Tournament selection
            Else
            Select p × population_size from the first front
            End
          End
    decision chromosomes ← elite chromosomes
End
```

An elite selection strategy is used in this paper as follow:

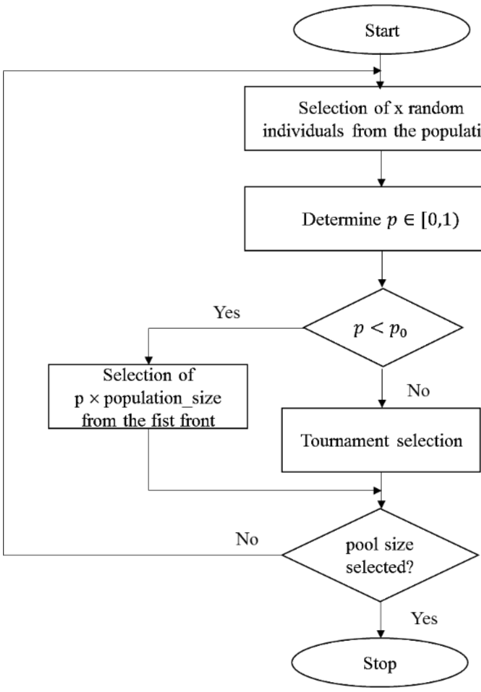


Figure7. Elite selection strategy

The algorithm will be stopped after “MaxIteration” iterations. Above NSGA-II algorithm is used to obtain the reference points needed for the R-NSGA-II algorithm.

4.2.1. Defining the reference points

To obtain the reference points, we first run the NSGA-II to achieve to the final Pareto curve. The final Pareto curve would be as follows.

$F_1^{Pareto,\min}, F_2^{Pareto,\min}$: Minimum value of the profit, service level objectives among the final Pareto solutions.

$F_1^{Pareto,\text{mean}}, F_2^{Pareto,\text{mean}}$: Average value of the profit, service level objectives among the final Pareto solutions.

$F_1^{Pareto,\max}, F_2^{Pareto,\max}$: Maximum value of the profit, service level objectives among the final Pareto solutions.

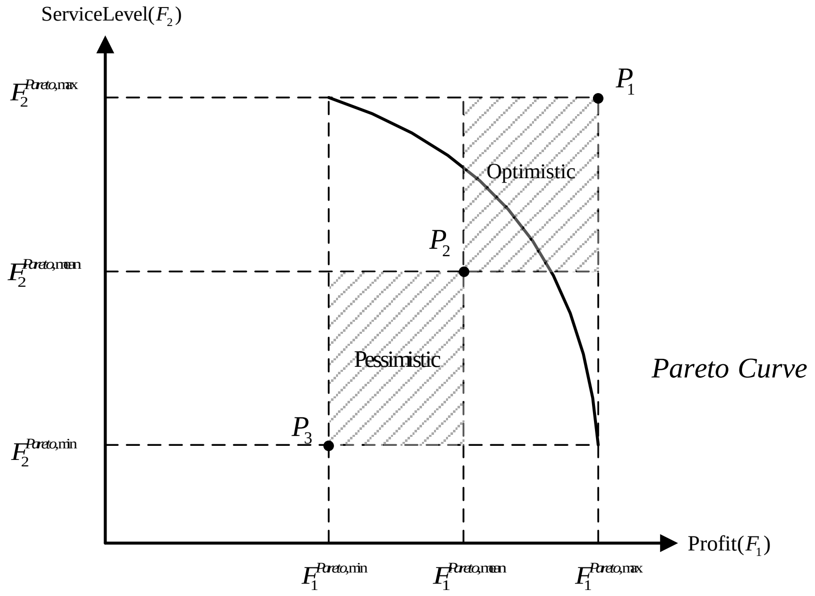


Figure 8. A final Pareto Curve resulted from the proposed NSGA-II

A decision maker may prefer to set his\her preference points optimistically. A decision maker may prefer to set his\her preference points optimistically. In this case one of the reference points would be P_1 (maximum service level and maximum profit) and P_2 (mean service level and mean profit). On the other hand, another decision maker would prefer to set his\her preference pessimistically. In this case the reference points are: P_2 (mean service level and mean profit) and P_3 (minimum service level and minimum profit).

4.2.2. R-NSGA-II

The NSGA-II was explained in the section 4-2. The R-NSGA-II is on the basis of NSGA-II, but there are two differences between these algorithms (Assume that $X_1,...,X_n$ are n Pareto solutions):

1- In R-NSGAII algorithm, the concept of crowding distance will be changed to the preference operator (the normalized Euclidean distance of each solution of the front). Using this operator, closer solution to the reference points have more importance.

$$d_{X_i} = \sqrt{\frac{1}{2}\left(\frac{F_1(X_i)-z_1}{F_1^{\max}-F_1^{\min}}\right)^2 + \frac{1}{2}\left(\frac{F_2(X_i)-z_2}{F_1^{\max}-F_1^{\min}}\right)^2}$$

Where F_i^{max} and F_i^{min} represent the maximum and minimum of the F_i among the all population members. In addition, z_i is the i-th reference point (i$\in${1,2}).

Closest solutions to all reference points are assigned rank 1 and likewise, other solution with relation to the distance to the reference points are ranked.

2- The other important difference between RNSGA II and NSGA II is de-emphasizing ε neighbors of frontier solutions. In the first step, in this approach a random non-dominated solution is selected. For this purpose, a normalized difference in objective functions is calculated as follows:

$$D_{X_i,X_j} = \sqrt{\frac{1}{2}\left(\frac{F_1(X_i)-F_1(X_j)}{F_1^{\max}-F_1^{\min}}\right)^2 + \frac{1}{2}\left(\frac{F_2(X_i)-F_2(X_j)}{F_1^{\max}-F_1^{\min}}\right)^2}$$

All solutions with sum of D equals to ε or less, are grouped with each other. In other words, solutions with value of D smaller or equal to ε are assigned a large d (preference operator) to neglect them in the selection procedure.

5. Numerical example

In this paper a numerical example is adopted from Merzifonluoglu (2015). As mentioned before, in this paper the problem is extended to multiple periods and multiple retailers and suppliers. The goal is to find the Pareto solutions with respect to the objective functions: maximum profit and maximum service level. In this section we are going to survey the role of the utilization of different number of realizations in the simulation procedure and the role of utilization of the preference point in the optimization. 10 retailers and 10 suppliers are considered in the model. 20 contract periods are considered and each contract period consists of 3 time units. Followings, details of the parameters and variables are shown.

$D_{i,t} \sim N(\mu_i, \sigma_i)$ (demand)	N(1000, 100)
$\pi_{j,t} \sim N(\mu_j^{\pi}, \sigma_j^{\pi})$ (disruption intensity)	$\mu_j^{\pi} \sim U(0.01,\ 0.03),\ \sigma_j^{\pi} \sim U(0.0001,\ 0.003)$
$\omega \sim N(\mu^{\omega}, \sigma^{\omega})$ (spot price)	N(250,40)
c_j^1 (ordering cost of primary supplier)	U (196, 198)
c_j^2 (ordering cost of secondary supplier)	165
f_j (cost of reservation)	40
p (price of the product)	300
h (holding cost)	10
θ (shortage cost)	10
Cap_j^1 (fixed capacity of primary suppliers)	1000
Cap_j^2 (fixed possible reservation capacity)	200

Initial values of the uncertain parameters remain fixed during the optimization. The probability of the disruption is considered as a uniform distribution between [0.01, 0.05]. The disruption effect (or the length of disruption) is assumed as a uniform distribution between [0, 1] time units. The maximum number of disrupted suppliers is assumed as a uniform distribution between [0, Number of suppliers]. Same as Merzifonluoglu (2015) it is assumed that the demand and the spot price are correlated with parameter ρ (ρ>0), Such that: $\mu_1 = \mu$; $\mu_2 = \mu^{\omega}$; $\sigma_{11} = \sigma$; $\sigma_{22} = \sigma^{\omega}$; $\sigma_{12} = \sigma_{21} = \rho\sigma\sigma^{\omega}$. In the next section, tuning of the parameters of the meta-heuristic algorithm is described.

5.1. Parameter tuning of the NSGA-II

In this paper Taguchi method is used to calibrate parameters of the NSGA-II. Same as Hassanzadeh et al. (2016) four criteria have been considered to use in Taguchi method: Spacing metric (SM), Mean ideal distance (MID), Number of non-dominated solutions in the Pareto front (NSP) and diversification metric (DM). Followings, SM, MID and DM are defined briefly.

Spacing metric (SM): This metric measures dispersion uniformity of solutions in the Pareto front. Assume i and j are two solutions on the Pareto front and o_1, o_2 are the objective functions. Let d_i be the minimum distance of solution i with other solutions in the Pareto front (i.e. $d_i = \min(|o_1^i - o_1^j| + |o_2^i - o_2^j|), i \neq j, \forall j$). The SM could be calculated as follow:

$$SM = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\frac{(\bar{d}-d_i)^2}{(\bar{d})^2}}$$

N is the number of solutions in the Pareto front and $\bar{d}$ is the average of d_i s.

Mean ideal distance (MID): This metric measures the average Euclidean distances of Pareto solutions from an ideal point. $MID = \frac{\sum_{i=1}^{N} C_i}{N}$. N is the number of solutions of the Pareto. C_i is the Euclidean distance between the non-dominated solution i and the ideal point. An ideal point is defined as the minimum value of each objective function among all of the non-dominated solutions in the Pareto front.

Diversification metric (DM): This metric measures the diversity between the non-dominated solutions in the Pareto front.

$DM = \sqrt{\sum_{i=1}^{N}\max(x_j - y_j)}$, where $x_j - y_j$ is the Euclidean distance between two non-dominated solutions: x_j, y_j.

Same weights have been given to these criteria and summation of the weighted value of these criteria is used in the Taguchi method. Because of the maximization nature of the problem, S/N ratio used is as follow:

$SNratio = -10\log(\frac{\sum \frac{1}{Y^2}}{n})$, Where Y is the responses for different factor levels and n is the number of responses in the factor levels. Different factors of NSGA-II and their possible levels are as follow:

Table3. Different factors of NSGA-II and their possible levels

	Symbol	Level 1	Level 2	Level 3	Level 4	Level 5
Initial population	Initpop	10	50	100	150	200
tournament selection size	Toursize	3	6	9	12	15
Mutation probability	Mutpr	0.1	0.15	0.2	0.25	0.3
Crossover probability	Crosspr	0.7	0.75	0.8	0.85	0.9

Different parameters of the NSGA-II are tuned as follows:

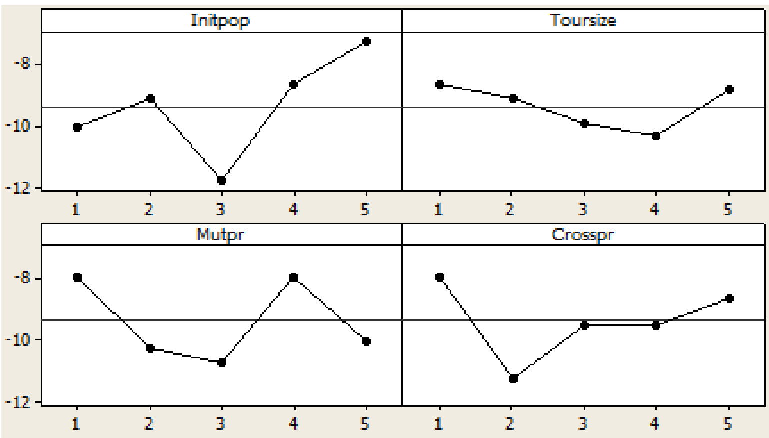


Figure 8. S/N ratios for different factors

Based on the results of applying Taguchi method, the best values for parameters obtained as: initpop=100, Toursize=12, Mutpr=0.2, crosspr=0.75. Additionally termination condition of optimization algorithm is considered 200 iterations. Figure 9 shows the improvement of the Pareto front during the iterations: 50, 100, 150 and 200.

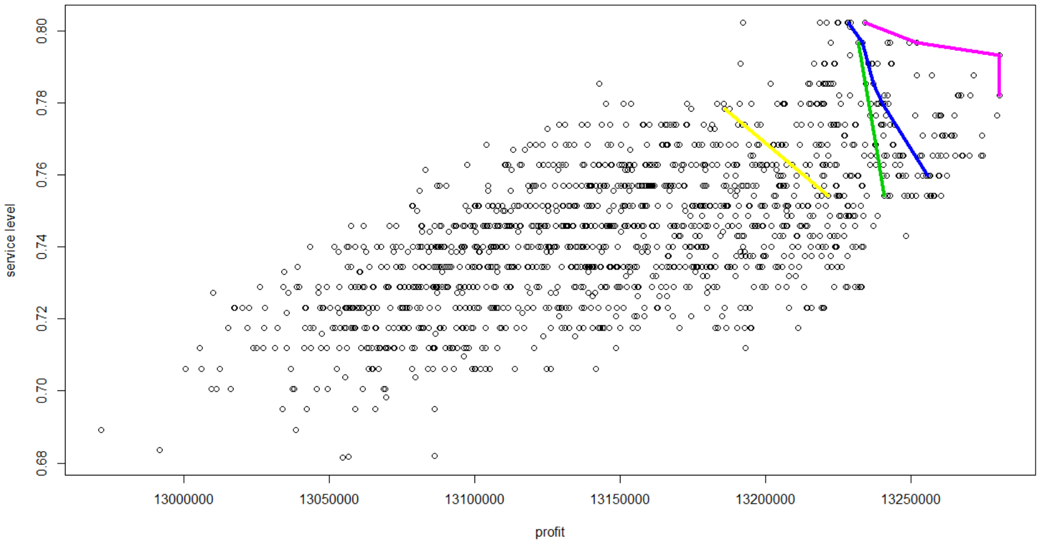


Figure 9. The result of the Sim-NSGA-II in different iterations: 50, 100, 150 and 200

In the next two sections, the basic Sim-NSGA-II has been developed.

5.2. The effect of different number of the realizations

In the section 4-1, a general approach was introduced to consider different realizations of the uncertain parameters in the simulation optimization algorithm. Indeed, in each iteration of the optimization, the averages of the objective functions (resulted from different realizations) are calculated. Each realization is produced from a replication of the simulation. In the simulation optimization algorithm, the same set of R realizations is used for all iteration steps. The optimization is conducted using these estimations. Figure 10 shows the final Pareto fronts of the Sim-NSGA-II with 5, 10, 20, 50 and 100 replications.

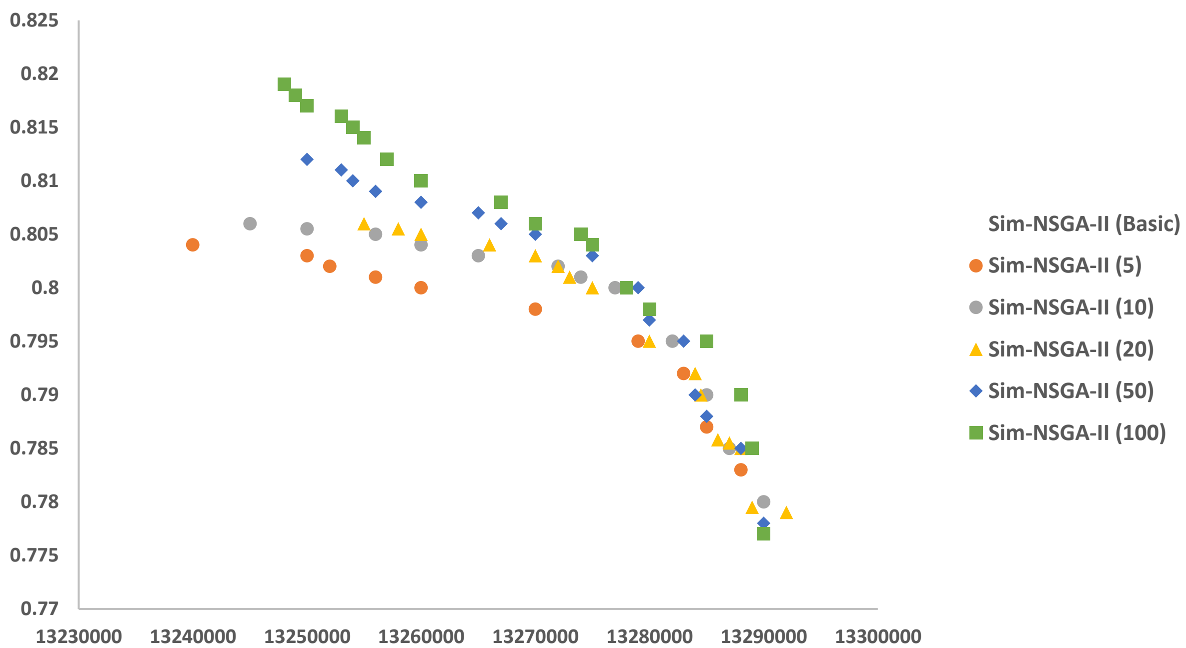


Figure 10. Sim-NSGA-II Pareto fronts with different number of realizations

It could be concluded from figure 10 that increasing the number of replications results in better Pareto fronts but the problem is the run time of the algorithm. Table 4 shows the run time of the Sim-NSGA-II with different number of realizations. Results were obtained by a PC with Intel(R) Corei7, 3.1 GHz CPU and 6 GB RAM.

Table 4. Run time of the Sim-NSGA-II

Number of replications	Run time (second)	No. of solutions in the Pareto front
Basic Sim-NSGA-II	953	4
5	1606	10
10	3420	12
20	7345	15
50	16491	16
100	24142	18

5.3. The effect of reference points

In the previous section, the effect of increasing the number of the realizations (simulation replications) on the Pareto front was surveyed. In this section the simulation is run once per each iteration of the optimization. Figure 11 shows the final Pareto resulted from the NSGA-II and 3 reference points.

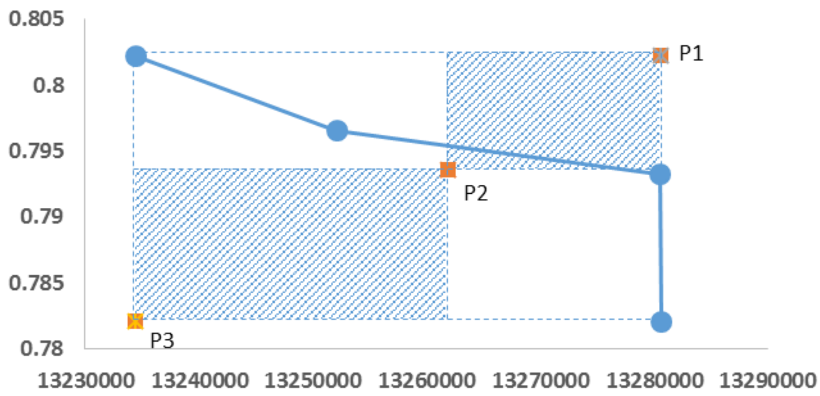
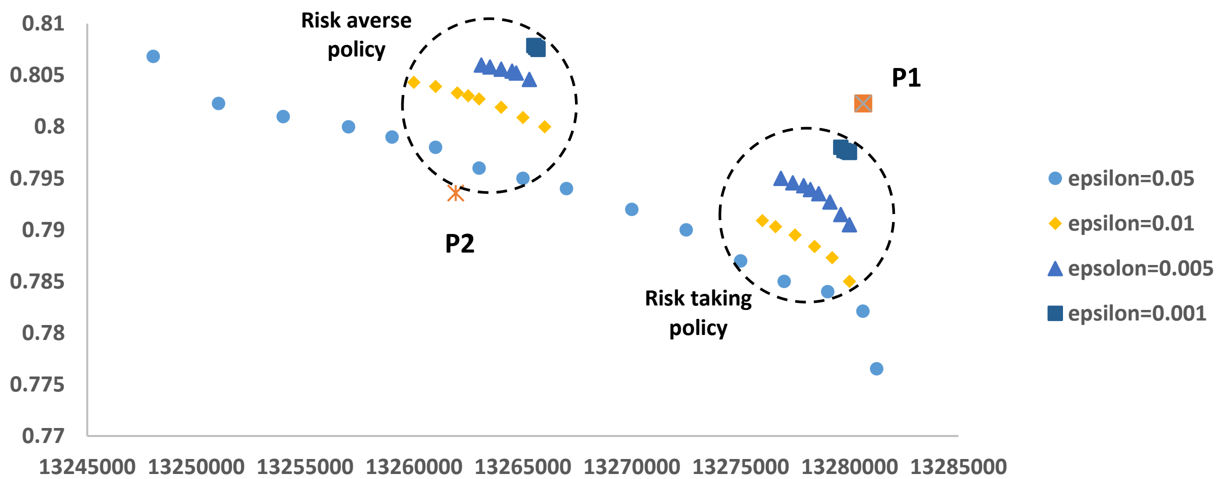


Figure 11. The final Pareto front resulted from the basic Sim-NSGA-II

As explained in the section 4-2-2, in the R-NSGA-II, to control the extent of obtained Pareto front, solutions within a ε-neighborhood of a reference point are de-emphasized. The results of the R-NSGA-II algorithm are as follows.



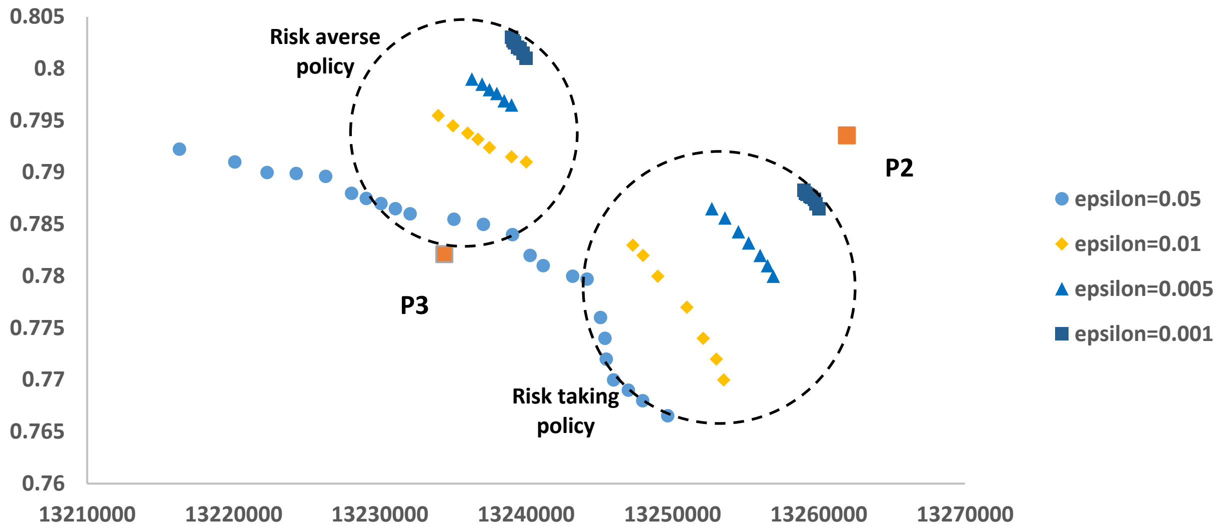


Figure 12. Different sets of the Pareto solutions based on the reference points (Up: Pareto fronts in the optimistic area, Down: Pareto fronts in the pessimistic area)

Based on the results of the figure 12, a decision maker with an optimistic viewpoint must expect 13248000 for the profit function and 0.807 for the service level function approximately if he/she prefers a higher service level rather than the profit. On the other hand, if he/she prefers a higher profit rather than the service level, approximately 13280000 for the profit and 0.776 for the service level must be expected. In a pessimistic area, if the service level is more important than the profit, he/she expects approximately 13216000 and 0.792 for profit and service level objectives respectively. In this area, if the profit is more important than the service level, approximately 13247000 and 0.769 for the profit and service level objectives must be expected. These estimations of the objective functions are obtained from the Pareto fronts with ε=0.001. If the decision maker prefers to obtain a neighborhood of solutions near the preference points, a larger value of ε must be selected.
In addition, results showed that adopting more risk averse policies during the contract periods will result in a larger service level and smaller profit rather than adopting more risk taking policies. We have shown the result of adopting different risk sensitive policies in the optimistic and pessimistic decision areas in the figure 12.

6. Conclusions

In this paper a decision making model in a stochastic supply chain network was developed based on a newsvendor problem by using a multi-agent model. The network consists of a number of retailers which one of them is risk sensitive and the others are risk neutral. In addition, there are some unreliable suppliers interacting with the retailers during the multiple periods. To cope with these uncertainties two kinds of contracts are considered: forward and option contracts. These contracts are common in many industries such as semiconductors, telecommunications and pharmaceuticals. In addition, retailers have an option to buy from the spot market which its price is correlated with the remained unsatisfied demand. Moreover, the proposed model could be used in the multi-period supply chain management decision making with uncertain demand and supply.
Simulation is powerful technique in the uncertain condition, but it is not an optimization process and does not yield the best solution but can provides a set of responses in different conditions. In this paper a simulation estimation approach is used to calculate the objective functions by applying a solution to a sampling of the stochastic parameters. In order to obtain

the optimal solution, a reference point NSGA-II algorithm is used to develop a simulation optimization algorithm. One of the limitations of the proposed algorithm is to define the reference points in the optimization section. Heuristic algorithms could be used to obtain more precise points in further works.
The proposed algorithm was developed by using two mechanisms in the simulation and optimization parts of the algorithm: 1- Increasing the number of uncertain parameter realizations, 2- Utilization of preference points. In the first mechanism, different numbers of the realizations were used.
The results of the algorithm showed a better efficiency with higher number of realizations. Although increment of the number of realizations results in a better front, the running time increases considerably. The second mechanism was applied using R-NSGA-II concept. The reference points were derived from the final Pareto of the basic Sim-NSGA-II based on the optimistic and pessimistic viewpoints of the decision maker. Different Pareto solutions were derived using the ε-neighborhood concept of the RNSGA-II. Using these Pareto solutions, different decision makers could decide on his/her risk attitude during the periods.
Results of the numerical studies showed that adopting more risk averse policies during the contract periods will result in a larger service level and smaller profit rather than adopting more risk taking policies. Also results showed that, disruptions have an important effect on the satisfaction of the customer demands. Therefore, in an uncertain condition, procurement managers should have a set of reliable secondary suppliers to support the forward contracts with the primary suppliers.
Some suggestions for future researches are: considering multiple products in the problem, considering negotiation process and transportation assumptions. In addition, improving the agent's decision ability, comparing different coordination policies between the agents would be future trends on the solution approach.

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