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A Bi-Objective Programming Model for Reliable Supply Chain Network Design under Facility Disruption

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Abstract: Supply chain networks generally are composed of four main entity types: supplier, production centers, distribution centers and demand zones that consist of facilities whose activities involve the transformation of raw material into finished products that are later delivered from the suppliers to the end customers. Supply chain network design as the most important strategic decision in supply chain management, plays an important role in overall environmental and economic performance of the supply chain. The nature and complexity of today's supply chains network make them vulnerable to various risks. One of the most important risks is disruption risk. Disruptions are costly and can be caused by internal or external sources to the supply chain, thus it is crucial that managers take appropriate measures of response to reduce its negative effects. Recovery time of disrupted facilities and return it to normal condition can be an important factor for member of the supply chain. In this paper, a bi-objective model is developed for reliable supply chain network design under facility disruption. To solve this model, we have applied two approaches, i.e., ε constraint method as an exact method and non- dominated sorting genetic algorithm (NSGAII) as a meta-heuristic method.

Keywords: Bi-objective Programming, Supply Chain Network Design, Reliability, Disruption Risk, Recovery Time.

1. Introduction

Supply chains (SCs) now run into numerous changes which contribute to increasing their complexity, including businesses globalization and the adoption of some business philosophies as lean, efficient consumer response, as well as quick response programs. Implementing these philosophies or practices can bring about other new problems, for the SCs may become more vulnerable to disturbances. In complex and uncertain business environments, manufacturing companies are managing their Supply chains efficiently so as to increase efficiency and reactivity [1]. According to Hishamuddin et al. [2], nowadays, the complex nature of supply chains (SCs) makes them vulnerable to various risks. These risks may be divided into different terms, such as disruptions, uncertainties, and disturbances. One must realize the type of risks and their sources in order to control and manage them. There are several categorizations for supply chain risks in the literature review. For instance, Chopra and Sodhi [3] categorize potential supply chain risks into nine categories: (a) Disruptions (natural disasters, terrorism, war, etc.), (b) Delays (inflexibility of supply source), (c) Systems (information infrastructure breakdown), (d) Forecast (inaccurate forecast, bullwhip effect, etc.), (d) Intellectual

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property (vertical integration), (e) Procurement (exchange rate risk), (f) Receivables (number of customers), (g) Inventory (inventory holding cost, demand and supply uncertainty, etc.), and (h) Capacity (cost of capacity). Tang [4] considers two types of risks: (a) operational risks, inherent uncertainties which include uncertain customer demands, uncertain supply, and uncertain costs, and (b) disruption risks, major disruptions caused by natural and man-made disasters namely earthquakes, floods, hurricanes, terrorist attacks, as well as economic crises encompassing currency fluctuation or strikes.

Disruption is defined as an event interrupting the material flows in the supply chain, which results in an abrupt cessation in the movement of goods. These are the noticeable examples of disruptions which have occurred in the real world. For one thing, we can mention the west-coast port lockout in 2002 and the subsequent inventory shortages which imposed upon the economy a day cost of more than $1 billion [5]. The 1995 earthquake hitting Kobe caused extreme damage to all of the transportation links in the area, and almost destroyed the world’s sixth-largest shipping port. This 7.2 scale Richter quake seriously affected Toyota, where it affected an estimated production of 20,000 cars as a result of which caused a loss of $200 million to revenue due to parts shortages [6]. Although disruptions occur with very low probability, they have had a high negative financial impact. Disruptions may lead to spoiling sales, increasing costs or both, and seriously disrupt or delay material, information and cash flow [7-8]. Therefore, it is important for managers to reflect disruption risks in the design phase of the supply chain networks [2].

Moreover, SC disruptions can be caused by internal or external sources of the SC. These include Supplier bankruptcy, port stoppages, labor strikes, accidents and natural disasters ,war, terrorism, quality issues and machine breakdown technological uncertainty, and market thinness [1]. Six basic supply chain disruption modes were identified by Sheffi et al. [6]. These are: disruptions in supply, transportation, facilities, communications and demand, in addition to freight breaches. Wagner and Bode [9] classify disruptions into five sources: (a) demand-side, (b) supply-side, (c) regulatory, legal and bureaucratic, (d) infrastructure, and (e) catastrophic [10]. Researchers and practitioners have recently paid considerable attention to supply disruption management (DM). Implementing correct strategies which enable the SC to quickly return to its original state is one of the goals in DM. This minimizes the relevant costs associated with the recovery of the disruption at the same time [11]. One of the significant issues for supply chain management is the potential economic impact of a disruption, which increases the awareness of the significant risks caused by supply failures, thus emphasizing the needs for effective disruption-management strategies.

Managing future disruptions is a critical question for any organization. Disruption Management (DM) has recently attracted the attention of researchers. Schmitt et al. [12] indicate that supply disruptions, if not protected against, have significant negative effects on a company performance. Therefore, it is crucial for companies to learn how to manage and control potential supply disruptions sine its loss can be huge. There are two strategies to manage the risk of disruptions. These are mitigation and contingency (or recovery) tactics [13]. A firm is required to act in advance of a disruption in the former strategy, while taking action during the occurrence of a disruption is the characteristic of the latter strategy. It is not free to implement mitigation and recovery tactics; conversely, it involves a cost which affects the attractiveness of the most effective strategy for a given firm.

The disruption risks and the uncertainties in the supply chain parameters are two close concepts in supply chain risk management. The reliability strategies are used to cope with disruption risks while the robustness strategies are employed to model the existing uncertainties in the supply chain parameters. Reliability and robustness are commonly used interchangeably in situations when supply chain risks arise from supply uncertainties, namely, failure of suppliers. According to Azad et al. [14], robustness is defined as the ability of the system to function normally when components or subsystems fail. Reliability, on the other hand, is defined as the most effective performance of a system or a component function within a required time span and the environment. A supply chain is robust when it efficiently performs in uncertain future conditions, like demands, lead times, supplies and etc.; on the contrary, it is considered reliable on the condition that it performs optimally when parts of the system fail, like when a distribution center becomes unavailable because of weather. That is, ‘‘robustness’’ is generally referred to solutions that perform well among different scenarios, in expected performance, worst-case performance, any other measures which have appeared in the literature over the past years. In contrast, ‘‘reliability’’ is a different approach to uncertainty in which we hedge against those failures in the system which described by a given solution. Finally, robustness is associated with uncertainty in the data, while reliability refers concentrates on the solution itself.

Supply chain risk management tries to design and implement a supply chain which is powerful enough to anticipate, cope with, and quickly recuperate from disruptions [15]. Adding built-in redundancies, expanding capacity, installing structural reinforcements and barriers, preventing maintenance, and monitoring and inspecting are among general measures taken so as to avoid disruption and reduce recovery time. Facility’s recovery time is the time span when a facility is out of work. Optimally, recovery time can be reduced to zero, resulting in a component which is fully protected from failure and its associated costs [16].

Building upon the above mentioned considerations, this study presents a bi-objective model for reliable supply chain network design based on facility disruption. This includes three echelons in forward direction (i.e., manufacturers, distribution centers and markets). Then a recovery strategy, defined in the proposed model, is considered as a new objective function which helps us minimize the recovery time from facility disruptions. The remaining part of the paper is organized as follows. Section 2 provides a comprehensive literature review of the existing studies on supply chain network design under disruptions. In Section 3, a mixed-integer non-linear programming model of the reliable supply chain network design is presented with two objective functions. This section describes thoroughly the objective functions, variables, and constraints. To solve the proposed bi-objective model, section 4 focuses on solving approaches, these being the epsilon constraint method and a non-dominated sorting genetic algorithm (NSGAII) as a meta-heuristic method. Section 5 summarizes numerical examples and their results. Finally, conclusions and suggestions for further research are presented in section 6.

2. Literature review

Today's competitive markets and volatile customers' preferences, as well as the astonishing progression of technology and globalization, forces organizations to operate cooperatively as members of a supply chain rather than acting on their own [1]. There is increasing awareness that competition cannot bring about the optimal results for organizations. In contrast, cooperating in a network would be more convenient. The supply chain provides the required products and services in due time, with the required specifications, at the suitable place and to the right customer [1]. Supply Chain Networks (SCNs) consist of four major entity types: suppliers, production centers, distribution centers and demand zones, which in turn encompass facilities or entities of which is the transformation of raw materials into finished products. These finished products are then sent from supplier to the customer. The supply chain tries to satisfy customers' needs by minimizing the costs. The success of a Supply Change rests on the integration and coordination of its constituting parts to form a coherent and effective network structure. When the network is effective it leads to economical operations in the entire chain and helps provide customers' needs quickly [1]. Three levels form the problems in a supply chain. These are: strategic, tactical, and operational. Strategic level, also called the long-range planning, includes decisions concerning the company selection and facility location, number, and capacities. Decisions about production, inventory, and logistics are made at the tactical or medium-range planning level. And eventually, at the Operational or short-range planning level, decisions about shifts such as routing and scheduling are made [3]. As an important strategic decision in supply chain management, Supply chain network design, has a significant role in overall environmental and economic function of the supply chain. On the whole, supply chain network design consists of the determination of locations, numbers, and capacities of network facilities as well as the arrangement of the material flows between them. Usually, a SCND problem specifies the components of the network and the missions regarding its locations. Facilities may be opened, closed, or transformed by different capacity options. Depending on the capacity options available at each location each selected facility is assigned one or several productions, assemblies, or distribution activities. The literature focusing on SCND can be divided into two parts, namely forward logistic (FL) and reverse logistics (RL). The former only addresses the forward network. The reverse logistic itself consists of problems which fully concentrate on the backward network, called recovery network. Those with which the backward network is integrated via the forward network, are known as closed-loop network. In forward, usually as a conventional logistic, after purchasing from suppliers, raw materials are converted to finished products in manufacturing plants. In the next step, these products are delivered to customers through distribution centers to satisfy their needs. In the reverse logistic, on the contrary, the influx of returned products is started from the customers back to the collection centers for repair, remanufacturing or disposal [4]. Many SCND models have been developed and optimized during the last decade among which is a wide scope of models from simple linear single product deterministic problems to complex non-linear multi-product stochastic ones. Melo et al. [17] suggested a general review of SCND models in order to support the development of richer SCND models. Conventionally, the focus of SCND is concentrated on a deterministic approach and single objective (i.e., minimizing costs or maximizing profit) in a forward logistic.

Growing research in the past few years takes into account facility disruptions within the supply chain design and logistics literature. Tang [18], using various examples, puts emphasis on the requirements for designing supply chains which can resist disruptions. From a management perspective, he discusses robust strategies for mitigating supply chain disruptions, enabling a supply chain to function smoothly and to continually serve customers during disruptions. Kleindorfer and Saad [1] presented a conceptual framework for disruption risk management in supply chains. This is based on the risk management literature and models of supply chain coordination. Also, Drezner [19] presented a mathematical model for facility location with unreliable suppliers. This model uses unreliable p-median and (p,q)-center location problems, in which a facility has a given probability of becoming inactive. Snyder and Daskin [20], in order to minimize the weighted sum of the nominal cost (the cost in the absence of disruptions) and the expected cost accounting for random disruptions by formulating reliable versions of the incapacitated fixed-charge location problem (UFLP) and the P-median problem. As to tractability, however, they make the strong claim that all facilities have the same probability of failure. Cui et al. [21], Li and Ouyang [22], Lim et al. [23] analyze models which resemble Snyder and Daskin, but manage the uniform-disruption-probability assumption using a variety of modeling approaches. Our model maintains this assumption using a scenario-based stochastic programming approach. It is different from works cited above in that it considers general, multi-echelon network design problems (of which facility location problems are special cases) and also considers a robustness constraint instead of utilizing an expected-cost objective. Snyder [24] applied a series of strategic planning models for facility location and supply chain network design problems in case of disruption threat. These include a network design model which resembles ours, the difference being that it uses an expected-cost objective rather than a robustness constraint.

Multi sourcing, flexibility, backup options, and increasing buffer stock and capacity are among the strategies which have been considered for managing supply disruptions [25]. All disruption management strategies are classified into two main categories, preventive and recovery. Preventive solutions can be grouped as follows [18]:

- Robustness strategies.
- Resiliency strategies.
- Security-based strategies.
- Agility strategies.

Several researchers have applied disruption strategies and scenarios to manage disruptions coming about in the supply chain. Hatefi and Jolai [26-27] and Torabi et al. [28], for instance, devised disruption scenarios so as to overcome complete and partial disruptions going on in facilities in a supply chain network. Moreover, in order to model random facility disruptions to solve a forward-reverse supply chain network design problem, Hatefi et al. [29-31] developed several disruption strategies. In the same way, Azad et al. [32] expanded reliability scenarios to control the existing disruptions happening in facilities and transportation paths. A resilient supply chain model which is protected against supply or demand interruptions is proposed by Jabbarzadeh [33]. Here, the probability of disruption occurrence is defined as the function of facility fortification investment. Jabbarzadeh et al. [34] proposed a stochastic bi-objective optimization model which considered resilience strategies to deal with disruption risks. Namdar et al. [35] proposed several sourcing strategies such as single and multiple sourcing, backup supplier contracts, spot purchasing, and collaboration and visibility for supply chain resilience under disruptions.

Paul et al. [36] developed a mathematical model for a three-tier supply chain system with multiple suppliers, a single manufacturer and multiple retailers, in which the supply chain network may face random disruption in its raw material supply. Ghavamifar et al. [37] developed a bi-level multi-objective programming approach for designing a supply chain network in automobile industry under facility and route disruption. Diabat et al. [38] presented a bi-objective robust optimization model the design a perishable product supply chain network under disruption risks. The aims of their proposed model were minimizing the time and cost of delivering products to customers when disruptions were occurred in facilities and routes.

Recovery time from disruptions has been used to deal with disruptions by several researchers. Friesz et al. [15], for example, by reducing the recovery time from disruption planned a supply chain network. In another study, Losada et al. [16] proposed a model to determine which facilities must be hardened to speed-up recovery time from disruptions. In addition, Sahebjamnia et al. [39] programmed a new framework for integrating business continuity as well as disaster recovery planning. The aim of the model proposed in this study to controlling the loss of resilience by maximizing the point of the recovery and minimizing recovery time objectives. The study proposes a bi-objective model for reliable supply chain network design under facility disruption. The model has two objective functions which aim to minimize the total costs of the supply chain network and minimize the recovery time from disruptions. Therefore, a new objective function is introduced which minimizes the recovery time to manage facility disruptions. Furthermore, to solve the proposed model, the epsilon constraint method and NSGAII are used.

3. Proposed reliable supply chain network under facility disruption

3.1 Tables Problem definition

Supply chain network studied in this paper is composed of three main entity types: production centers, distribution centers and demand zones. In the mentioned supply chain network, the raw materials are converted to the finished products and later transformed from the suppliers to the end customers. Supply chain network design consists of the several important strategic decisions in supply chain management, which has an important effect on the overall environmental and economic performance of the supply chain. The main decisions in the supply chain network design are determining locations of network facilities, numbers and capacities of them and the aggregate material flow between facilities. The nature and complexity of today's supply chains network make them vulnerable to various risks. The structure of the studied supply chain network is graphically depicted in figure 1. The proposed supply chain network is designed under partial and complete facility disruptions. It is assumed that disruptions may be occurred in production and facility centers. To cope with facility disruption, a novel objective function is proposed which minimizes the recovery time of disrupted facilities so that they return to a normal situation from disruption in the shortest possible time. The proposed model considers the following assumptions and limitations:

- The model is single-product and single-period.
- Customer locations and its demands are known and fixed.
- The potential locations of network facilities including manufacturing and distribution centers are known.
- The number of potential opened facilities and their capacities are both not restricted and not predetermined.
- Supply of production centers and capacity of distribution centers are restricted. Furthermore, all production centers can send the final product to each distribution center and there isn't any restriction.
- All demand of customers completely must be satisfied.
- All customers can receive the final product from any distribution centers.

- Transportation costs between network facilities are known.
- Production centers and distribution centers may face disruptions.
- Disruption rate can be complete or partial.
- Some factors such as, wage of staff, the price of energy and materials are different, so costs of recovery and outsourcing are not same in all candidate locations.

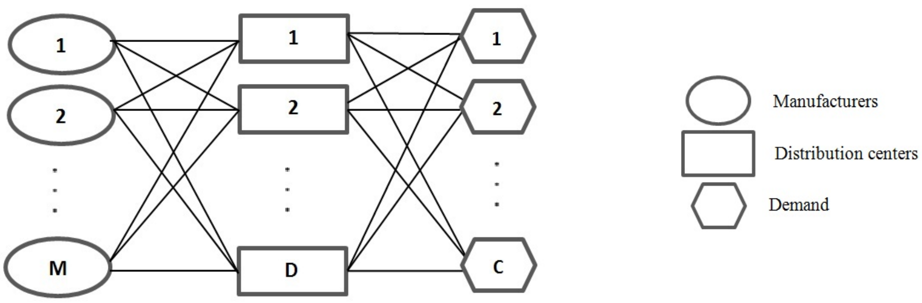

Fig. 1: Proposed Supply chain network

3.2 Sets, parameters and decision variables

Sets:

$\boldsymbol{i}$: index for production centers (i =1, 2, 3,…, m)
$\boldsymbol{j}$: index for distribution centers (j =1, 2, 3,…, d)
$\boldsymbol{k}$: index for demand zones (k =1, 2, 3,…, c)

Parameters:

$\boldsymbol{Fi}$: Fixed cost of opening of manufacturing facility i
$\boldsymbol{Fj}$: Fixed cost of opening of manufacturing facility j
$\mathbf{y_{ij}}$: Unit transportation cost from i to j per product
$\mathbf{y_{jk}}$: Unit transportation cost from node node j to k per product
$\boldsymbol{s_i}$: Max supply of manufacturer i
$\boldsymbol{z_j}$: Capacity of distribution center j
$\mathbf{D_k}$: Demand in node k
$\boldsymbol{a_i}$: Percentage of disruption in facility i
$\boldsymbol{a_j}$: Percentage of disruption in facility j
$\mathbf{R_i}$: Max protection resource when facility i faces disruption
$\mathbf{R_j}$: Max protection resource when facility j faces disruption
$\boldsymbol{TB_i}$: Total protection budget for production centers in disruption condition
$\boldsymbol{TB_J}$: Total protection budget for distribution centers in disruption condition
$\boldsymbol{m_i}$: Proportion of consumer resource to recovery time in facility i
$\boldsymbol{m_j}$: Proportion of consumer resource to recovery time in facility j
$\boldsymbol{w_i}$: Outsourcing cost per time unit in facility i
$\boldsymbol{w_j}$: Outsourcing cost per time unit in facility j

Decision variables:

$\boldsymbol{q_{ij}}$: Amount of product flow from node i to j
$\boldsymbol{q_{jk}}$: Amount of product flow from node j to k
$\boldsymbol{Xi}$: Is binary, if facility i be open is one, otherwise is 0
$\boldsymbol{Xj}$: Is binary, if facility j be open is one, otherwise is 0
$\boldsymbol{t_i}$: Recovery time for disrupted facility i
$\boldsymbol{t_j}$: Recovery time for disrupted facility j
$\boldsymbol{rb_i}$: Recovery budget invested for facility i
$\boldsymbol{rb_j}$:Rrecovery budget invested for facility j
$\boldsymbol{osb_i}$:Outsourcing budget invested for facility i
$\boldsymbol{osb_j}$:Outsourcing budget invested for facility j

3.3 Model formulation

In this section, a supply chain network is designed under facility disruptions. It is assumed that disruptions are occurred at production and facility centers. To deal with facility disruption, a novel objective function is proposed which minimizes the recovery time of disrupted facilities so that they return to a normal situation from disruption in the shortest possible time. According to the aforementioned definitions and explanations, the proposed bi-objective model for reliable supply chain network design with facility disruption can be written as follows:

$$\text{minimize } \sum_{i=1}^{m} Fi\,Xi + \sum_{j=1}^{d} Fj\,Xj + \sum_{i=1}^{m}\sum_{j=1}^{d} q_{ij}\,\mathrm{y_{ij}} + \sum_{j=1}^{d}\sum_{k=1}^{c} \mathrm{q_{jk}}\,y_{jk} + \sum_{i=1}^{m}(rb_{\mathrm{i}} + osb_i) + \sum_{j=1}^{d}(rb_{\mathrm{j}} + osb_j) \quad (1)$$

$$\sum_{j=1}^{d} q_{ij} \le s_i X_i (1 - a_i) \qquad i = 1,2,\dots,m \quad (2)$$

$$\sum_{i=1}^{m} q_{ij} - \sum_{k=1}^{c} q_{jk} = 0 \qquad j = 1,2,\dots,\mathrm{d} \quad (3)$$

$$\sum_{j=1}^{d} q_{jk} = D_k \qquad k = 1,2,\dots,\mathrm{c} \quad (4)$$

$$\sum_{i=1}^{m} q_{ij} \le z_j X_j (1 - a_j) \qquad j = 1,2,\dots,\mathrm{d} \quad (5)$$

$$\text{minimize } \sum_{i=1}^{m} t_i + \sum_{j=1}^{d} \mathrm{t_j} \quad (6)$$

$$rb_i = R_i a_i X_i \qquad i = 1,2,\dots,m \quad (7)$$

$$rb_j = R_j a_j X_j \qquad j = 1,2,\dots,\mathrm{d} \quad (8)$$

$$t_i = (1/m_i) rb_i X_i \qquad i = 1,2,\dots,m \quad (9)$$

$$t_j = (1/m_j) rb_j X_j \qquad j = 1,2,\dots,\mathrm{d} \quad (10)$$

$$osb_i = t_i\,w_i \qquad i = 1,2,\dots,m \quad (11)$$

$$osb_j = t_j w_j \qquad j = 1,2,\dots,\mathrm{d} \quad (12)$$

$$\sum_{i=1}^{m} (rb_i + osb_i)\,X_i \le TB_i \qquad i = 1,2,\dots,m \quad (13)$$

$$\sum_{j=1}^{d} (rb_j + osb_j)\,X_j \le TB_j \qquad j = 1,2,\dots,d \quad (14)$$

$$q_{ij}, q_{jk}, rb_i, rb_j, osb_i, osb_j, t_i, t_j \ge 0 \quad \forall\, i,j \quad (15)$$

$$X_i, X_j \in \{0,1\}\ \forall\, i,j \quad (16)$$

The objective function (1) minimizes the nominal costs, which include fixed location costs, transportation costs and protection costs after disruptions. The fifth term in the objective function (1) expresses the recovery and outsourcing budgets invested in production facilities when they are faced with disruptions. The last term in the objective function (1) expresses the recovery and outsourcing budgets invested for distribution facilities when they are faced with disruptions. Constraint (2) ensures that the total flow through a production facility does not exceed its capacity, when it is opened. Constraint (3) states that all products shipped from production facilities to a distribution facility must be transported from that distribution facility to customer zones. Constraint (4) ensures that all demand of the customer must be satisfied. Constraint (5) restricts the capacity of distribution facilities.

In second objective function, the objective function (6) seeks to minimize total recovery time of disrupted facilities so that they earlier return to normal situation. Constraints (7-8) calculate the amount of recovery budget for manufacturers and distribution centers when it is opened and faced with disruptions, respectively. Constraints (9-10) demonstrate the reduction of recovery time in manufacturers and distribution facilities when they are opened. Constraints (11-12) calculate the amount of budget for outsourcing facility's functions when disruptions occurred at manufacturers and distribution centers, respectively. Constraints (13-14) enforce the amount of protection resources invested in all facilities to be less than or equal to the total protection budget. Constraint (15) shows the non-negativity restriction on decision variables while constraint (16) ensures the binary nature of decision variables.

4. Solving approach

4.1 ε-constraint method

Multi-objective optimization programming models simultaneously manipulate several objective functions and are efficient tools to find efficient solutions. An efficient solution has the property, which it is impossible to improve any objective values without sacrificing on at least one other objective [40]. In this paper, the ε-constraint method introduced by Haimes et al. [41] is utilized to provide a set of Pareto-optimal SC configuration. In the ε–constraint, one objective function is optimized while other objectives are considered as constraints with allowable bounds. Then, to generate different Pareto-optimal solutions, the bounds are consecutively modified. The ε–constraint method is formulated as follows:

$$\begin{aligned}&\text{Min } f_1(x)\\&\text{Subject to: } f_2(x) \le \varepsilon_2, f_3(x) \le \varepsilon_3, \ldots, f_p(x) \le \varepsilon_p,\ x \in S\end{aligned} \tag{17}$$

According to model (17), a set of Pareto-optimal solutions can be obtained by changing values of ε_1 , ε_2 and ε_p . It is worthy to mention that each Pareto solution shows a SC configuration.

4.2 NSGA-II Algorithm

NSGA-II is a popular multi-objective evolutionary algorithm (MOEA), which has three special characteristics, including fast non-dominated sorting approach, fast crowded distance estimation procedure and simple crowded comparison operator [42]. NSGA-II is population-based search MOEA that can generate a set of Pareto Optimal solutions involving two or more conflicting objectives. One of these MOEAs that was frequently used in many optimization problems as the best Technique to generate Pareto frontiers is the non-dominated sorting genetic algorithm-II (NSGA-II) proposed by Deb et al. [42]. Deb et al. [42] designed several test problems using NSGA-II optimization technique. The authors compared NSGA-II with other MOEAs and claimed that this technique outperformed PAES (Pareto-archived evolution strategy) and SPEA (strength Pareto evolutionary algorithm) in terms of finding a diverse set of solutions [43-44]. The chromosome encoding in NSGA-II algorithm is described below.

Chromosome encoding

Encoding is used to translate a genetic solution of the problem into a chromosome string suitable to the application of genetic operators. For our problem, the chromosome contains four sections. First and second sections belong to close or open of manufacturers and distributed facility. (Fig 2) Third and fourth section present the transportation matrix from manufacturers to distribution centers and from distribution centers to customers (Fig 2, 3, 4).

1	1	0	1

Fig 2

manufacturer	Distribution center		
	500	0	150
	0	0	0
	200	100	0

Fig 3

Distribution center	customer			
	0	0	0	0
	0	200	20	100
	200	100	0	50

Fig 4

Fig 2 present a manufacturer or distribution centers chromosome with four candidate facility, that facility 3 is close.

NSGA II Algorithm steps

Initialization

In this step of the algorithm we generate random chromosome to the number of primary generation size. Then eliminate infeasible chromosomes. Hence resume this generation, up to we have feasible chromosome to the number of primary generation size. Then, we evaluate chromosome according to their objective functions and use Fast non-dominated sorting method and crowding distance for sorting of chromosomes.

Selection strategy

In this step we use tournament method for selection strategy. We select two random chromosomes and chromosome with lower front select as a first parent. If the front of chromosomes becomes equal, we calculate crowding distance, second parent is selected with the same method. Hence we have two parent chromosomes for generating new offspring.

Crossover Operator

After selection of two chromosomes with tournament method as parents, we use the crossover operator for generating better offspring by combining the selected parents directly with probability p_c. In crossover operator, first we select one chromosome from one of manufacturers or distribution centers with 1/2 probability, then one point of this chromosome is selected randomly, and then two parts of this chromosome are displaced. Assume manufacturer is selected. (See fig 5).

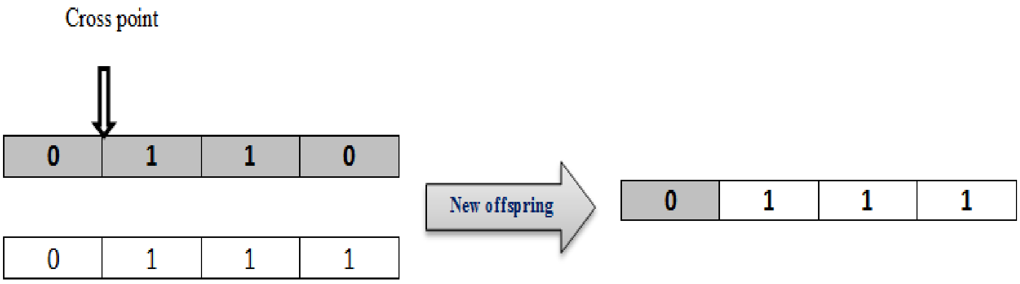

Fig. 5: First section of Crossover operator

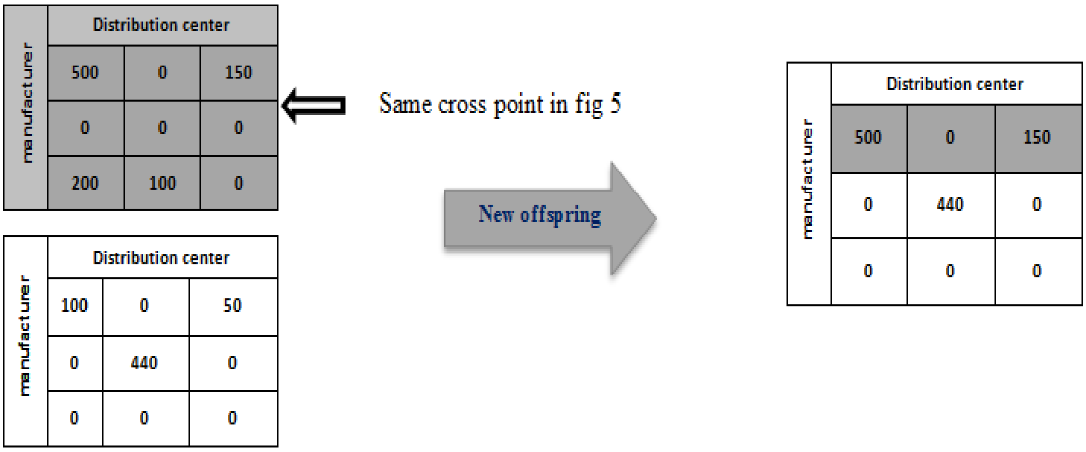

Fig. 6: Second section of Crossover operator

After performing above operations, we first consider feasibility of offspring generation, if new offspring is feasible, it is compared to all answers of last front, if it is better, the new generated offspring is transferred to the next generation.

Mutation Operator

In mutation operator each offspring is assigned a small probability of mutation, so that the solutions are more diversified. With probability p_m, select an individual from the population and swap two random genes. For mutation operator, we first select one of the manufacturers or distribution centers with probability ½ and select a chromosome randomly.

Fig. 7: First section of mutation operator

Fig. 8: Second section of mutation operator

After performing above operations, we first consider feasibility of offspring generation, if new offspring is feasible, it is compared to all answers of last front, if it is better, the new generated offspring is transferred to the next generation.

Termination criteria

Algorithm terminates when maximum generation is achieved.

Archive Operator

After crossover and mutation operators, we archive all solutions in first front. Hence, after completion of the maximum generation (termination conditions) we have an archive from all solutions on first front in any generation. Finally, we sort all solutions in the archive, and solutions in first front are the final solution.

5. Computational results

The studied problem is solved on a Pentium dual-core 2.20 GHz computer with 4.00 GB RAM in order to generate a different Pareto optimal solution. First for evaluation of NSGA II Algorithm we generated 8 random data sets of different problems with small sizes and the results compared with ε-constraint method. (See table 1)

For large scale problem, we generated 5 problems with random data. For design of experimental problems, we fixed cost for opening of manufacturers facility is drawn uniformly (200000, 550000), and for distribution centers is (50000, 100000), unit transportation costs are uniformly (200, 1000), max supply of manufacturer and Capacity of distribution centers are uniformly (500, 2000), (1500, 4000) respectively, demand of customers is uniformly (200, 450), probability disruption for manufacturers and distribution centers are uniformly (0, 1), max protection resource for manufacturers and distribution centers are uniformly (2000, 7000) ,(1000, 3000) , proportion of consumer resource to recovery time for manufacturers and distribution centers are uniformly (5,15) ,(2, 8) , Outsourcing cost for per time unit for manufacturers and distribution centers are uniformly (20,40) ,(10, 25).

For small scale of this model, we used ε constraint method and solve the problem in GAMS software and for large scale problems, we coded problem with NSGAII in MATLAB. For validation of NSGAII algorithm, we solved small scale problem with this algorithm and for the future comparisons of NSGA II. As Table 1 shows the results of NSGA II and ε constraint method are similar for small scale problems. Therefore, it is recommended that ε constraint method should be used as an exact method to obtain Pareto optimal solutions.

For large scale problems, the NSGAII is proposed to obtain the solution in a logic solving time. Furthermore, for large scale problems, we used a scale of Peng et al. [45] problems, and we analyzed the performance of NSGA II algorithm with some criteria like NPS (Number of pareto solutions) MID (Mean Ideal Distance), SNS (Spread of Non-dominance Solution) and MS (Maximum Spread). According to the results of Table 2, NSGAII provided the Pareto optimal solution in smaller solving time. Therefore, it is recommended to use the NSGAII for solving large scale problems.

Table 1: Small scale problems and compare results of NSGA II and ε constraint method

Manufactures , distribution centers, customer	*NSGA II*		*ε constraint*	
	F_1	F_2	F_1	F_2
3, 4, 5	1082133.333	1714.44444	1082133.3	1714.444
	1358737.857	2204.04761	1358737.8	2204.048
	1578476.190	2520.15873	1578476.1	2520.159
3,4, 6	1196152.857	1355.71428	1196152.8	1355.714
	1216948.333	1706.11111	1216948.3	1706.111
	1489491.191	2091.82539	1489491.1	2091.825
4, 5, 7	2063258.524	2492.15873	2063258.5	2492.159
4, 6, 7	2123526	1812.31349	2123526	1812.313
	2448715.083	1842.71500	2448715.0	1842.563
5 , 6, 6	1488724.762	2873.96825	1488724.7	2873.968
	1570025	3792.77777	1570025	3792.778
	2048632.619	4604.68254	2048632.6	4604.683

Table 2: large scale problems and its results

Manufactures , distribution centers, customer	*NSGA II*		*ε constraint*	
	F_1	F_2	F_1	F_2
20, 30, 40	10564498.88	1934.195778	TIME(min)	96
	10860877	1963.286333	NPS	6
	10970961.43	3311.64044	MID	0.7295
	11534148.73	4650.112662	MS	0.7704
	11788320.06	4949.611299	SNS	3720.9
	13514773.02	5183.481081		
20, 40, 50	12869724.8	4898.160741	TIME(min)	122.185
	12976678.24	4899.246317	NPS	3
	15146332.21	5146.063057	MID	0.9989
			SM	0.9060
			SNS	4526.9
30, 40, 50	14238320.37	5249.013064	TIME(min)	156.54
	14773918.04	5441.088996	NPS	4
	15210824.91	5675.689016	MID	0.8285
	15757331.8	5697.801516	SM	0.0914
			SNS	4471.3
30, 50, 60	18243137.01	5940.451262	TIME(min)	320
	19004627.31	6030.643485	NPS	5
	19340329.32	6110.419444	MID	0.8958
	19690298.48	6748.499666	SM	0.4461
	20718777.92	6863.065666	SNS	4924.2
40, 50, 60	17845441.19	7785.931457	TIME(min)	365.44
	18638421.05	7810.343217	NPS	4
	18754225.77	7811.823155	MID	0.9148
	19830020.86	7872.344441	SM	0.5500
			SNS	5002.3

Also best non-dominated solutions for large scale problems indicated in fig 9 – 13.

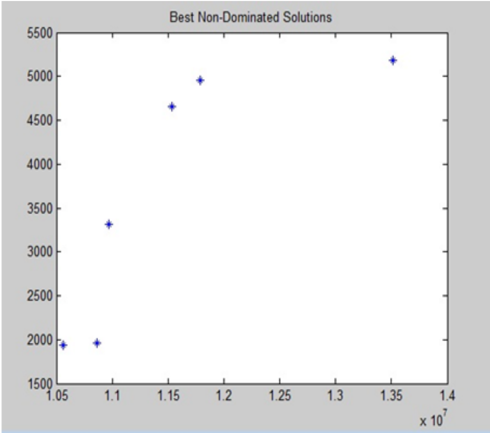

Fig 9: 20, 30, 40

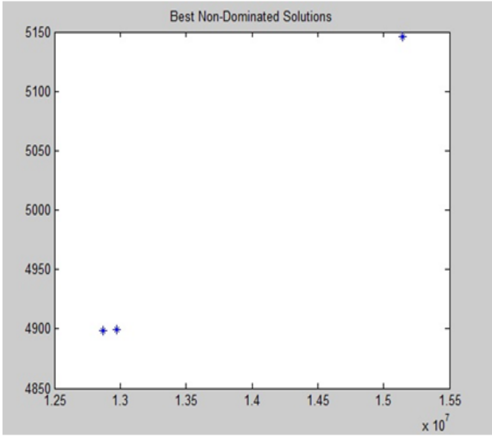

Fig 10: 20, 40, 50

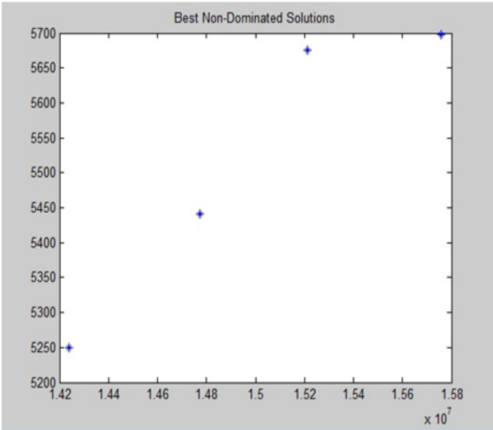

Fig 11: 30, 40, 50

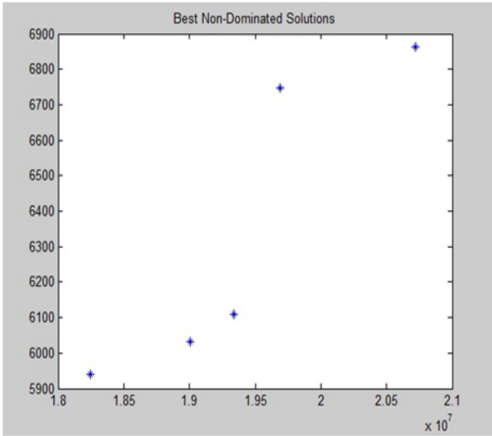

Fig 12: 30, 50, 60

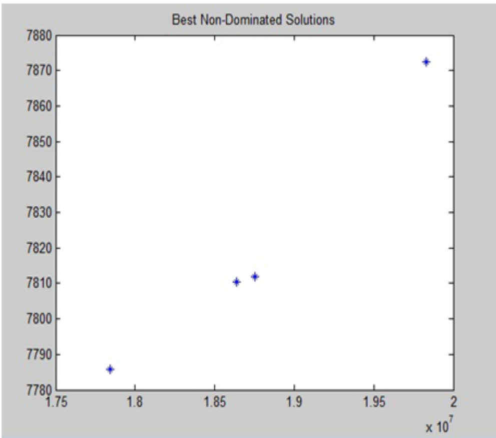

Fig 13: 40, 50, 60

6. Conclusion and suggestions for further research

In this paper, we propose a bi-objective model for reliable supply chain network design under facility disruptions. For solving our proposed model, we applied two approaches, namely, ε constraint method and NSGAII algorithm as an exact and meta-heuristic method, respectively. The model has two objective functions, minimizing of total cost in supply chain contains fixed costs, transportation costs and protection costs after disruptions in the first objective and maximizing of total reduction in recovery time when facilities faced with disruptions in the second objective. Our focus in this paper was on the second objective function, and we would like to consider the behavior of recovery time in model and identify the optimal allocation of protection resources for a disrupted facility for rapidly recovering after disruptions. For small scale of this model, we used ε constraint method and solve the problem in GAMS software and for large scale problems, we coded problem with NSGAII in MATLAB. For validation of NSGAII algorithm, we solved small scale problem with this algorithm and for the future comparisons of NSGA II, we calculated some criteria like NPS, MID, SNS and MS. Results are demonstrated in computational results section.

There are some potential directions for future works. Our proposed model is a single period and model will be more real and some parameters will have different behavior in multi period model. Another subject that can be considered in future research is some parameters have stochastic nature and present a robust model for SCND. Also, we can integrate the reverse logistic follow into the forward flow and study the influence of recovery time and protection resources in a closed loop supply chain network.

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