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Research Article

Multi-objective Optimization for Multi-product Multi-period Four Echelon Supply Chain Problems under Uncertainty

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Abstract

The multi-objective optimization for a multi-product multi-period four-echelon supply chain network consisting of manufacturing plants, distribution centers (DCs) and retailers each with uncertain services and uncertain customer nodes are aimed in this paper. The two objectives are minimization of the total supply chain cost and maximization of the average number of products dispatched to customers. The decision variables are the number and the locations of reliable DCs and retailers, the optimum number of items produced by plants, the optimum quantity of transported products, the optimum inventory of products at DCs, retailers and plants, and the optimum shortage quantity of the customer nodes. The problem is first formulated into the framework of a constrained multi-objective mixed integer linear programming model. After that, the problem is solved by using meta-heuristic algorithms that are Multi-objective Genetic Algorithm (MOGA), Fast Non-dominated Sorting Genetic Algorithms (NSGA-II) and Epsilon Constraint Methods via the MATLAB software to select the best in terms of the total supply chain cost and the total expected number of products dispatched to customers simultaneously. At the end, the performance of the proposed multi-objective optimization model of multi-product multi-period four-echelon supply chain network design is validated through three realizations and an innumerable of various analyses in a real world case study of Bangladesh. The obtained outcomes and their analyses recognize the efficiency and applicability of the proposed model under uncertainty.

Keywords: Supply chain management; Multi-objective optimization; MOGA; NSGA-II; Uncertainty

1. Introduction

Nowadays, supply chain management (SCM) which covers production planning for entire supply chain from the raw material supplier to the end customer has recently been the focus of many researchers. Though SCM has become the fundamental of the enterprise management in the 21st century, there is a high interest to exploit the full potential of SCM in enhancing organizational competitiveness. SCM has a tremendous impact on organizational performance in terms of competing based on price, quality, dependability, responsiveness, and flexibility in the global market and it is becoming a more matured discipline. In most of the classical supply chain network designs, the goal has been to send products from one layer to another in order to supply demands such that sum of strategic and tactical/operational cost is minimized. For instance, Amiri (2006) developed a two stage SC model to select optimum location of production plants and distribution warehouses in order to dispatch the products from plants to customers with the goal of minimizing the total costs of the distribution network. A new three-stage production–distribution system with safety stock was formulated to minimize total supply costs by Gebennini. et at., (2009). Konak.A. et al., (2006). has shown that most of the real engineering problems actually do have multiple objectives, i.e., minimize cost, minimize risk, maximize performance, maximize reliability, etc. These are difficult but realistic problems. The multi objectives are conflict each other, single objective can result in unacceptable results with respect to the other objectives. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. In general, a multi-objective optimization, a single point optimal solution is not obtained, that can optimize all the objective function simultaneously. Therefore, multi objective optimization is not to search for the optimal solution, but for an efficient solution, which will make all the objective function as minimum as possible or that can provide best solution.

There are two general approaches to multiple-objective optimization. One is to combine the individual objective functions into a single composite function or move all but one objective to the constraint set. In the former case, determination of a single objective is possible with methods such as utility theory, weighted sum method, etc., but the problem lies in the proper selection of the weights or utility functions to characterize the decision-maker's preferences. In practice, it can be very difficult to precisely and accurately select these weights, even for someone familiar with the problem domain. Compounding this drawback is that scaling amongst objectives is needed and small perturbations in the weights can sometimes lead to quite different solutions. The weighting method has several drawbacks (Ripon et al., (2011): (1) it is difficult to determine the weight for each objective function beforehand; (2) only one Pareto optimal solution generated in one run; (3) as all the objective functions are added up linearly, this method is

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unable to find the Pareto optimal solutions that cannot be represented in linear form; (4) different combinations of weights may result in the same Pareto optimal solution. In the latter case, the problem is that to move objectives to the constraint set, a constraining value must be established for each of these former objectives. This can be rather arbitrary. In both cases, an optimization method would return a single solution rather than a set of solutions that can be examined for trade-offs. For this reason, decision-makers often prefer a set of good solutions considering the multiple objectives. The second general approach is to determine an entire Pareto optimal solution set or a representative subset. A Pareto optimal set is a set of solutions that are non-dominated with respect to each other. While moving from one Pareto solution to another, there is always a certain amount of sacrifice in one objective(s) to achieve a certain amount of gain in the other(s). Pareto optimal solution sets are often preferred to single solutions because they can be practical when considering real-life problems since the final solution of the decision-maker is always a trade-off. Pareto optimal sets can be of varied sizes, but the size of the Pareto set usually increases with the increase in the number of objectives.

In this paper, a multi-product multi-period four echelon supply chain consisting of a manufacturing plant that produces several products, distribution centers (DCs) that receive the products and stores them in order to satisfy customer's demands and the demands of retailer. Retailers receive the products from DCs and store them in order to satisfy customer's demands and customer nodes as final recipients of the products is considered, in which the distribution center and retailers are subject to random failure with demand uncertainty. The goal is to determine the optimum number of items produced by plants, the optimum quantity of products to be dispatched from plants to DCs and from DCs to retailers and to customers, and from retailers to customer nodes, the optimum inventory of products at DCs and plants, and the optimum shortage quantity of the customer nodes. The problem has two conflicting objectives. The first is to minimize the total chain cost and the second is to maximize the average total number of products dispatched to customers from DCs and retailers. The problem is first formulated into a bi-objective mixed-integer linear programming model. The customer demands are satisfied directly from distribution center or via retailers. Note that while the uncertainty involved in both distribution and retailers facilities of supply chain networks with demand uncertainty has not been considered in most of relevant works, this paper aims to provide a framework to address it by assuming that the distribution and retailers facilities are subject to random failures due to natural events, terrorist attacks, weather condition, labor absence, change in owner, politically unstable situation and so on. Moreover, the customers' demands are satisfied directly from distribution centers or via retailers. There are different methods are suggested to model two conflicting objectives in this research. These methods reflect different expectations and willing of decision makers.

1.1 Literature review

A supply chain consists of all parties involved, directly or indirectly, in fulfilling a customer request. The supply chain includes not only the manufacturer and suppliers, but also transporters, warehouses, retailers, and even customers themselves. Supply chain (SC) is an integrated system of facilities and activities that synchronizes inter related business functions of material procurement, material transformation to intermediates and final products and distribution of these products to customers. Scavarda et al. (2010), formulated a product variety problem considering emerging and developed markets and they utilize different techniques to collect data. The supply chain network design under demand uncertainty has been received significant importance in the recent time. Ren et al (2015) developed a Mixed-Integer Non-linear Programming (MINLP) model in order to help the stakeholders/decision-maker to find out the most sustainable design in sustainable environment. For instance, Cardona-Valdés et al. (2011) proposed a bi-objective two-echelon production distribution network under demand uncertainty to minimize both the total supply chain cost and the total service time, where they solved the stochastic optimization problem by L shaped algorithm. El-Sayed et al., (2010), extended a multi-period three-echelon forward-reverse logistics network design under uncertainty where they considered three echelons in forward direction and two echelons in reverse direction in order to maximize the total expected profits. In the meanwhile, Schüt et al. (2009), formulated another two-stage SC stochastic problem under the short-term operations and demand uncertainty to minimize the total expected supply costs. After that, Chen et al. (2004), viewed a multi-product, multi-stage, and multi-period scheduling model was proposed with multiple incommensurable goals for a multi-echelon supply chain network with uncertain market demands and product prices.

The uncertain market demands are a realistic situation for any kind of product and service due to this uncertainty is a common phenomenon in supply chain cost estimation. Georgiadis et al. (2011), mentioned a multi-product supply chain network design problem considering time varying uncertainty in terms of a number of likely scenarios and they solved the problem by using branch and bound algorithm. Facility location and task allocation problem with stochastic demand was examined by Wang et al. (2012), to make decisions at both strategic and operational levels to maximize profit, where an improved genetic algorithm (GA) was employed to solve the problem. Furthermore, Olivares-Benitez et al. (2012), formulated a new bi-objective mixed-integer SC problem which they solved by three classical ε-constraint methods to produce Pareto-optimal points for decision making. Zhang et al. (2012) proposed a multi-echelon production system supply chain network for an automobile which involves material supply, component fabrication, manufacturing, and final product distribution activities under price and demand uncertainty. Pishvaee et al. (2010), proposed a bi-objective MIP model to minimize the total SC costs and maximize the responsiveness of the closed loop logistics network and they used memetic algorithm and dynamic search algorithm was developed to solve the problem. Easwaran and Uster (2010), calculated a closed-loop multi-product logistics network design problem where hybrid manufacturing/remanufacturing facilities and finite-capacity hybrid distribution/collection centers are considered and the problem was solved by benders' decomposition method. Mehrbod et al. (2012), developed a multi-objective MIP formulation to minimize the SC total cost, the delivery time, and the collection time of used products in the closed loop network. Lu and Bostel (2007), presented a two-level location problem in which the forward and reverse flows are considered simultaneously and Lagrangian heuristics was developed to validate the problem. Ruiz-Femenia et al. (2013), analyzed the effect of demand uncertainty on the multi-objective optimization of chemical supply chains, simultaneously considering their economic and environmental performance. Moreover, Rodriguez et al. (2014), proposed an optimization model to redesign the supply chain of spare part delivery under demand uncertainty from strategic and tactical perspectives in a planning horizon consisting of multiple periods. They addressed the risk-pooling effect was taken into account when defining inventory levels in distribution centers and customer zones.

There are numerous method to solve multi-objective optimization that are discussed in different literature, for example, Shankar et al. (2013), conducted multi-objective optimization for four-echelon supply chain problem to reduce the total supply chain cost as well as to maximize fill rate. They used MOPSO algorithm which can be optimized more than two conflicting objectives simultaneously under uncertainty. Sarrafha et al. (2014) developed a multi-periodic structure for a supply chain network design for multi-product to reduce the total supply chain costs and the average tardiness of product to the distribution centers as well as to increase the responsiveness using a novel multi objective biography based optimization (MOBBO). Pasandideh et al. (2015), proposed a bi-objective mixed-integer linear programming model for multi-product multi-period three-echelon supply chain network where they used six MODM methods to reduce the total cost and increase the responsiveness. Amin et al. (2013), proposed a facility location model for a general closed-loop supply chain network. The model was designed for multiple plants (manufacturing and remanufacturing), demand markets, collection centers, and products. The goal was to know how many and which plants and collection centers should be open, and which products and in which quantities should be stock in them. The objective function minimizes the total cost. Then, the model was solved by two methods including weighted sums and ε-constraint methods. Furthermore, trade-off surfaces of test problems are examined. The multi-objective model also is extended by stochastic programming (scenario-based) to examine the effects of uncertain demand and return on the network configuration.

Pishvaee, et al. (2014) presented a mixed integer multi-objective programming model for a medical supply chain network under uncertainty. Their model aimed to optimize three conflicting objectives including minimization of the total costs, minimization of the environmental effects, and maximization of social responsibilities. They defined several constraints and binary variables to convert the nonlinear model into a linear one and used an accelerated benders decomposition algorithm to solve the problem. Kannan et al. (2013), proposed an approach to rank and select the best green suppliers according to economic and environmental criteria in a SC, and then to allocate the optimum order quantities among them. The proposed approach is an integration of the fuzzy multi-attribute utility theory and multi-objective programming. Maximizing the total value of purchasing and minimizing the total cost of purchasing simultaneously are the objectives of the model. Pasandideh et al. (2015) proposed a bi-objective optimization of a multi-product multi-period three-echelon supply chain network consisting of manufacturing plants, distribution centers (DCs) each with uncertain services, and customer nodes is aimed in this paper. The two objectives are minimization of the total cost while maximizing the average number of products dispatched to customers. In these paper only considered uncertainty in DCs and to solve the problem using the GAMS software, six multi-objective decision-making (MODM) methods are investigated. Pasandideh et al. (2015) also proposed bi-objective optimization of a multi-product multi-period three-echelon supply chain network under uncertainty was aimed. The network consists of some manufacturing plants, distribution centers (DCs), and customer nodes. The contribution of this paper was to bring the existing models closer to reality. To solve the complicated problem, a non-dominated sorting genetic algorithm (NSGA-II) was utilized next. As there was no benchmark available in the literature, another GA-based algorithm called non-dominated ranking genetic algorithm (NRGA) was used.

Ren et. Al. (2015), developed a mixed integer non-linear model with the aim of helping the decision-maker to select the most sustainable design and planning supply chain network. The SC structure considers multiple feed stocks, transport modes, regions for production and distribution centers. A sustainable measure was explored, which was based on the energy sustainability index trough a life cycle perspective. Fung et al. (2015), developed a procedure with the aims of infrastructure expansion minimization cost to face future demand variability in a mineral supply chain. A Meta heuristic formulation was designed based on the hybridization of mixed integer linear programming (MILP) and a simulated annealing approach taking advantages of different levels of data aggregation. The procedure demonstrated the ability to solve industrial problems of different sizes. Camacho et al. (2015), considered in its work the production planning and distribution of a supply chain with the aim of operation and transport costs minimization in a four echelon supply chain. A heuristic algorithm based on

Scatter Search that considers the Stackelberg's equilibrium was developed for the problem solution.

Many researchers have widely applied GA to solve SCM problems. At first Ulungu et al. (1999) proposed a multi-objective SA (MOSA) are the meta-heuristics commonly used to find the Pareto front solutions in NP-hard multi- objective problems. Altiparmak et al. (2006), proposed a GA to find the set of Pareto- optimal solutions of a multi-objective four-echelon supply chain using two different weighting approaches. Hnaiena et al. (2010), developed a model for a SC of a two-level assembly system under lead time uncertainty in order to minimize the expected component holding costs and to maximize the customer service level for the finished product. They employed two multi-objective meta-heuristics based on GA to solve these problems. Prakash et al. (2012), provided a knowledge-based GA (KBGA) to optimize a SC network. Shi et al. (2017), formulated a multi-objective Mixed Integer Programming model for a closed loop network design problem is. In addition to the overall costs, the model optimizes overall carbon emissions and the responsiveness of the network. An improved genetic algorithm based on the framework of NSGA II is developed to solve the problem and obtain Pareto optimal solutions. Rabiee et al.[36] compare the result obtain from NSGA-2, NRGA, MOGA and PAES in case of bi-objective partial flexible job shop scheduling problem. Furthermore, Marufuzzaman et al. (2014), considered a two-stage stochastic programming model used to design and manage biodiesel supply chains. The model captures the impact of biomass supply and technology uncertainty on supply chain-related decisions. They solved this problem using algorithms that combine the Lagrangian relaxation and the L-shaped solution methods. Srinivas and Deb (1994) in NSGA classify the population into non-dominated fronts using the algorithm. Bandyopadhyay and Bhattacharya (2014), proposed a tri-objective optimization problem for a two echelon serial supply chain. They considered a modification of non-dominated sorting genetic algorithm-II (NSGA-II) with a mutation algorithm that has been embedded into the modified NSGA-II to solve the problem. The algorithm of NSGA-II shown better results than the existing best known results in the literature for these reason the author choose to find out the Pareto optimal solution.

In the current work, multi-objective optimization methodology of a multi-product multi-period four-echelon supply chain network under uncertainty is aimed. The network consisting of manufacturing plants, distribution centers (DCs) and retailers each with uncertain services and customer nodes is aimed in this paper. The two objectives are minimization of the total supply chain cost while maximizing the average number of products dispatched to customers. From the above literature it is seen that the uncertainty involved in both distribution and retailers facilities of supply chain networks with demand uncertainty has not been considered in most of relevant works, this paper aims to provide a framework to address it by assuming that the distribution and retailers facilities are subject to random failures due to natural events, terrorist attacks, weather condition, labor absence, change in owner, politically unstable situation and so on. Moreover, the uncertain customers' demands are satisfied directly from distribution centers or via retailers that means if any retailer is unable to satisfy the customer demand the distribution centers are used to satisfy these demands.

In a nutshell, the main contributions of the current paper that differentiate it from the available works in the literature are as follows:

- Developing a new multi-objective MILP model for multi-product multi-period four echelon supply chain network design under uncertainty.
- Proposing two conflicting objectives that are minimization of total supply chain cost and maximization of customer satisfaction by maximizing average total number of product dispatched to customer simultaneously under uncertain environments.
- Moreover, the uncertain customer demand is satisfied directly from DCs and retailers.
- The customer demand, DCs and warehouse are simultaneously considered in uncertain environments.
- Solving the proposed problem by using number of recent well known multi-objective meta-heuristic techniques: Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi-Objective Genetic Algorithm (MOGA) and ε-constraint method is used to justify the obtained result.
- In addition, the proposed optimization model has applied in a real world case study in Bangladesh to verify the obtained result.

1.2 Research objectives

The two conflicting objectives of this research paper are to

- Minimization of total supply chain cost under uncertain environments.
- Maximization of customer satisfaction by maximizing average total number of product dispatched to customer under uncertain environments.

This research develops and demonstrates generalized formulation to manage uncertainty in supply chain, which provides decision support to logistics and supply chain managers.

1.3 General methodology

Based on the presented literature review and discussed issues, less attention has been devoted to development of a model under uncertainty. In addition, most of the studies in this area have focused on locations, numbers and capacities of network facilities as well as the material flow through the network. Furthermore, very limited studies have been conducted that consider the inherent uncertainty of various parameters of an integrated supply chain network. Taking these gaps into consideration, the following research methodology has been proposed in this research proposal.

Phase 1:
In this phase, a comprehensive study have been performed to have better understanding of the current situation of the problem in manufacturing company located in Bangladesh in terms of products, infrastructures, and the material flow in their supply chain. For conducting the research, all types of products with their sources have recognized in their supply chain.

Phase 2:
Afterwards, the initial architecture of the closed loop supply chain that shows the supply chain entities (Manufacturers, DCs, and Customers etc.) and material flows have been designed.

Phase 3:
In the third phase, a multi-objective mathematical model has been developed for SC network configuration while the uncertainties of various parameters are considered. The proposed model has optimized multiple objective functions including total supply chain cost and customer scarification simultaneously. The outputs of the model have provided the optimum locations, numbers and capacities of network facilities as well as the material flows throughout the network. To solve the proposed model, pareto-efficient optimization approaches such as a non-dominated sorting genetic algorithm (NSGA-II) and MOGA have been utilized that implemented using appropriate optimization software. To justify the proposed model, a real-world case study in RFL Plastic industry in Bangladesh has applied to measure the efficiency of the proposed model. The optimization model solved two objective functions where the first objective of the model will be minimizing total supply chain cost and second objective will be maximizing customer satisfaction.

2. Problem Description

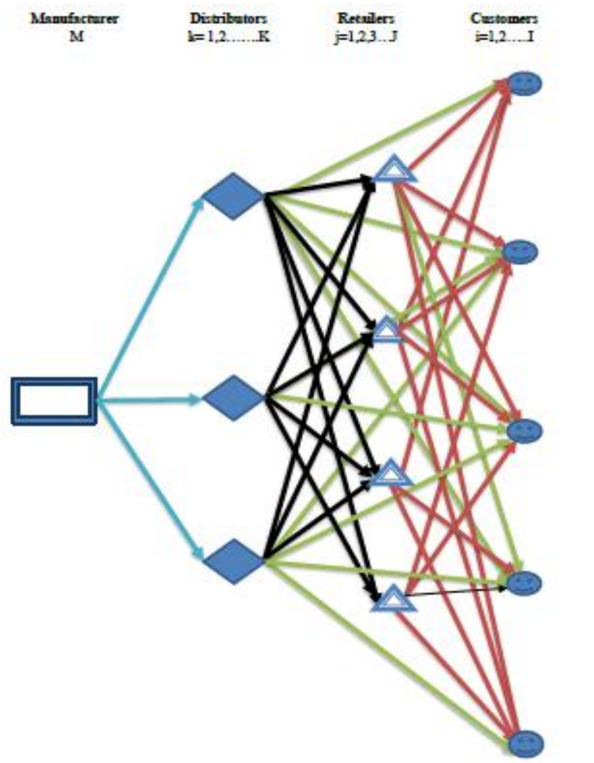
In this section, nomenclatures, the problem, and the assumptions required to model the problem are introduced before the mathematical formulation.

2.1. Nomenclatures

The notations including indices, parameters, and decision variables are:

The figure 1 indicates that one manufacturing plant produces several products that are transferred to the three DCs to store and satisfy the demand of customer and retailer. The figure 1 also indicates that four retailers receive products from DCs to store and satisfy the five customer demands. In addition, the customer demand is satisfied from direct DCs when the retailer is unable to satisfy the demand.

Manufacturer	**Distributors**	**Retailers**	**Customers**
M	k= 1,2…….K	j=1,2,3…J	i=1,2…..I



Periods t=1,2,3..T & Products p=1,2,3….P

Fig. 1. A four echelon Supply Chain Network Configuration

Indices:

m	index used for a manufacturing plant
k	index used for a potential location of DCs, k = 1, 2, ..., K
j	index used for a potential location of retailers, j = 1, 2, ..., J
i	index for a customers, i = 1, 2, ..., I
p	index for a finished products, p = 1, 2, ...,P,
t	index used for a period with a fixed length of τ, t = 1, 2, …, T, Z=Inflation rate
N	Number of Year

Parameters:

C^p_{mt}	unit production cost of product p by manufacturing plant m in period t
d^p_{kmt}	unit transportation cost of product p to DC k by plant m in period t
d^p_{jkt}	unit transportation cost of product p to retailer j by DC k in period t
d^p_{ikt}	unit transportation cost of product p to customer i by DC k in period t

d_{ijt}^{p}	unit transportation cost of product p to customer I by retailer j in period t
H_{jt}^{p}	unit inventory holding cost of product p by retailer j in period t
H_{kt}^{p}	unit inventory holding cost of product p by DC k in period t
H_{mt}^{p}	unit inventory holding cost of product p by plant m in period t
CA_{mt}^{p}	setup cost of producing product p by plant m in period t
CS_{it}^{p}	unit shortage cost of product p in supplying the demand of customer i in period t
f_k	fixed cost of selecting a center to establish DC k
PT_{m}^{p}	production time needed by plant m to produce one unit of product p in period t
A_{mt}^{p}	set up time of producing product p by plant m in period t
TT_{mt}^{p}	total available production time for plant m to produce product p in period t
W_j	total storage capacity available in retailer j to store product in a period t
W_k	storage capacity available for DC k to store products in a period t
W_m	storage capacity available for plant m to store products in a period t
N_{m}^{p}	total transportation capacity available for plant m to dispatch product p in a period t
D_{it}^{p}	uncertain demand of product p by customer i in period t
V_p	volume of one unit product p (m^3)
λ_{kt}	the parameter of an exponential distribution used for failure rate of DC k in period t
λ_{jt}	the parameter of an exponential distribution used for failure rate of retailer j in period t

Decision variables:

Z_{mt}^{p}= 1, if product p is produced by plant m in period t, 0 otherwise
Y_k= 1, if warehouse j is established, 0 otherwise
Q_{mt}^{p}= quantity of product p produced by plant m in period t
U_{kmt}^{p}= quantity of product p dispatched by plant m to DC k in period t
R_{jkt}^{p}= quantity of product p dispatched by DC k to retailer j in period t
X_{ijt}^{p}= quantity of product p dispatched by retailer j to customer i in period t
O_{ikt}^{p}= quantity of product p dispatched by DC k to customer i in period t
S_{it}^{p}= shortage quantity of product p for customer demand i in period t
I_{mt}^{p}= inventory of product p in plant m at the end of period t
I_{kt}^{p} = inventory of product p in DC k at the end of period t
I_{jt}^{p} = inventory of product p in retailer j at the end of period t

2.2 The Problem statement

Consider a multi-product multi-period four echelon supply chain consisting of a manufacturing plant that produces several products, distribution centers (DCs) that receive the products and stores them in order to satisfy customers demands when retailers is unable to satisfy the customers demand and the demands of retailers, retailers receive the products from DCs and stores them in order to satisfy uncertain customers' demands and customer nodes as final recipients of the products is considered, in which the distribution center and retailers are subject to random failure with demand uncertainty Fig. 1. The network operates in a stochastic environment where all the input parameters such as demands, warehouses and DCs that do not operate perfect all the time, are known with certainty. Besides, the manufacturing plants are 100% reliable with limited production and transportation capacities in a period and that the capacity of a warehouse to store products is limited in a period. The time required DC k to fail in a period T_k follows an exponential distribution with a mean of λ_{kt}, and the time required retailer j to fail in a period T_j follows an exponential distribution with a mean of $e^{-\lambda_{jt}}$ This may happen due to natural events, terrorist attacks, change in owners, labor mistake, weather conditions, political instability, etc. As a result, the reliability of DC (R_k), in dispatching products to the customers in a period is

$$R_k= P(T_k > \tau) = e^{-\lambda_{kt}\tau};\ \forall k =1; 2; \ldots K \qquad (1)$$

The reliability of retailer (R_j), in dispatching products to the customers in a period is

$$R_j= P(T_j > \tau) = e^{-\lambda_{jt}\tau};\ \forall j =1; 2; \ldots J \qquad (2)$$

Moreover, at the beginning of the planning horizon, all of the DCs and retailers are functional and that their return to the functional state after their failure is not possible. This means that the average number of product k dispatched from potential DC k to customer i is $e^{-\lambda_{kt}\tau}\, O_{ikt}^{p}$, and the average number of product k dispatched from potential retailer j to customer i is $e^{-\lambda_{kt}\tau}\, R_{jkt}^{p}$, as well as the average number of product dispatched from potential retailer j to customer i is $e^{-\lambda_{jt}\tau}\, X_{ijt}^{p}$. In addition, based on the fixed establishment costs, the capacities, and the reliabilities of the warehouses, the network manager must decide on a subset of potential warehouses to be located at certain places to fulfill customers' demands. The decision-making issues to locate warehouses with certain reliabilities are strategic and require long-term planning. In this case, most of decision changes at length of short or even medium period involve exorbitant expenditures and hence are not justifiable. Moreover, the mean and standard deviations of demands are calculated carefully in order to consider the demand uncertainty.

2.3. Problem Modeling

One of the important goals of a supply chain network is the customer satisfaction of the product fill. Thus, the DCs and Retailers with the highest reliability in the planning horizon must be established to fulfill customers' demands as much as possible.

The proposed model is an extended version of the model proposed by Pasandideh et all (2015). The main distinctions of this paper with respect to the paper presented by Pasandideh et all (2015), are as follows:

- Pasandideh et all (2015), presented a mathematical model for a three-echelon supply chain network. Here, the authors extend the presented SCN problem for a four-echelon SCN problem including manufacturers, DCs, Retailers and Customers.
- Their proposed model aimed to merely minimize the total cost and maximize product fill rate considering only warehouse reliability. Here, the authors extend the presented SCN problem to a multi-objective mixed integer non-linear programming model considering both DCs and retailers reliability.
- Moreover, Pasandideh et all (2015), presented a mathematical model where the customer demand is satisfied only from DCs, but here the authors presented a mathematical model where the customer demand is satisfied from both DCs and retailers that means customer satisfaction rate must be increased.
- Their proposed model considers deterministic demand and validates the model using estimated data in these model authors considers uncertain demand and the model is validated using primary data.
- The authors improved the model by incorporating inflation rate, stipulated lead time and the problem is solved by using well-known multi-objective meta-heuristics algorithms .

The proposed model according to the assumptions and the objectives, the model of the problem at hand is a mixed-integer linear programming (MIP) as follows.

$$\begin{aligned}\text{Minimize } Z_1 = {} & \sum_{k=1}^{K} f_k\, y_k (1+Z)^N + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{K} d_{kmt}^{p} U_{kmt}^{p} (1+Z)^N \\ & + \sum_{t=1}^{T}\sum_{p=1}^{P} CA_{mt}^{p} Z_{mt}^{p} (1+Z)^N + \sum_{p=1}^{P}\sum_{t=1}^{T} C_{mt}^{p} Q_{mt}^{p} (1+Z)^N \\ & + \sum_{p=1}^{P}\sum_{t=1}^{T} H_{mt}^{p} I_{mt}^{p} (1+Z)^N \\ & + \sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{t=1}^{T} H_{kt}^{p} I_{kt}^{p} (1+Z)^N + \sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{t=1}^{T} H_{jt}^{p} I_{jt}^{p} (1+Z)^N \\ & + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{j=1}^{J} d_{jkt}^{p} R_{jkt}^{p} (1+Z)^N + \sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{t=1}^{T} d_{ijt}^{p} X_{ijt}^{p} (1+Z)^N \\ & + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{K}\sum_{i=1}^{I} d_{ikt}^{p} O_{ikt}^{p} (1+Z)^N + \sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{it}^{p} S_{it}^{p} (1+Z)^N \end{aligned} \tag{3}$$

$$\text{Max } Z_2 = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J} e^{-\lambda_{kt}} R_{jkt}^{p} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{k=1}^{K} e^{-\lambda_{kt}} O_{ikt}^{p} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J} e^{-\lambda_{jt}} X_{ijt}^{p} \tag{4}$$

Subject to:

$$\sum_{p=1}^{P} PT_m^p\, Q_{mt}^p + \sum_{p=1}^{P} A_m^p\, Z_{mt}^p \le TT_{mt}^p \qquad \forall m, t \tag{5}$$

$$\sum_{p=1}^{P}\sum_{m=1}^{M} V_p U_{kmt}^p \le W_k Y_k \qquad \forall k, t \tag{6}$$

$$\sum_{j=1}^{J} X_{ijt}^p \le DC_{it}^p \qquad \forall i, t, p \tag{7}$$

$$\sum_{k=1}^{K} V_p I_{kt}^p \le w_k y_k \qquad \forall p, t \tag{8}$$

$$\sum_{k=1}^{K} U_{kmt}^{p} \leq N_{m}^{p} Z_{mt}^{p} \qquad \forall p, t, m \qquad (9)$$

$$\sum_{p=1}^{P} V_{p} Q_{mt}^{p} \leq W_{m} \qquad \forall t, m \qquad (10)$$

$$\sum_{p=1}^{P} V_{p} I_{mt}^{p} \leq W_{m} \qquad \forall t, m \qquad (11)$$

$$\sum_{p=1}^{P} V_{p} I_{jt}^{p} \leq W_{j} \qquad \forall t, j \qquad (12)$$

$$\sum_{p=1}^{P} V_{p} I_{kt}^{p} \leq W_{k} \qquad \forall t, k \qquad (13)$$

$$I_{jt}^{p} = I_{jt-1}^{p} + R_{jkt}^{p} - \sum_{i=1}^{I} X_{ijt}^{p} \qquad \forall t, k, p, i, j \qquad (14)$$

$$I_{kt}^{p} = I_{kt-1}^{p} + U_{kmt}^{p} - \sum_{j=1}^{J} R_{jkt}^{p} - \sum_{i=1}^{I} O_{ikt}^{p} \qquad \forall t, k, p, i, j \qquad (15)$$

$$I_{mt}^{p} = I_{mt-1}^{p} + Q_{mt}^{p} - \sum_{k=1}^{K} U_{kmt}^{p} \qquad \forall t, k, p, i, j \qquad (16)$$

$$S_{it}^{p} = S_{it-1}^{p} + DC_{it}^{p} - \sum_{i=1}^{I} X_{ijt}^{p} - \sum_{i=1}^{I} O_{ikt}^{p} \qquad \forall t, k, p, i, j \qquad (17)$$

$$Y_{k}, Z_{mt}^{p} \in \{0,1\} \qquad \forall t, k, m, p \qquad (18)$$

$$Q_{mt}^{p}, U_{kmt}^{p}, R_{jkt}^{p}, X_{ijt}^{p}, O_{ikt}^{p}, I_{mt}^{p}, I_{kt}^{p}, I_{jt}^{p}, S_{it}^{p} \geq 0; \qquad \forall t, k, m, p, i, j \qquad (19)$$

The first objective function shown in Eq. (3) aims to minimize the total cost of the SC network, where the first term in the right hand side (RHS) refers to the fixed cost of establishing warehouses. The rest of the terms in RHS of Eq. (3) refer respectively to the transportation cost of the products from the plants to warehouses, the setup cost of production, the production cost of the plants, the end inventory holding cost of the products in warehouses at plant, the end inventory holding cost of the products in warehouses at DC, the end inventory holding cost of the products in warehouses at retailer, the transportation cost of products from DC to retailers, the transportation cost of products from retailers to customers, the transportation cost of products from DC to customers, the shortage cost of customers' demands. The second objective function in Eq. (4) considers customer satisfaction by maximizing the average total number of products dispatched to customers from both DCs and retailers. The constraints in Ineq. (5) guarantee that the total required time to produce the products cannot exceed the total available time. Constraints (6) limit the volume of the products dispatched to potential warehouses to their total storage capacity. Constraints (7) require that the quantity of a product dispatched to each customer in a period cannot exceed his/her demand. The constraints in Ineq. (8) restrict the end-product inventory of potential warehouses to their available capacity. Constraints (9) specify that the total quantity shipped from a plant cannot exceed its capacity. The constraints in Ineq. (10) state that the production volume must be less than the total storage capacity at the plants. Constraints (11) ensure that the end-product inventory is less than the total storage capacity at the plants. Constraints (12) ensure that the end-product inventory is less than the total storage capacity at the retailers. Constraints (13) ensure that the end-product inventory is less than the total storage capacity at the DC. The constraints in Eq. (14) are balance equations for the end-product inventory at potential retailers. Similarly, Constraints (15) are balance equations for the end-product inventory at the DC. Constraints (16) are balance equations for the end-product inventory at the plant. The constraints in Eq. (17) are balance equations for shortages of the customers' demands. To conclude the formulation, types of the variables and their possible values are defined in (18) and (19).

3. Implementation

In this section, the case study that has been conducted in Bangladesh at RFL Plastic Limited in Hobigonj is described. RFL has the most sophisticated distribution network through partnership, collaboration and knowledge sharing. Currently the company is serving more than 36 countries around the globe. RPL aims to make each of its products a paragon of quality and technical excellence. Through its constant endeavors of research and innovation it strives to come up with new products that help architects and builders to bring new creations in market. The strength behind this business growth is large production capacity, good quality of products, international standards for products maintenance, having technically sound production & operation team, strong distribution network and after sales service. In 2015, about 175,000 orders was cancelled in Bangladesh due to political instability, natural events, terrorist attacks, weather condition, labor absence, change in owner etc. The total supply chain cost was high because the lack of coordination. Moreover, the customer satisfaction was not the primary factor of that company. In order to collect data, a Plastic Industry situated at Hobigonj, was visited by the authors. Data was collected on main products plastic flash tank and round mirror.

3.1 Data description

To demonstrate the practicality of the proposed methodology, RFL Plastic Limited was used as a study. RFL Plastic Limited is situated at Hobigonj Industrial Park (HIP), Hobigonj. Here many types of products are produced two of them are considered here. They are:

1. Plastic flash tank
2. Round mirror

Let, Plant1=M-1, Customer-1= Cus-1 to Customer-5= Cus-5, Distribution Center-1 = DC-1 to Distribution Center-3= DC-3, Period 1=T_1 and Period 2=T_2.
Here all of the cost is in taka and time in hours.

Table 1
Unit production cost of product p by manufacturing plant m in period t

	M-1
Product-1	600
Product-2	320

Table 2
Unit transportation cost of product p to DC k by plant m in period t

	DC-1(P_1&P_2)	DC-2 (P_1&P_2)	DC-3 (P_1&P_2)
M-1	10,5	9.9,4.9	10.10,5.10

Table 3
Unit transportation cost of product p to DC k by plant m in period t

	Retailer-1(P_1&P_2)	Retailer-2 (P_1&P_2)	Retailer-3 (P_1&P_2)	Retailer-4(P_1&P_2)
DC-1	9.9,4.9	10,5	10.10,5.10	10,5
DC-2	10.10,5.10	10,5	9.9,4.9	10,5
DC-3	9.9,4.9	10,5	10,5	10.10,5.10

Table 4
Unit transportation cost of product p to customer i by retailer j in period

	Cus-1(P_1&P_2)	Cus-2(P_1&P_2)	Cus-3(P_1&P_2)	Cus-4(P_1&P_2)	Cus-5(P_1&P_2)
Retailer-1	9.9,4.9	10,5	10.15,5.15	10,5	10.10,5.10
Retailer-2	10.10,5.10	10,5.5	9.9,4.9	10,5	9.9,4.9
Retailer-3	9.9,4.9	10,5	10,5	10.20,5.20	10,5
Retailer-4	10.10,5.10	10,5.2	9.5,4.5	10.5,9.5	9.5,4.5

Table 5
Unit transportation cost of product p to customer i by DC k in period t

	Cus-1(P_1&P_2)	Cus-2(P_1&P_2)	Cus-3(P_1&P_2)	Cus-4(P_1&P_2)	Cus-5(P_1&P_2)
DC-1	12.5,6.5	13.5,7.5	11.5,7	12,6	13,7
DC-2	11.5,7	12,6	13,7	12.5,6.5	13.5,6.5
DC-3	12,6	12.5,6.5	13.5,7.5	13.5,7	11.5,6

Table 6
Unit Inventory holding cost of product p by plant m in period t

	M-1,(T_1&T_2)
Product-1	2, 2.1
Product-2	1.2, 1.1

Table 7
Unit inventory holding cost of product p by DC k in period t

	DC-1,(T_1&T_2)	DC-2,(T_1&T_2)	DC-3,(T_1&T_2)
Product-1	1.9, 2	2, 1.9	2.1,2
Product-2	1.1,1	1.2,1	1.10, 1.2

Table 8
Unit inventory holding cost of product p by retailer j in period t

	Retailer-1,(T_1&T_2)	Retailer-2,(T_1&T_2)	Retailer-3,(T_1&T_2)	Retailer-4,(T_1&T_2)
Product-1	2.2, 2	2,2.20	2.15, 2	2,2.15
Product-2	1.3,1.15	1.15,1	1.50,1.10	1.20,1.15

Table 9
Setup cost of producing product p by plant m in period t

	M-1(T_1 &T_2)
Product-1	8,8
Product-2	7,7

Table 10
Unit shortage cost of product p in supplying the demand of customer i in period t

	Cus-1	Cus-2	Cus-3	Cus-4	Cus-5
Product-1	800	700	750	900	700
Product-2	550	500	450	500	550

Table11
Fixed cost of selecting a center to establish DC k

	DC-1(Tk.)	DC-2(Tk.)	DC-3(Tk.)
Fixed-Cost	2050000	2100000	2000000

Table 12
Production time needed by plant m to produce one unit of product p in period t

	Product-1	Product-1	Total available time (P_1&P_2)
M-1	0.25 h	0.20 h	1584, 1056 same for T_2

Table 13
Set up time of producing product p by plant m in period t

	Product-1, (T_1 &T_2)	Product-1, (T_1 &T_2)
M-1	8, 8	7,7

Table14
Total storage capacity available M^3

Item	Retailer-1	Retailer-1	Retailer-1	Retailer-1	DC-1	DC-1	DC-1	M-1
Storage capacity	1000	800	900	900	1350	1200	1000	3500

Table 15
Total transportation capacity available for plant m to dispatch product p in a period t

	Product-1(T_1 &T_2)	Product-1(T_1 &T_2)
M-1	3200, 2800	2600, 2400

Table16
Uncertain demand of product p by customer i in period t

	Cus-1	Cus-2	Cus-3	Cus-4	Cus-5
Product-1	1300	1200	1200	1400	1150
Product-2	1100	950	1200	900	1100

Total 11500

Table17
Volume of one unit product p (M^3)

Item	Product-1	Product-2
Volume (M^3)	0.44	0.28

Data Source: All of the data are collected from RFL plastic limited.

3.2 A solution procedure

There are generally two approaches to solve complicated multi-objective optimization problems. In the first approach, the problem is first converted to a single-objective optimization using some multi-criteria decision making (MCDM) methods described in Hwang and Masud (1979).Then, a single-objective evolutionary algorithm (SOEA) such as GA, simulated annealing (SA), imperialist competition algorithm (ICA), harmony search algorithm (HAS), and particle swarm optimization (PSO), epsilon constraint methods, is employed to solve the single-objective problem in one single simulation run, Deb et al. (2001). In the second approach, a multi-objective evolutionary algorithm (MOEA) such as non-dominated sorting genetic algorithm (NSGA-II), non-dominated ranking genetic algorithm (NRGA), and multi-objective particle swarm optimization (MOPSO), is directly used to find a set of optimal solutions called Pareto optimal front in a single simulation run. As MOEAs are usually fast to find Pareto fronts in a single simulation run and that SOEAs require several runs to obtain a front, a MOEA is utilized in this section to solve the complex bi-objective optimization problem at hand. Among MOEAs, the NSGA-II due to its popularity, its capability to solve similar problems, and its ease of use is chosen.

Genetic Algorithm (GA)

Genetic Algorithms relies on the mechanics of the natural selection and natural genetics. They conjugate the survival of the fittest string structures. The structured creates randomized information exchange to make an algorithm of the innovative flair of human search. Genetic Algorithms have been developed by Holland (1975) which is a population based probabilistic and optimization technique. They are classified as global search heuristics and they also are a specific class of evolutionary algorithms that use techniques stimulated by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination).They are implemented as a computer simulation of candidate solutions to an optimization problem expresses towards better solution. Conventionally, solutions are described in binary strings of 0s and 1s, but other encodings are not also impossible. The evolution usually begins from a population of randomly produced individuals and occurs in generations. In each generation, the fitness of every individual in the population is appraised, multiple individuals are selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to originate a new population. The new population is also used in the next iteration of the algorithm. Commonly, the algorithm completes when either a maximum number of generations has been generated, or an optimal fitness level has been reached for the population. If the algorithm has completed owing to a maximum number of generations, an optimal solution may or may not have been reached.

Working Cycle of a GA:

1. A set of beginning population of individuals is produced indiscriminately.
2. Fitness of every individual of the population is appraised.
3. The appraised function is given by the programmer and delivers the individuals a score.
4. Two individuals are chosen based on their suitability, the higher the suitability, the higher the chance of being chosen.
5. These individuals then "reproduce" to generate one or more offspring, after which the offspring are mutated randomly.
6. This continues until an optimal solution has been obtained or a particular number of generations have exceeded, depending on the necessity of the programmer.

General Criteria of Genetic Algorithm (GA)

1. Initialization
2. Selection
3. Crossover
4. Mutation
5. Termination

Initialization

Initially the individual solutions are indiscriminately produced to form a beginning population. The population size relies on the characteristics of the problem, but symbolically holds several hundreds or thousands of possible solutions. Traditionally, the population is produced indiscriminately, covering the whole range of possible solutions (the *search space*).

Selection

During every possible generation, a ratio of the existing population is chosen to reproduce a new generation. Separate solutions are chosen via a *fitness-based* process, where fitter solutions (as measured by a fitness function) are commonly to be selected. Particular selection methods rate the fitness of every solution and discriminately choose the best solutions. Another methods rate only an indiscriminate sample of the population, as the process may be time-consuming. Most functions are stochastic so that a proportion of less perfect solutions are chosen.

Crossover

Crossover is a mechanism that produces new individuals by joining parts from two Individuals. Crossover is experimental which makes a huge jump in between two areas. Single point, Multipoint and identical crossovers are available. Simulated Binary Crossover produces children solutions to the different in parent solution.

Mutation

Mutation is a mechanism that produces new individual by creates alternates in a single Individual. Mutation is experimental that produces indiscriminate light deviations, so staying close to the parent. Simply mutation can present new information.

Termination

This process is repeated until the termination condition has been succeeded.

Common terminating conditions are:

1. An optimal solution is got that satisfies the minimum criteria.
2. Fixed number of generations succeeded.
3. Allocated budget reached
4. The highest ranking solution's fitness has reached a bulk that possible iterations no longer generate better results.
5. Manual inspection
6. Any Combinations of the above.

Genetic Algorithm in Step by Step

Step1: Produce random population of n chromosomes.

Step2: Calculate the fitness f(x) of the n chromosomes in the population.

Step3: Generate new population by iterating three steps (selection, crossover and mutation) until new population is created.

Step4: Use new produced population for the operation of algorithm.

Step5: If the condition is satisfied, stop and get the best solution in the running population.

Step6: If the condition is not satisfied, then go to step2 and repeat the loop.

3.3 Epsilon constraint method

The ε- constraint method was actually suggested by Haimes, et al. (1971). This method lessens the number of objectives of multi objective problems. Only one of the objectives is considered as main objective functions and other objective functions are turned into constraints. So the multi objective problems are turned into single objective problems, then it is called ε- constraint problem. By changing ε values with the proper interval, a number of Pareto optimal solutions can be found. This method can also quash the disadvantages of the weighting method proposal by Berube, et al. (2009). Ideal point and nadir point can be determined by acquiring the full Pareto front. Ideal point and nadir point specifies the lower and upper bounds of Pareto optimal points.

Working cycle of ε- constraint method:

1. Calculate the ideal and nadir point of the objective functions.
2. Produce a Pareto optimal starting point.
3. Ask for favorable information from the decision maker (set of new solutions to be produced).
4. Produce new Pareto optimal solution according to the favorable.
5. If some solutions are produced, ask the decision maker to choose the best solution.
6. Stop (If the decision maker wants; otherwise go to step3).

This process can solve problems with integer objective values and may achieve dominated points. So, the full non dominated set can be achieved after finishing dominated solutions. The ε- constraint problems can be solved through continuously diminishing the values of ϵ.

3.4 NSGA-II

NSGAII, first introduced by Deb et al. (2001), is one of the most applicable and propounded algorithms based on GA to solve multi-objective optimization problems. NSGA-II starts generating a random parent population of size nPop. During several consecutive generations, the objective values of a population are evaluated using an evaluation function. Then, the population is ranked based on the non-domination sorting procedure to create Pareto fronts. Each individual of the population under evaluation obtains a rank equal to its non-domination level (1 is the best level, 2 is the next-best level, and so on), where the first front contains individuals with the smallest rank, the second front corresponds to the individuals with the second rank, and so on. In the next step, the crowding distance between members on each front is calculated by a linear distance criterion. As a binary tournament selection operator based on a crowded-comparison operator is used, it is necessary to calculate both the rank and the crowding distance of each member in the population. Using this selection operator, two members are first selected among the population. Then, the member with the larger crowding distance is selected if they share an equal rank. Otherwise, the member with the lower rank is chosen. Next, a new population of offspring with a size of n is created using the selection, the crossover, and the mutation operators to create a population consisting of the current and the new population of the size of (nPop + n). Finally, a population of an exact size of nPop is obtained using the sorting procedure. In this procedure, solutions are sorted twice: first based on their crowding distances in descending order, second based on their ranks in ascending order. The new population is used to generate the next new offspring by repeating the above steps in order. This process is repeated until the stopping condition is met. At the end of NSGA-II implementation, a set of non-dominated Pareto-optimal solutions are obtained, as all the solutions are the best in a sense of multi-objective optimization.

Procedure of NSGA-II

- Step 1: Create a random parent population P_0 of size N.
- Set t = 0.
- Step 2: Apply crossover and mutation to P_0 to create offspring population Q_0 of size N.
- Step 3: If the stopping criterion is satisfied, stop and return to P_t.
- Step 4: Set $R_t = P_t \cup Q_t$.
- Step 5: Using the fast non-dominated sorting algorithm, identify the non-dominated fronts F_1, F_2, …….,F_k in R_t.
- Step 6: For i = 1,……,k do following steps:
- Step 6.1: Calculate crowding distance of the solutions

- Step 6.1.1: Rank the population and identify non-dominated fronts F_1, F_2……….. F_R. For each front j = 1,…….., R, repeat Steps 6.1.2 and 6.1.3
- Step 6.1.2: For each objective function k, sort the solutions in F_j in the ascending order. Let $l = |F_j|$ and $x_{[i;k]}$ represent the ith solution in the sorted list with respect to the objective function k. Assign $cd_k(X_{[i;k]}) = \infty$ and $cd_k(X_{[i;k]}) = \infty$, and for i = 2, …., *l*-1 assign
  - $cd_k(X_{[i,k]}) = \frac{Z_k(X_{[i+1,k]}) - Z_k(X^k_{[i-1,k]})}{Z_K^{Max} - Z_K^{Min}}$
- Step 6.1.3: To find the total crowding distance cd(x) of a solution x, sum the solution's crowding distances with respect to each objective, i.e., $cd(x) = \sum_K Cd_K(X)$.
- 6.2: Create P_{t+1} as follows:
- Case 1: If $|P_{t+1}| + |Fi| \leq N$, then set $P_{t+1} = P_{t+1} \cup F_i$;
- Case 2 If $|P_{t+1}| + |Fi| > N$, then add the least crowded N - $|P_{t+1}|$ solutions from F_i to P_{t+1}.
- Step 7: Use binary tournament selection based on the crowding distance to select parents from P_{t+1}. Apply crossover and mutation to P_{t+1} to create offspring population Q_{t+1} of size N.
- Step 8: Set t = t + 1, and go to Step 3.

4. Results Analysis

When the Problem size was small then the results were approximately same for Fast Non-dominated Sorting Genetic Algorithms (NSGA-II), Multi-objective Genetic Algorithms (MOGA) and Epsilon Constraint Methods. The considered small size problem was as follows:

1) Shimizu and Aiyoshi (2013)

$\min_x f_1(x, y) = x^2 + (y - 10)^2$

s.t.

$-x + y \leq 0$

$x \in [0, 15]$

$\min_y f_2(x, y) = (x + 2y - 30)^2$

s.t.

$x + y - 20 \leq 0$

$y \in [0, 20]$

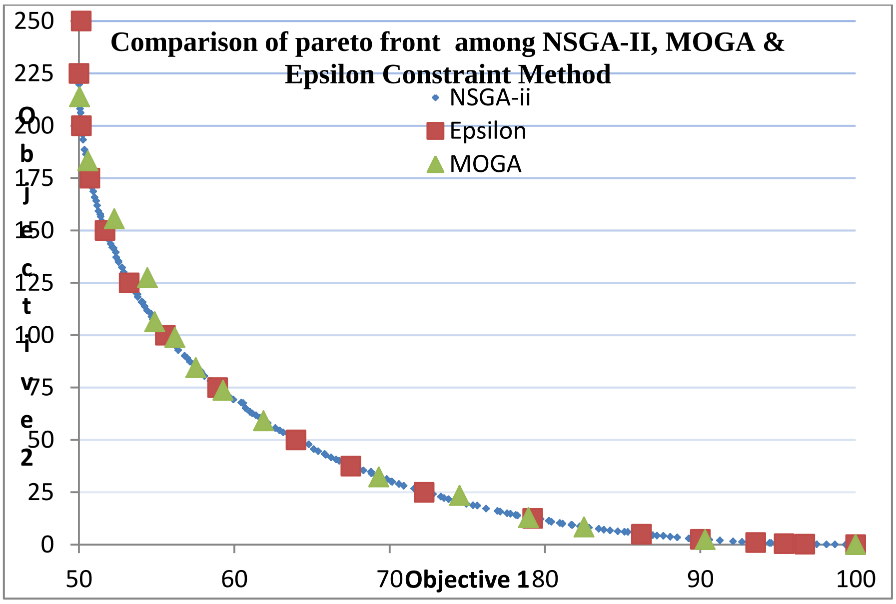


Fig.2. Comparison of pareto front among NSGA-II, MOGA & Epsilon Constraint Methods

In epsilon constraint method one objective was considered primary function where the other objective was considered as constraints. In epsilon constraint method would return a single solution rather than a set of solutions that can be examined for trade-offs to take proper decision. For this reason, decision-makers often prefer a set of good solutions considering the multiple objectives. From the above figure 02 it has seen that the epsilon constraint method gives twenty points at twenty simulations run that means one point in one simulation run. From the above figure 02 it also seen that NSGA-II gives more pareto optimal points than MOGA & Epsilon Constraint Methods. So among the three methods NSGA-II is best methods because it gives more Pareto optimal solution in a single simulation run which are effective to take proper decisions. The epsilon constraint method gives the approximate same result though it was a small size problem, and MOGA gives the moderate results in this case because it gives moderate number of Pareto optimal solution in a single simulation run that can be examined for trade-offs to take proper conclusion. Based on the average time required to produce the set of pareto optimal solution the MOGA gives the best result because it takes less time to produce the same amount of pareto optimal solution in a single simulation run than NSGA-II. In epsilon constraint method would return a single solution rather than a set of solutions that's why average time required to produce the set of pareto optimal solution is very high.

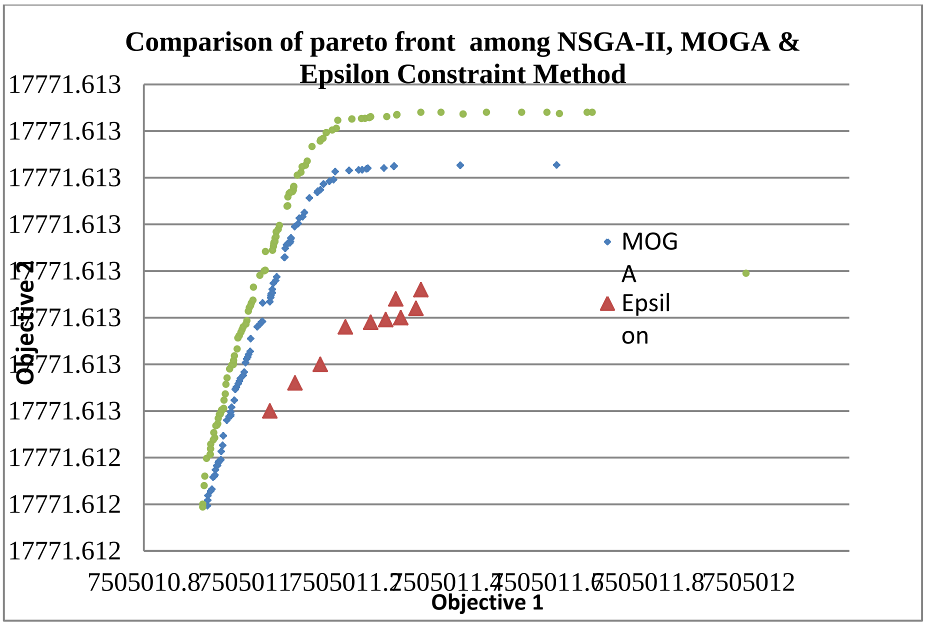


Fig. 3. Comparison of pareto front among NSGA-II, MOGA & Epsilon Constraint Method

When the authors considered the proposed large size problem then algorithms gives different result. From the figure 03 it has seen that the NSGA-II gives more pareto optimal points that are very important for trade off for the two conflicting objectives to take proper decisions. The MOGA gives the moderate results in this case because it gives moderate number of pareto optimal solution in a single simulation run that can be examined for trade-offs to take proper decision. In epsilon constraint method would return a single solution rather than a set of solutions in a single run that is why it is the worst method among these methods. Therefore among the three methods NSGA-II is best methods in that case because it gives more pareto optimal solution in a single simulation run that can be examined for trade-offs to take proper decision. The epsilon constraint method gives the different poor result though it is a large size problem, and its very time consuming to produce set of pareto optimal points that can be examined for trade-offs to take proper decisions. MOGA gives the more diversified set of solution and it was very fast to find set of pareto optimal points. Based on the average time required to produce the set of pareto optimal solution the MOGA gives the best result because it takes less time to produce the same amount of pareto optimal solution in a single simulation run than NSGA-II. In epsilon constraint method would return a single solution rather than a set of solutions that's why average time required to produce the set of pareto optimal solution is very high and convergence rate are slow. The proposed technique increased the number of product dispatched to customer by providing optimum amount of product directly from distribution center to customer area as shown in table 18.

The table 19 is indicated the product flow from retailers to customer zone. In this case the product flow is reduced as the product is transferred from both DCs and retailers. The first objective function indicates minimize average total Supply chain cost is z_1= Tk. 7505011 and the second objective function indicates maximize average number of product dispatched to customer from retailer and directly form distribution in case when retailer is unable to satisfy the demand is z_2= 16772 units per 6 months. The authors considered the time horizon for six months because in fixed time horizon and it is easy to calculate the number of accident that may happen due to natural events, terrorist attacks, change in owners, labor mistake, weather conditions, political instability, etc.

Table 18
Product dissemination from distribution centers to customer zone.

Period	DCs	Product	Customer Zone (Units)				
			1	2	3	4	5
1	1	1	89	89	89	88	89
		2	**91**	88	90	89	88
	2	1	88	89	89	92	89
		2	89	89	90	88	90
	3	1	89	91	89	91	88
		2	90	89	90	90	89
2	1	1	88	90	88	89	89
		2	89	89	91	90	88
	2	1	89	88	88	89	92
		2	91	88	89	90	92
	3	1	90	89	89	89	90
		2	89	90	88	89	91

Table 19
product distribution from retailers to customer zone.

Period	Retailer	Product	Customer Zone (Units)				
			1	2	3	4	5
1	1	1	75	71	71	72	72
		2	72	73	73	72	71
	2	1	70	71	73	71	71
		2	72	72	74	75	74
	3	1	73	73	72	73	73
		2	72	75	74	72	72
	4	1	72	72	72	74	72
		2	72	72	72	74	72
2	1	1	73	72	74	74	72
		2	71	74	72	75	72
	2	1	74	72	73	73	71
		2	73	73	73	72	72
	3	1	73	73	72	74	72
		2	74	73	71	72	74
	4	1	71	71	72	72	72
		2	73	71	71	73	71

5. Conclusions and Future Work

A new multi-objective optimization model for multi-product multi-period four echelon supply chain problem under uncertainty was considered in this paper. The proposed model aims to optimize two conflicting objectives simultaneously, that were minimize total supply chain cost and maximize the average total number of products dispatched to the customer. The problem was first formulated into the framework of a constrained multi-objective mixed integer linear programming model. As the model developed in this study was hard and time consuming to be solved analytically, a multi-objective genetic algorithm (MOGA) was utilized to find Pareto fronts. Since there was no benchmark available in the literature to validate the results obtained, another GA-based multi-objective evolutionary algorithm called non-dominated sorting GA (NSGA-II) was used as well. The proposed multi objective mixed integer linear programing problem was also solved Epsilon Constraint Methods via the MATLAB software to find pareto front but it was very time consuming because it would return a single solution rather than a set of solutions in a single run. So among the three methods NSGA-II was best methods in that case because it gives more pareto optimal solution in a single simulation run that can be examined for trade-offs to take proper decision. The proposed model was validated by using multi objective Meta heuristics algorithms MOGA & NSGA-II. To demonstrate the practicality of the proposed methodology, RFL Plastic limited was used to as a study. This research can be beneficial to all SCs and logistics manager under uncertain environments. Food, pharmacological, and industrial product supply chains are some instances for which this work can be applicable. In the developed model the back word supply chain are not considered.

There are several recommendations for future work as follows:

- Considering using other meta-heuristics such as MOPSO, multi-objective harmony searches (MOHS) and multi-objective simulated annealing (MOSA) to solve the problem.
- Designing and analyzing the problem under a four-echelon SCN to minimize total supply chain cost and maximize total number of product dispatched to customer considering the whole network uncertainty.
- Using other probability distributions such as the uniform distribution to model uncertainties involved and using queuing models to hybridize the problem further.
- Considering some input parameters as fuzzy numbers to bring the application closer to reality
- In addition, one can formulate the problem considering lost sale or a mixed form of backorder and lost sale.

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