MULTIOBJECTIVE OPTIMIZATION FOR SUPPLY CHAIN NETWORK USING ELITIST NON-DOMINATED SORTING ALGORITHM

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Abstract : **Supply Chain is a complex ecosystem of individuals, organizations, resources, activities, and technologies involved in the transformation of raw materials and constituents into a consummate product that is delivered to the customers. A typical Supply Chain incorporates several processes; hence, there arises a need for optimization of operations to achieve a precise modus-operandi that gets a good trade-off among different objectives like the quality of deliverables, cost of production and time of delivery. Several attempts have been made to implement multi-objective optimization methods for the complications of Supply Chain Management. This study aims to deal with the logistic component of supply chain problem using modified Multi-Objective Non-dominated Sorting Genetic Algorithm-II (NSGA-II). In this paper, we attempt to minimize the total transportation cost and time. The problem is taken directly from the literature and a comparative study has been conducted in order to illustrate the performance of the presented model. The results show that the proposed modified algorithm is able to achieve a better Pareto-optimal solution as compared to the standard algorithm.**

Index Terms - **Supply Chain Management, NSGA-II, Multi-Objective Optimization, Artificial Intelligence**

I. INTRODUCTION

During the early phase, various authors attempted to lay down the crux of Supply Chain Management as a single definition, which constituted the object of the management philosophy, the target group, the objective(s) and the broad means for achieving these objectives [1]. The term "supply chain management" was coined and came into existence in the 1990s. The antecedent terms were "logistics" and "operations management" instead [2]. The primary objective of Supply Chain Management is, undoubtedly, handling Supply Chain Network which is a ". . . network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the ultimate consumer " [3]. The extensive study of SCM comprises of supervision of manufacturing, administering inventories, product development, commercialization, fulfilling orders, and managing customer relationship, which are practicable for the business in competitive environment.

Supply chains and supply chain management (SCM) have transpired as progressively paramount fields of corporation practice. Originally recognized in the 1980s, SCM has engaged fascination and attention on the part of both academics and practitioners [4]. As a result, industrial supplier-consumer relations have experienced major changes following a certain amount of synergy, mainly in the area of information sharing, that was lacking before. The information sharing could range from being generalized (e.g. type of inventory control policy being used, type of production scheduling rules being used) to specialized (e.g. day-to-day inventory levels, exact production schedules). There is a requirement for new models dealing with these recent advancements in information sharing because the traditional models no longer universally held in the manufacturing sector [5].

Supply Chain Management problems are functions using various parameters like lead time at each level, inventory management, customers' requirements, manufacturer's capacity, logistic issues, stochastic nature of Supply Chain, etc.[6][7][8]. The fundamental objective of SCM optimization is to minimize the overall cost of the system while maintaining customer service, quality of end-product at a pre-specified level [9] and maximize the profitability of all the entities in the network [6]. Other objective functions may include minimizing lead-time, designing optimal networks, coordinating processes, etc. In addition, these functions are mutually-conflicting in nature. For example, the objective of a company is to design, build and deliver the product minimizing the cost of development and transporting while avoiding any compromise with the quality of the product, or customer satisfaction. Another example of such discrepancy could be minimizing the delivery time while aiming for maximization of profits. In such scenarios, there arises a need for an array of options to the decision analysts, such that all trade-offs are taken into account and an optimal solution is achieved [10].

Multi-Objective optimization deals with multiple, possibly conflicting, objectives that are naturally observed in the real world. The field of multiple-objective optimization is well established, investigated by many researchers and scientists, and widely applied in practice. Multiobjective optimization problems were usually solved by scalarization, where the problem is converted into one single or a family of single objective optimization problems. This new problem has a real-valued objective function that possibly depends on some parameters and it can be solved using single objective optimizers [11]. The newly generated problem has a real-valued objective function (that may depend on some parameters) and can be solved using single objective optimizers. This can be achieved using various methods like the weighted sum, distance functions, goal programming and ε – constraint [12][13][14]. In contrast, it has been observed that Evolutionary algorithms are a better choice for optimization than scalarization. "Evolutionary algorithms seem remarkably preferable to deal with MOO problems, because they deal simultaneously with a set of possible solutions (the so-called population), which encourages us to discover a few individuals from the Pareto ideal set in a solitary keep running of the calculation, rather than playing out a progression of independent keeps running as on account of the customary scientific programming strategies"[13]. Furthermore, evolutionary algorithms are less vulnerable to the shape or progression of the Pareto front (e.g., they can undeniably handle intermittent or concave Pareto fronts), while these two issues are a genuine lookout for scientific programming methods [15]. Genetic algorithms, which are commonly used evolutionary methods, have been shown to give a good approximation of the Pareto fronts [12][16].

Cohen and Lee(1988) [21], and Arntzen et. al. (1995) [22] have attempted to optimize the supply chain problem as single objective problem. Howbeit, the results obtained were not close to the true pareto optimal set and quite deceptive as the solution was optimal only for a specific scenario and not the other entities' objectives.

In this research, we utilize the NSGA-II algorithm proposed in [23] that is an improvised version of NSGA. NSGA introduced in [23] depended precisely on MOGA with the exception of the detail of the sharing parameter. The computational complexity of NSGA is $O(MN^3)$ where M is the number of objectives and N is the population size. The predecessor needed elitism and required specifying a sharing parameter for the fitness value. Its successor, NSGA-II executes elitism that preserves best-fit individuals in a population to guarantee solutions with good fitness do not get lost in subsequent generations. Its computational complexity is $O(MN^2)$. NSGA-II utilizes binary-tournament selection operator in which two individuals participate in a tournament and the winner is decided by the fitness level of each individual. It has been demonstrated that it beats most contemporary MOEAs like SPEA, PAES, and so forth and its performance has been tried on multiple test problems where it has been successful in generating Pareto fronts[6][23].

Our choice of NSGA-II for our research is based on the fact that it uses an elitist approach, and it is fast, modular and flexible as well as emphasizes on the non-dominated solutions. It can be applied to a wide category of problems.

This paper is organized as follows: we describe the problem of Supply Chain Network in section 2 where we introduce the objective functions and assumptions in the form of a mathematical model. The proposed methodology is explained in section 3 pursued by computed results and discussion in section 4. Finally, section 5 concludes our paper.

II. Description Of The Problem

Consider a general inventory network model specifying arrangement of suppliers, manufacturers, distributors and retailers/customers as shown in Fig.1 below. The providers are organizations from which crude materials are purchased. We expect that every provider supplies a particular crude material. In addition, there are transporting vehicles of distinguished capacities that is responsible for transporting raw materials. The products are developed in manufacturing units. The distributors store the products before they are transported to the retailers. Each DC may have different storing capacity. So we have to plan an inventory network that permits key choices like choosing providers of crude materials amounts, deciding the subsets of plants and DCs to be opened, and a network dissemination strategy that fulfills all customers' demands and storage capacities so that the total expense and time delays are minimized.

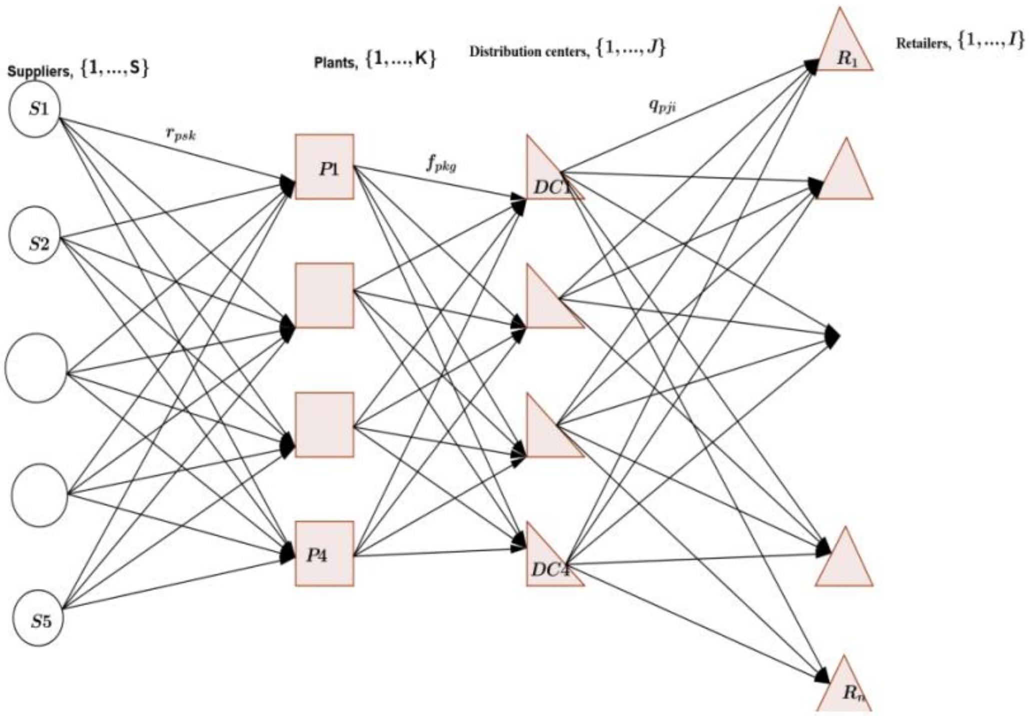

Figure 1 Inventory Network Model

Ideally, the products need to be delivered on time and in the right quantity as demanded by the retailers. This spares stockpiling cost and boosts client administrations. In spite of the fact that items are stored prior to delivery, due to storage constraints of the

DCs and manufacturing plants, it might not be possible to fulfill all the requests on time, consequently, we either need to deliver prior or late in some cases, acquiring abundance stockpiling and incurring cost in the process.

In this research, we aim to optimize the following two objectives: total expense of the supply network that incorporates the expense of opening and running manufacturing plants and DCs, cost of purchasing and transporting crude materials, cost of transporting items from plants to DCs and from DCs to retailers, and cost of temporarily storing items at DCs.

In terms of optimizing cost, it would be expensive if the products are supplied early to the DCs but are delivered late to the retailers as it will increase storage costs. While for optimizing on-time delivery, it is desirable that the products are supplied to the warehouses earlier such that the customers' demands are not missed. Thus, we require a trade-off between minimizing inventory costs and product delivery-time while maximizing customer service.

We assume that there are finite and known number of suppliers and retailers and that capacity of each supplier is known. Similarly, there are finite and known number of manufacturing plants and DCs and their maximum capacities are known. Despite the fact that the demands of retailers are uncertain, it can be determined from demand history. It must be noted that we only consider storage costs that are incurred at Warehouses since that is where the products may remain for a long time before being delivered. Each retailer is served from one warehouse while manufacturing plants deliver their items to many DCs. Each plant gets crude materials from every one of the providers.

We use the mathematical model from [24] for optimizing inventory cost and delivery time. The mathematical model precisely considers all factors including availability of the product in DC, cost of storage in every DC, storage capacities, and furthermore.

III. Research Methodology

In general, Multi-Objective Optimization Problem can be defined as the problem of finding [17] "a vector of decision variables which satisfies constraints and optimizes a vector function whose elements represent the objective functions. These functions form a mathematical description of performance criteria that are usually in conflict with each other. Hence, the term "optimize" means finding such a solution which would give the values of all the objective functions acceptable to the designer."

It can formally be described as:

Find the vector $x^* = [x^*_1, x^*_2, \ldots, x^*_n]$ T that satisfies the r inequality constraints:

$$g_i(x) \geq 0 \qquad i = 1, 2, \ldots, r \qquad \ldots(1)$$

and s equality constraints

$$h_i(x)=0 \qquad i = 1, 2, \ldots, s \qquad \ldots(2)$$

and optimizes the objective function vector

$$f(x)=[f_1(x), f_2(x), \ldots, f_k(x)]^T \qquad \ldots(3)$$

In MOO, a feasible solution x_1 is said to be dominating over another solution x_2 if and only if $fi(x1) \leq fi(x2)$, $i = 1, 2, \ldots, N$ and $fj(x1) < fj(x2)$ for at least one objective function j. A Pareto-optimal solution is the one that is not dominated by any other solution. And the set of all Pareto optimal solutions is called Pareto-optimal set. Pareto-optimal solution is the corresponding objective values on the graph. Therefore, our ultimate objective in MOO is to discover the fronts that describe the trade-offs between the objective functions to be optimized. It must be noted that the Pareto fronts cannot be improved for an objective function without affecting at least one other objective function.

For many multi-objective problems, distinguishing a Pareto-optimal set is practically inconceivable because of their size, complexity; also, for combinatorial problems like the presented Inventory network problem, proof of optimality is computationally infeasible [12].

We use NSGA-II since it has been tested on several problems and has been proved to provide better solutions and convergence as compared to PAES and SPEA. The fundamental principle of the algorithm is that we order all solutions into ranks and calculate the crowding distance for each individual solution. The step-by-step procedure of NSGA-II is simple and straightforward. To determine the ranking, we calculate two entities: N_p the number of solutions dominating p, and S_p set of all solutions dominated by q. All solutions which are non-dominated have $N_p=0$ and are categorized as First non-dominated front. Next, we find the solutions from S_p where $N_p=0$ when the first non-dominated front is removed. Similarly, we obtain all the remaining fronts. Thus, all solutions are categorized into distinguished fronts with ranks. Solutions with rank 1 are the best solution for the present generation. Thereafter, we calculate the crowding distance of each solution. The advantage of crowding distance operator is that it introduces diversity in the solutions along the front, and uniformly distributed solutions are obtained over the True Pareto Fronts.

NSGA-II utilizes a two-stage selection process that combines Binary Tournament Selection with ($\mu+\lambda$) selection [18]. The binary tournament permits only the fittest individuals to be placed by competing among the pool of individuals. The ($\mu+\lambda$) selection selects the parents or children that should be a part of the next generation. To preserve elitism, N individuals from the global pool are selected based on their non-dominated front and crowding distance. The steps of the algorithm are shown as follows:

Step 1: Initialize the parent population P_i of size N.

Step 2: Produce the offspring population Q_i of size N using genetic algorithm operators: selection, crossover, and mutation.

Step 3: Combine the parent generation P_i and offspring generation Q_i into a single set S of size 2N.

Step 4: Classify and rank the individuals in S.

Step 5: Select the best solutions from S using rank and crowded distance to create the parent population for the next generationP_{i+1}.

Step 6: Repeat steps 1-5 until the termination criteria are satisfied.

For each manufacturing plant, DC and retailer/consumer, we dedicate a part of the chromosome as represented in Fig.2.

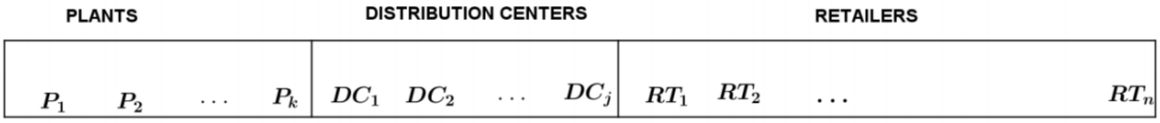

Figure 2 A sample chromosome

Where P_k represents the quantity of crude materials received by each plant P, while DC_j represents the quantity of products delivered to Distribution Centres. RT_n represents the quantity of products delivered to each Retailer RT.

IV. RESULTS AND DISCUSSION

In this research, data was gathered from SBC Tanzania that is a supply chain company that produces and vend soft drinks to both wholesalers and retailers (SBC Tanzania, 2010)[19]. The simulation was run in C++ using the Dev C++ Integrated Environment with the following parameters:

- Population size=1290
- Initial population= uniform
- Selection= tournament operator
- Crossover probability=0.6
- Mutation probability=0.01

The probabilities of crossover and mutation are chosen as proposed by [21] on choices of parameters for NSGA-II. The output is plotted using GNUPlot version 5.2. Fig.3 represents the Pareto front for maximum generations of 500 and default maximum values in C++:

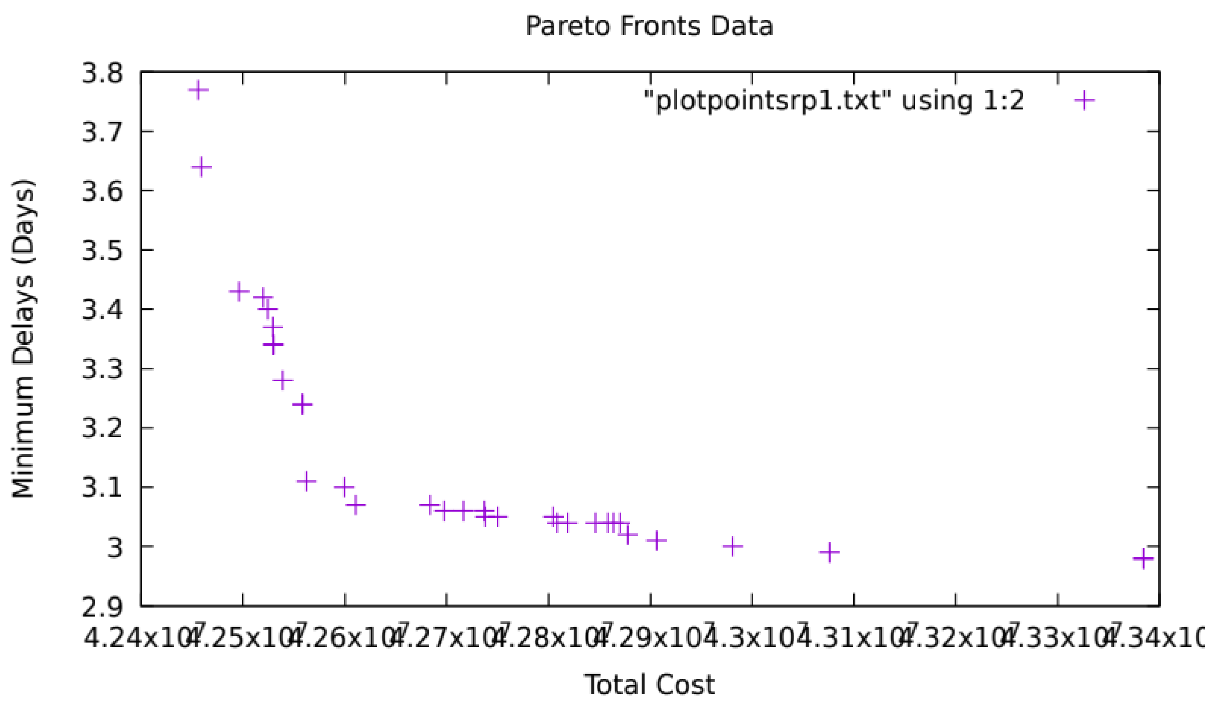

Figure 3 Pareto front at 500 generations

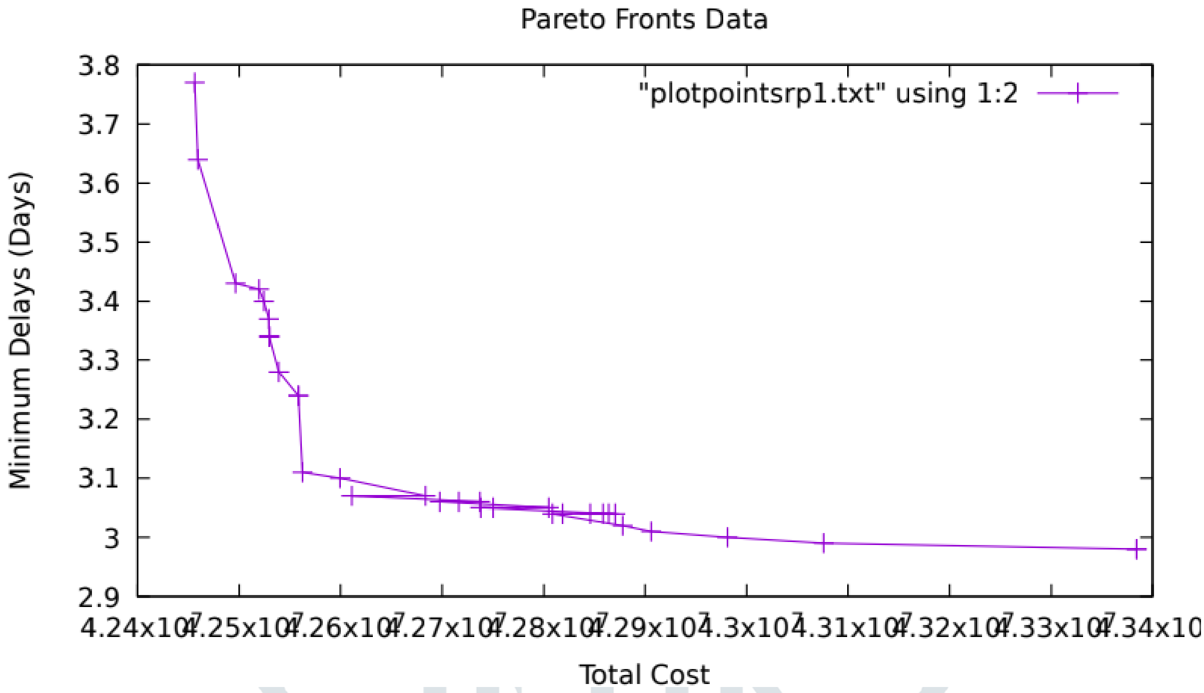

Figure 4 Line simulation of the Pareto front at 500 generation

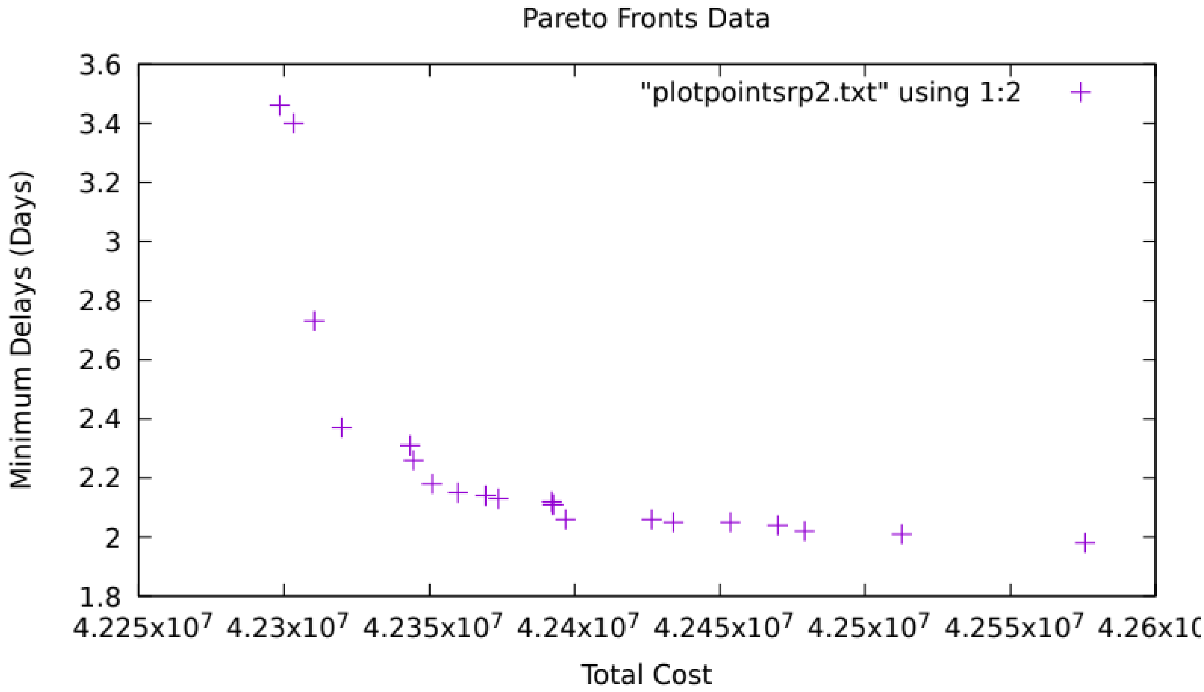

Figure 5 Pareto front at max generations

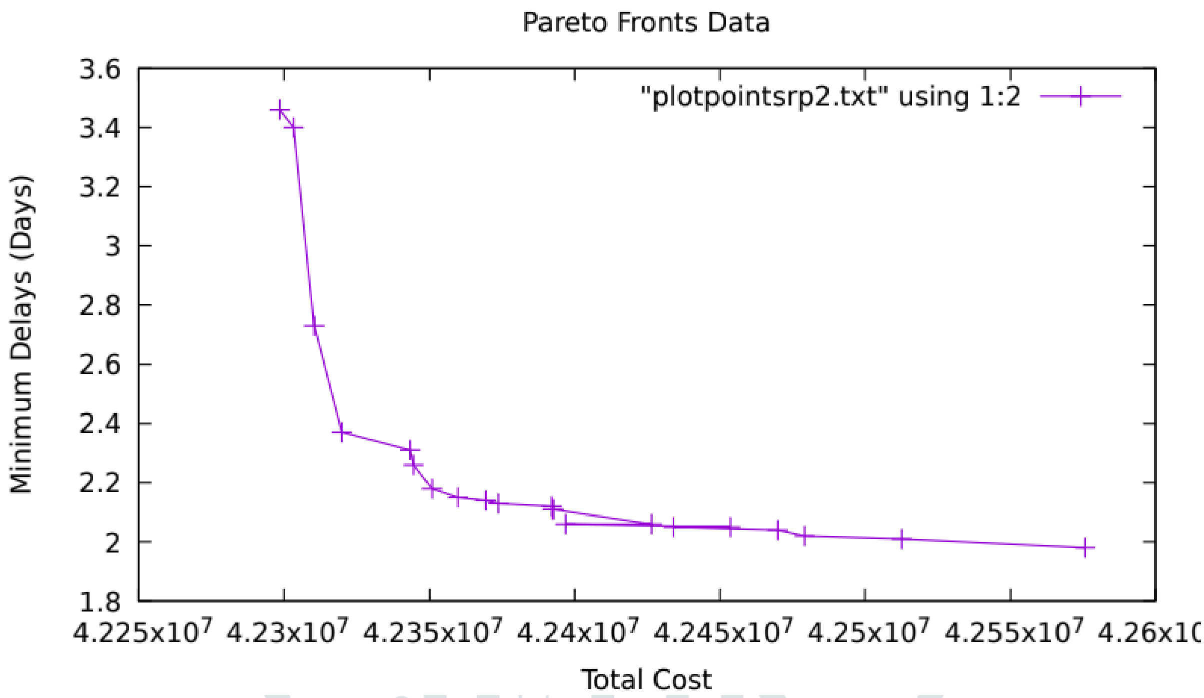

Figure 6 Line simulation of the Pareto front at max generations

With this vector of optimal decisions offering multiple trade-offs, the management can, therefore, decide based on the expertise to assess those arrangements that would be most helpful and beneficial to the company from the optimization perspective. In the results, it was found that there exists an inverse relationship between the expenses and the time delay in both simulations however with a slight distinction. In the event that items are postponed for a long time, the absolute expense diminishes and if requests are met with least defers the expense increases. The outcomes can be deciphered as follows: to fulfill clients' requests we need least deferrals in conveying merchandise once they have ordered. Since products are developed in manufacturing plants and transiently stored in DCs we incur expenses in production since there arises a need to make more products with the goal that they are promptly accessible when they are requested. Similarly, these items might be kept for a long time at DC subsequently thus incurring more expenses. There might likewise be a requirement for even more transporting vehicles thus expanding transportation cost. With most extreme postpones these extra expenses might be little or not there at all as we can transport products as long as they are accessible with no pressure. From our viewpoint, we would prompt the business not to postpone the conveyances with over two days as it makes a good sense in terms of business. In short, the earlier the delivery the better. The outcomes obtained in this optimization ranges from 40-50 million TZ shillings that is actually less as compared to the actual amount spent by the company in a week, which is 45-65 mill TZ shillings on similar procedures considered.

V. Conclusion

In this research paper, we have built a mathematical model for the logistics component of the inventory network in a three-echelon supply chain that optimizes transportation and storage costs, and delays in the delivery of products. The model is designed for Multi-objective optimization problems taking into consideration the two conflicting objectives. We have discovered a few choices in which, for certain cases, we may decide on high expenses to look after client fulfillment, while in different cases relying upon the circumstance we may select to spare expenses. We used NSGA-II developed by Deb et al.(2002)[23] in Dev C++ Integrated Environment. The calculation obviously gives the Pareto fronts which are optimal solutions that can be used by the decision makers in the management in planning and designing to refine the Supply chain services. This work exhibits that Evolutionary Algorithms are effective in dealing with MOO problems and can possibly handle combinatorial problems. Despite the fact that the MOEAs have turned out to be effective in tackling MOOs, they become fruitless as the number of objectives increases from two as in our current problem. For future purposes, we recommend using MOEAs that can handle a higher number of objectives at a time and can find optimal solutions based on effectively utilizing search space, thus reducing space complexity.

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