Multi-Objective Differential Evolution (MODE) for Optimization of Supply Chain Planning and Management

B. V. Babu* and Ashish M. Gujarathi[1]

Abstract — Many problems in the engineering domain involve more than one objective to be optimized simultaneously. The optimal solution to a multi-objective function results in a set of equally good solutions (Pareto optimal set), rather than a unique solution. Several entities are present in a typical supply chain problem. Each of these entities has its individual objectives. When all the objectives of supply chain are combined they work towards a common goal of increasing the profitability of an organization. The supply chain model is thus multi-objective in nature which involves several conflicting objectives. A three-stage supply chain problem (involving a network of supplier, plant and customer zones) is solved using Multi-Objective Differential Evolution (MODE) algorithm in this work. Three cases of objective functions are considered in this study. Pareto optimal solutions are obtained for each case. The results are compared with those reported using NSGA-II in the literature.

I. Introduction

IN order to the lead market in terms of product quality and quantity, it is very important to make use of the limited resources and plan effectively to identify and select new opportunities. The ability of any company to handle the challenges of reduced lead-times, costs associated with production, increased customer service levels and improved quality of product decides the company's position in marketplace. Proper planning of various entities involved in the business are essential for successful running of business. Traditionally, different entities of business, such as procurement, production, distribution and marketing used to work independently. The ultimate goal of any industry is to maximize profit. But while maximizing profit these business entities have different objectives. For example, aim of marketing is to maximize customer service level and sales volume, but these objectives conflict with the objective of production and distribution. Raw material procurement decisions are based on minimum cost of goods while production and distribution decisions are based on maximum output from plant with minimum production costs and demand. Many companies do not pay attention on high levels of inventory or long lead times (amount of time between the placing of an order and the receipt of the goods ordered). Supply chain planning and management play an important role in coordinating and integrating different entities of business towards a common goal. Studies show that supply chain planning has great potential for improvement in achieving the aim of those objectives [1]-[3].

Several detailed studies have been reported in the literature on supply chain optimization. Ding et al. [4] dealt with an overview of the ONE system as an integrated toolbox for a holistic assessment and optimization of enterprise networks. They applied this tool and the associated approach to a small but realistic problem for the design and optimization of supply chain networks. Truong and Azadivar [5] proposed a hybrid algorithm based on genetic algorithm and mixed integer parameter model. They solved the supply chain optimization routine considering total cost as a single objective. Hunter et al. [6] have presented several case studies for illustration of re-estimation of demand and quick response (QR) versus traditional retail practice. Their case studies showed the importance of supply chain planning. They showed that useful information can be made available very early in the season to the buyer, apparel manufacturer and to the textile producer (to whom lead-time is critical by use of demand re-estimation). Comparisons of performance parameters for traditional and QR procedures showed QR procedures are superior to traditional practices. Berning et al. [7] arrived at a practical solution to a complex scheduling problem in a chemical process industry involving batch production. They showed that the successful implementation has lead to both quantitative and qualitative benefits. Supply chain problems are functions of several parameters, e.g., lead times at each node [8], inventory management [9], stochastic nature of supply chain[10], and logistics issue in supply chain [11] etc. These entities when combined together make supply chain problem very complex and difficult to solve.

Supply chain needs to be considered as a whole but not as an individual organization. Therefore a successful supply chain planning model should increase the value of entire supply chain by fulfilling customers demand with reduced product cost, raised quality of product, and by making sure that right product and services are delivered at right time, right place and at right location thus increasing the profitability. In this way, supply chain can be viewed as a framework which includes the methodologies and techniques to manage and control the flows of material, information,

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and financials in the supply chain to deliver value to all users (Starting from supplier to customer) of the model. Thus the task of successful supply chain model is to design, plan, and execute the activities at different levels (e.g., Supplier, producer, distributor and customer) so as to provide the desired level of service to supply chain customers efficiently.

There are many entities in a supply chain, as discussed earlier, each of which try to maximize their own inherent objective functions in business transactions. Many of their interests are conflicting in nature. Thus for two conflicting objectives of supply chain each objective correspond to different optimal solutions. An optimal solution obtained by traditional single objective optimization procedure may correspond to non-optimal design of supply chain when we look at the design from systems optimization perspective. The results can also be misleading in the situations of nonlinear and complex search space, where an inefficient algorithm may get attracted towards locally optimal solutions.

Therefore, the decision maker should be presented with a set of equally good solutions, which are referred as Pareto optimal solutions or non-inferior solutions. The decision maker then can choose the best design as per his convenience from the efficient set or Pareto solutions. Several algorithms are available in the literature for solving multi-objective optimization problems, e.g., non dominated sorting genetic algorithms (NSGA) and its variants, multi-objective genetic local search algorithm, multi-objective simulated annealing (MOSA), Pareto ant colony optimization (PACO), Pareto differential evolution (PDE), etc. [12]-[14]. It is observed that some of the multi-objective optimization algorithms are not able to give a well diversified and smooth Pareto front, while other algorithms gets converged to a single point solution. Multi-objective differential evolution (MODE), which is proposed earlier by Babu et al.[15], is found to give better results than those reported in the literature when applied to multi-objective optimization of styrene reactor [15] and several test problems [16].

II. Supply Chain Optimization using Multi-Objective Differential Evolution

The supply chain is basically the integrated network among retailers, distributors, transporters, storage facilities and suppliers that participate in the sale, delivery and production of a particular product for [17]:

1. Maximizing overall value generated
2. Increasing competitiveness of the whole chain
3. Minimizing systemwide costs while satisfying service level requirements
4. Matching supply and demand profitably for products and services

It is due to the above reasons that the supply chain optimization problem is considered as a multi-objective optimization problem (MOOP). The supply chain problem therefore has to be considered as a whole (system optimization) without placing the individual preferences of the individual objectives. The built up supply chain model should be capable of integrating all the entities so that the flow of information happens among the entities in order to meet the highly fluctuating demand of the market. The important issues that drive the supply chain models and govern its design are:

1. Inventory planning and management
2. Transportation and logistics management
3. Facilities location and layout design
4. Flow of information among the entities

These four drivers represent major flows associated with supply chain problem. In order to maximize overall profitability, it is not possible to get a unique solution that satisfies either all the criteria or the objectives. If all the objectives are satisfied then the solution obtained could be a non-Pareto optimal point. Hence in multi-objective optimization problem, we are interested in set of solutions (rather than a single solution) which are non-inferior with respect to each other and are part of Pareto optimal front.

Considering the complexity associated with the supply chain problems, very little work has been done in this area. Early attempts of solving supply chain model involved a single objective function [18], [19]. Recently researchers have started developing models based on multi-objective functions [20], [21]. However these models do not use an evolutionary algorithm perspective in developing non-dominated set of solutions. Researchers for many similar problems have used goal-programming methods. But the goal programming methods cannot develop an entire Pareto front. Multi-objective optimization of supply chain was carried out using non-dominated sorting genetic algorithm-II (NSGA-II) algorithm [10].

MODE [15] is an extension of Differential evolution (DE) [22] (an improved version of Genetic algorithm [23]) for solving multi-objective optimization problems. Several applications of DE are reported in literature [13], [14]. DE is modified to Multi-objective Differential Evolution to handle the multi-objective optimization problems. The pseudo-code for MODE is reported in literature [15]. The working of MODE can be explained in brief as follows: an initial population is generated at random using mapping rule. The dominated solutions are removed from the population. The remaining non-dominated solutions are retained for recombination. Three parents are selected at random out of non-dominated population points. A target vector is chosen. Three other variables are also selected from population. The difference of two vectors is multiplied by a scaling factor. This weighted difference is then added into third vector to create a noisy random vector. Cross over is carried out between the target vector and the noisy random vector to generate a trial vector. The cost of trial and target vectors is compared and the variables corresponding to best cost is passed into next generation. In this way another target vector is selected for further recombination. This continues till maximum value of number of population (NP) is reached. The non-dominated population at the end of each generation becomes the population for the next generation. This continues till the stopping criterion is met. The stopping criteria could be of two kinds. 1. There is no solution added to the non-dominated front for a specified number of generations, 2. Program has reached the assigned upper bound on number of generations. The stopping criteria may be a combination of the two as well. The detailed discussion on MODE is available in our earlier literature [15].

III. PROBLEM FORMULATION

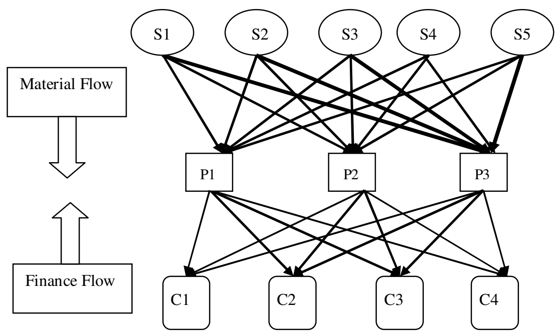

Fig. 1. Flow of financials, materials and the entities involved in supply chain problem.

A. Supply Chain Viewed as a Network Model

As a part of the planning process, the structure of the supply chain needs to be represented. This is usually done using a network model. A network model is used in this study to graphically represent a supply chain model. Fig. 1 represents the flow of material and entities involved in the supply chain. In Fig. 1 each node represents existing facilities (e.g., supplier, plant and customer). The arks and link are used to connect the nodes in supply chain model. These arks represent the flow of material from one node to another, e.g., the raw material supply from supplier to plant and then from plant to customer zone. In this problem, supplier also represents the most upstream entity whereas customer zone represents most downstream entity. Thus, the flow of material occurs from supplier to customer zone and the flow of financials occurs from customer zone to the supplier. The direction of these flows can change only in the case of reimbursement or rebate. In this problem we have considered only one way flow of material and the financials.

Present study considers that a single product is manufactured from three different components (raw materials). The nomenclature used in the present problem is as follows (Fig. 1): S1-S5 denotes the five suppliers; P1-P3 denotes the three Manufacturing establishments (plants), and C1-C4 denotes the four customer zones. The flow of goods and finance are also shown in Fig. 1.

In this problem we have considered that all five suppliers can supply three different components to all three plants. These components can be transported by road/rail or shipped to any of the three plants where the product is manufactured. The cost of transportation is also taken into account. The finished product from plant is then shipped to the customer zones based on demand. In actual practice, few suppliers are preferred over others depending on their previous performance, quality, timeliness of goods delivered. In order to give more value to the preferred suppler, we have added more value in terms of costs for supplier's previous performance, quality provided and timeliness of goods supplied. Thus the most preferred supplier has a lowest cost for particular component. Different indices describe the interactions between different entities in supply chain model. The set of those indices are

(i, j): Component-Supplier
(i, j, k): Component-Supplier-Plant
(k, l): Plant-Customer Zone

B. Problem Formulation

In this study, five objective functions are considered which are divided in three sets of two objective problems. The objective functions reported in this study are taken from literature [10]. The objectives are minimization of Total operating cost (TOC), Total cost (TC) and Machinery cost (MC) and maximization of profit and revenue.

Objective Functions

Three sets of objective functions used in this formulation are as follows:

1) Objective Functions Set 1

Objective Function 1: Minimize TOC
Objective Function 2: Minimize MC/TOC

Total operating cost plays an important role in statistics of manufacturing of product. Therefore, minimization of TOC has been given greater importance in supply chain optimization problems. The second objective function is the ratio of manufacturing cost to total operating cost. This objective function also holds importance since it is very important to ensure that manufacturing cost fall within a certain permissible bound as a percentage of the total operating cost. Those two objectives clearly show the trade-off among each other, as value of first objective (TOC) is appearing in the denominator of second objective function.

2) Objective Functions Set 2

Objective Function 1: Maximize Profit
Objective Function 2: Minimize MC

In this problem, the conflict is not easily seen. The results are analyzed in the subsequent section, which show the conflict among the objectives.

3) Objective Functions Set 3

Objective Function 1: Maximize Revenue
Objective Function 2: Minimize TC

This multi-objective optimization problem consists of maximization of revenue and minimization of transportation cost. The transportation cost plays a major role in total operating cost and it also acts as interacting medium between different entities of the supply chain model. Therefore it needs to be considered in every supply chain optimization problem.

C. Variables and Constraints

Total 36 variables are involved in the present study. The summary of these variables is as follows: 15 variables for 3 components transported from 5 suppliers to three plants; 12 variables for amount of product from 3 plants to 4 customer zones and 9 variables for inventory of each component (3) at each plant (3). The constraints are also imposed on plant capacities, supplier capacities, inventory balancing and total operating cost of the supply chain model. Penalty function method is used to handle constraints. This method involves penalizing the objective functions in proportion of constraint violation [13]. The constraints involved in the study are:

$$\sum_{l} Y_{k,l} \leq U_{k} \quad \forall k \tag{1}$$

$$\sum_{k} S_{i,j} X_{i,j,k} = L(i,j) \quad \forall i,j \tag{2}$$

$$\sum_{j} S_{1,j} X_{1,j,k} = \sum_{l} Y_{k,l} + I_{1,k} \ \forall k \tag{3}$$

$$\sum_{j} S_{2,j} X_{2,j,k} = \sum_{l} Y_{k,l} + I_{2,k} \ \forall k \tag{4}$$

$$\sum_{j} S_{3,j} X_{3,j,k} = \sum_{l} Y_{k,l} + I_{3,k} \quad \forall k \tag{5}$$

$$TC = \sum_{i} \sum_{j} \sum_{k} (X_{i,j,k} S_{i,j} STC(i,j,k)) + \sum_{k} \sum_{l} Y_{k,l} PTC(k,l) \tag{6}$$

$$TMC = \sum_{k} (LC(k) + MC(k) + IC(k)) \tag{7}$$

$$SC = \sum_{i} \sum_{j} (CS(i,j) S_{i,j} X_{i,j,k}) \tag{8}$$

$$TOC = TC + TMC + SC \tag{9}$$

Equations 1-5 represent the constraints used in the present study. Equations (1) and (2) represent the constraints on plant and supplier capacity respectively. Constraints are imposed on Inventory balance of component 1, 2 and 3, which is represented by set of equations (3), (4) and (5) respectively. A variable *S(i, j)* in the above constraints is a binary variable which denotes whether component *i* is supplied by supplier *j* or not. In this study, the *S(i, j)* values are fixed as 0 and 1 randomly. Equations 6, 7 and 8 are expressions for transportation cost (TC), total manufacturing costs [TMC; which include the plant labor, inventory (IC) and manufacturing costs (MC)] and supplier costs (SC). The last equation, (9) represents the total operating cost (TOC), which a sum of transportation cost, total manufacturing costs and supplier costs.

IV. Results and Discussion

The key critical parameters of MODE are population size (NP), crossover constant (CR) and Scaling Factor (F). Several simulations runs (more than 50) were carried on computer using different set of MODE parameters. Smooth Pareto front was obtained from each combination from which the decision maker can use the solutions of his/her interests. MODE also is tested for its robustness.

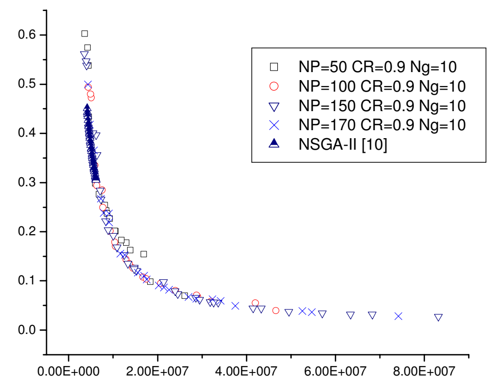

Fig. 2. Comparison of Pareto front between TOC and MC/TOC using NSGA-II (700 generations) and MODE (10 generations) and effect of NP on Pareto front using MODE. algorithm

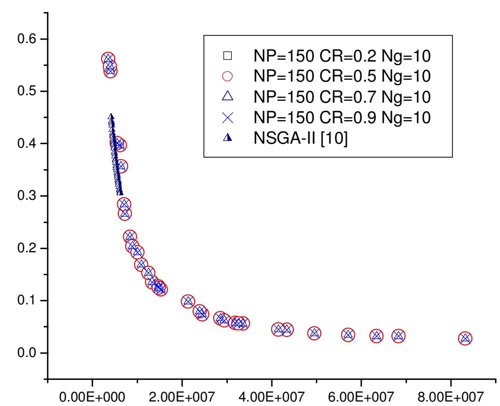

Fig. 3. Pareto front between TOC and MC/TOC after 10 generations and NSGA-II. Effect of CR on Pareto front (using MODE).

A. Objective Function Set 1

Fig. 2, 3 and 4 show the Pareto front between total operating cost and ratio of manufacturing cost to total operating cost for random seed. Fig. 2 also shows the effect of NP on Pareto front after 10 generations and comparison of results of MODE study with NSGA-II [10]. It is observed that number of non-dominated solutions remains same after 10 generations. Pareto front is well diverged and smooth for

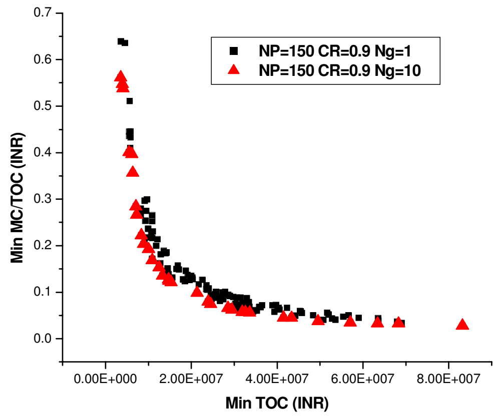

Fig. 4. Trade-off between TOC and MC/TOC after 10 generations and population points at generation 1

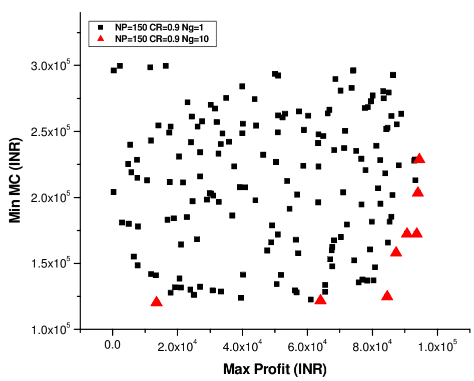

Fig. 5. Trade-off between Profit and MC after 10 generations and initial population points at generation 1.

all reported values of NP (Fig. 2). However, for NP=50, the number of non-dominated solutions is low (19). The Pareto front is found to be dragged towards right in the region of MC/TOC value of 1.5-2.0 for this NP value. Fig. 2 also illustrates that for NP value of 100, or greater than 100 although the Pareto front remains the same, the number of non-dominated solutions are found to be varying. The number of non-dominated solutions for NP value of 50, 100, 150 and 170 are 19, 23, 32 and 23 respectively. Fig. 2 and 3 show that the Pareto front obtained using NSGA-II is found to cover less than 20 % of MODE outcome in 700 generations.

Fig. 3 shows the effect of CR on Pareto front at fixed NP (=150) and fixed number of generation (Ng=10). Several simulation runs were carried out using various values of CR, and some of the combinations are shown in Fig. 3. MODE is found to give smooth and well-diversified non-inferior solutions for all values of CR in range. Population points at first generation (Ng=1) and Pareto front after 10 generations (Ng=10) are shown in Fig. 4. Population at first generation also illustrates the objective space for the set 1 of supply chain optimization problem. After 10 generations, TOC (INR) is found to vary between the value of 3514335 and 83175376 while the ratio of MC to TOC varies between the range of 0.027752 and 0.561639. There is a clear trade off in these solutions. Table I, shows the comparative analysis of current study with literature study [10]. As this is maximize-minimize type of multi-objective optimization problem, the extreme left point on the Pareto front would be the point that

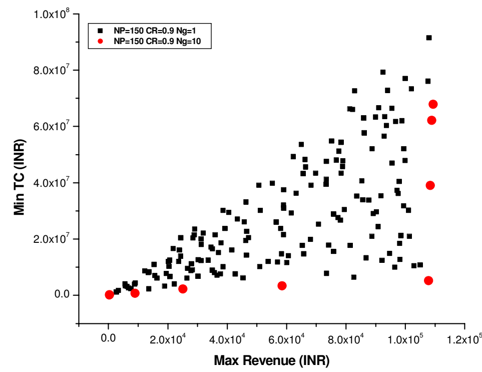

Fig.6. Trade-off between Revenue and TC after 10 generations and objective space at generation 1.

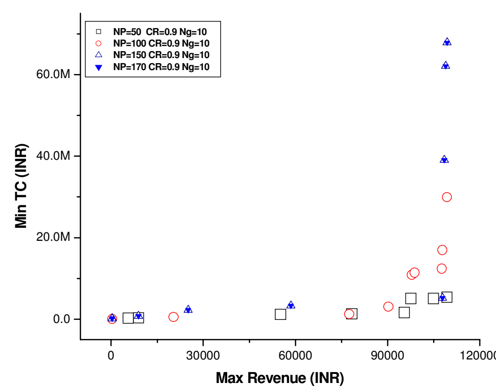

Fig. 7. Pareto fronts after 10 generations and effect of NP on Pareto front.

gives the maximum value of TOC and a minimum value of MC/TOC.

In the study mentioned in literature [10], the maximum value of objective function TOC does not correspond with minimum value of objective function MC/TOC. In the current study, the Maximum value of objective function TOC in the entire Pareto range is found to be 83175376, and corresponding value of MC/TOC is 0.0261639 which is the minimum value of MC/TOC in the entire Pareto set. This is evident from Table I. If the extreme right point on Pareto front is compared, then MODE is found to give better results than NSGA-II, which is shown in Table I. In this study also, although the values of decision variables involved in the study are different, MODE has given better results in terms of trade-off among the objectives.

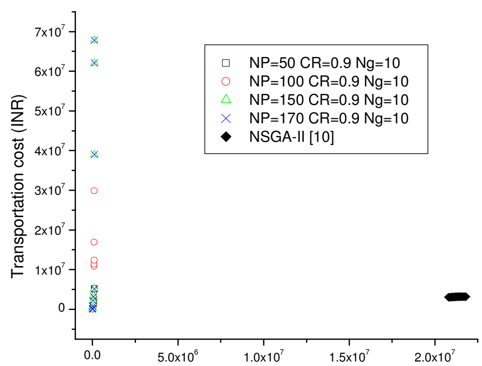

Fig. 8. Comparison of MODE and NSGA-II Pareto fronts.

TABLE I
ANALYSIS OF OBJECTIVE FUNCTIONS TOC VS. MC/TOC

	NSGA-II [10]		MODE (Present Study)	
	Objective Function	Corresponding Value	Objective Function	Corresponding Value
Statistic	TOC	MC/TOC	TOC (INR)	MC/TOC
Maximum	175129	0.327840	83175376	0.027752
Minimum	51477.0742	0.4800	3514335	0.561639
Mean	107536.784		24525698	
Std. Dev.	25382.0615		21106445	
	MC/TOC	TOC	MC/TOC	TOC (INR)
Maximum	0.494218	111098.08593	0.561639	3514335
Minimum	0.168562	87393.14848	0.027752	8317537
Mean	0.356052		0.175072	
Std. Dev.	0.051778		0.161984	

B. *Objective Function Set 2*

Fig. 5 shows the Pareto front between the objective functions profit and MC. This set consists of maximize-minimize type of objective functions. Values for profit (INR) vary between 287 and 94466 while values for manufacturing cost vary between 203990 and 228709. Fig. 5 shows the Pareto front between two objectives and objective space after generation 1 and the Pareto front after 10 generations respectively. As it can be seen, the objective space is discontinuous in nature. This could be due to the effect of several complex constraints on objective space. The discontinuous objective space has resulted in a discontinuous Pareto front but with better spread of solutions. The Pareto front remains the same for all reported values of the number of population points. The number of non-dominated points for NP values of 50, 100, 150, and 170 was 6, 6, 8 and 8 respectively. The effect of control parameter CR was also checked on the spread and diversity of Pareto front with NP=150 and after 10 generations. No change in number of solutions or Pareto front was observed for different CR values in range (0.2 to 1.0).

TABLE II
ANALYSIS OF OBJECTIVE FUNCTIONS REVENUE VS. TC

	NSGA-II [10]		MODE (Present Study)	
	Objective Function	Corresponding Value	Objective Function	Corresponding Value
Statistic	Revenue	TC	Revenue (INR)	TC (INR)
Maximum	497068.625	80233.382813	109382	6784773
Minimum	308609.468	47546.855469	332	112367.4
Mean	436037.487		58656.33	
Std. Dev.	36426.0705		50487.34	
	TC	Revenue	TC (INR)	Revenue (INR)
Maximum	82823.6171	493821.8750	67847736	109382
Minimum	47546.8554	308609.45875	112367.4	332
Mean	66736.9272		20080159	
Std. Dev.	6267.46296		28273803	

C. *Objective Function Set 3*

Transportation cost is considered as an important cost in every supply chain problem. The trade-off among the objectives of revenue and transportation cost is shown in Fig. 6. Pareto front is obtained for this supply chain multi-objective optimization problem. The Pareto front for CR value of 0.9 and after 10 generations with different NP values is shown in Fig. 7. It is interesting to note that with 50 number of population points (NP), the Pareto front is converged into the local region. But if NP is increased subsequently beyond the value of 100 the Pareto set of solutions remains the same in terms of number of solutions and objective function values. Simulation runs were carried out with NP=150 and Ng=10. Pareto fronts are obtained with good spread and diversity. Fig. 6 also illustrates the objective space for current supply chain problem. The objective space is found to be discontinuous in nature and the shape of objective space is nearly triangular with more number of solutions in dominated region. Also the objective space is constructed in such a way that there are very few points in the region of Pareto frontier. Because of very less number of solutions in the preferred region, the number of non-dominated solutions in the Pareto front is less. Fig. 8 shows the comparison of Pareto front obtained using MODE and NSGA-II [10]. Large deviation in result is observed as the range of decision variables considered in both studies is different. NSGA-II has shown good diversity but in the region of higher value of objective function revenue. Pareto front obtained using MODE is also well spread but in the range of lower value of revenue and higher value of TC.

Table II shows the analysis of results obtained in present and previous study [10] using revenue and TC as objective functions. The standard deviation and mean values for objective function revenue are 58656.33 and 50487.34 respectively (present study). For objective function TC, the values for mean and standard deviation are 20080159 and 287273803 respectively. Figures 2-8 show that Pareto front obtained with various values of key parameters is almost same (except for very low value of NP). It is observed that percentage of number of non-dominated solutions decreases with increase in number of population points. When CR values were changed from 0.2-0.9, the Pareto front obtained was same. F is assigned as a random value which range between 0 to 1. In our earlier study[24], robustness of MODE was tested on several benchmark test problems. Several simulation runs were carried out to test the effect of NP on the Pareto front. The % change in number of non-dominated solutions is found to decrease if NP value exceeds the value of 100. This is shown in Figure 9. Recently new new version of MODE i.e. *Elitist-* Multi-objective Differential Evolution (EMODE) algorithm is developed [25]. EMODE algorithm is tested on several benchmark test problems, and is found to perform better than MODE in terms of number of solutions in Pareto front. However, the computational time for EMODE is found to be more than MODE algorithm. EMODE involves the concept of crowding distance [12] to retain better population points which can be passed to next generation.

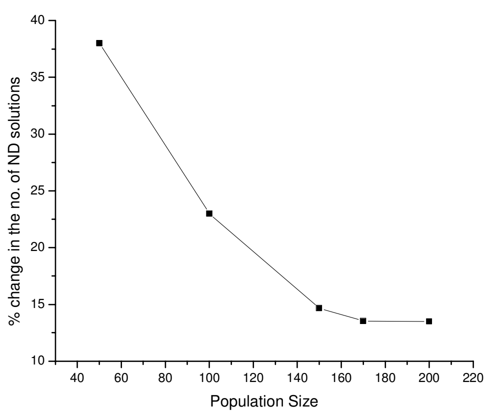

Fig 9. Change in number of non-dominated solutions vs. population size using MODE algorithm.

The success of MODE largely depends on its strong combined mutation and crossover policy. This combined operation is named as Recombination. Usually in genetic algorithm both mutation and crossover operations are carried out separately. Any multi-objective optimization algorithm need to include two very important aspects, i.e. convergence and divergence of solutions. In MODE, crossover operator takes care of divergence, which enables it to search for better solution in every step. At the same time the scaling factor takes care of convergence of diverted solutions, thus making algorithm faster and accurate in a single step.

V. Conclusions

Multi-objective differential evolution (MODE) algorithm is applied successfully on multi-objective optimization of supply chain planning. A hypothetical but realistic supply chain optimization problem was selected. MODE has provided a set of non-inferior solutions and these solutions can be used by the decision maker to design the supply chain. MODE is found to give a better spread of solutions, when compared with the results obtained by NSGA-II. MODE is also tested for robustness against its control parameters. For very complex objective space, with very low value of NP, MODE algorithm is found to converge towards local optima region. However, as NP value is increased, Pareto front is found to remain the same. It is observed that almost same Pareto front is obtained for all the three sets of multi-objective optimization problems under study. Evolutionary algorithms have the potential of solving challenging and combinatorial problems. This paper confirms the potential of MODE to solve complex problems like multi-objective optimization of supply chain model.

Nomenclature

CR	Cross over constant used in MODE.
CS (i, j)	Cost of making a component 'i' by supplier 'j'
D (l)	Demand at customer zone 'l'
F	Scaling factor used in MODE.
$I_{i,k}$	Inventory of component 'i' at plant 'k'
i	Component
IC (k)	Plant IC (k) Inventory cost of plant 'k'/unit
j	Supplier
k	Plant
L (i , j)	Capacity of supplier 'j' for component 'i'
l	Customer-zone
LC (k)	Labor cost of plant 'k'/unit
MC (k)	Manufacturing cost of plant 'k'/unit
NP	Number of initial population points in MODE.
PTC (k, l)	Plant transportation cost from plant 'k' to customer zone 'l'/unit
SP (l)	Selling price at customer zone 'l'/unit
STC (i, j, k)	Transportation cost of a component 'i' from supplier 'j' to plant 'k'/unit
U (k)	Capacity of plant 'k'
$X_{i,j,k}$	Amount of component 'i' from supplier 'j' to plant 'k]'
$Y_{k,l}$	Amount of product shipped from plant 'k' to customer zone 'l'

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