A Design Methodology to Optimize Supply Chain Network Performance

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***Abstract*— Organizations are constantly looking for new ways to reduce costs while still providing high customer service levels to face stringent competitive environments and the ever-increasing market globalization. An alternative these organizations can pursue to respond to these challenges and to gain a competitive differentiation is to optimize their supply chain network (SCN). This research aims to develop an effective SCN design strategy to locate facilities (i.e., plants and distribution centers) and to balance the allocation of customers to these facilities to satisfy capacity limitations and customer demands with minimum total cost and maximum level of service. It is anticipated that the results of this research will improve the strategic decision making of a manufacturing firm when locating facilities or redesigning the SCN and allow decision makers to determine tradeoffs among the organization's conflicting criteria.**

Keywords*— *balanced allocation, genetic algorithm, multi-objective optimization, supply chain network

I. INTRODUCTION

The design of a supply chain network (SCN) is a long-term, strategic-level decision which has a considerable impact on tactical and operational decisions. Common objectives when optimizing a SCN include improving the flow of products among supply chain entities and reducing cost, while simultaneously maintaining customer service levels. Important decisions when optimizing the design of a SCN involve finding locations for facilities (e.g., plants, distribution centers (DCs), etc.) and allocating customers to these facilities [1].

This research proposes a methodology to generate feasible solutions to the multi-objective, single-source capacitated facility location-allocation problem (SSCFLAP) with a balanced allocation of customers (BAC) for a two-echelon SCN. The performance measures *total cost* and *balance level of transit time* were employed to assess the quality of solutions. These performance measures were chosen because they provide strategic insight to decision makers to better analyze the performance of their SCN and formulate a more effective SCN design strategy.

II. LITERATURE REVIEW

A. Facility Location Problems

Establishing new facilities when designing a SCN (e.g., factories, warehouses, or DCs) is considered a complex strategic challenge and usually involves a high initial startup cost [2]. Doong, Lai, and Wu [3] developed a mixed integer non-linear programming (MINLP) model to minimize total cost. The authors proposed a hybrid method known as genetic subgradient to solve the single-source capacitated facility location problem (SSCFLP). Continuous decision variables were used in the model to represent the physical locations of facilities, whereas discrete decision variables were used to indicate which customers should be allocated to which facilities. There were also some restricted areas where facilities could not be located. Guastaroba and Speranza [4] solved the SSCFLP with the objective of minimizing the total cost (i.e., fixed opening cost and assignment costs) when assigning customers to facilities. A heuristic algorithm called kernel search was applied to obtain feasible solutions to the SSCFLP where each facility had limited capacity and a fixed opening cost. Li, Chu, Prins, and Zhu [5] used a hybrid method to solve a MILP model whose objective was to minimize the total cost (i.e., fixed depot opening cost, unit transportation cost, and handling costs) of a two-echelon, multi-product capacitated facility location problem consisting of plants that supplied different types of products, depots, and customers.

B. Customer Allocation Problems

The customer allocation problem aims to allocate a set of demand points (or customers) to a predetermined set of facilities to be opened with respect to an organization's preferred criterion (or criteria). One way to optimize the design of SCN is to balance the allocation of customers which improves the utilization of facilities and the service levels. The problem of a BAC involving more than two facilities is classified as an NP-hard problem [6], [7]. Therefore, many practitioners have approached the BAC problem without considering a facility capacity constraint in the SCN. Marín [8] formulated two integer programming (IP) models to balance the allocation of customers on a discrete space. The main objective was to minimize the difference between the maximum and minimum number of customers assigned to any candidate plant. Rajesh, Pugazhendhi, and Ganesh [9] developed an algorithm based on simulated annealing to solve the BAC to third-party logistics (i.e., 3PL) warehouses playing the same role as DCs. The objective was to minimize the maximum total sum of the edge weights, which represented the total shipping cost between customers and each warehouse.

C. Facility Location-Allocation Problems

Multiple decisions or objectives must be considered simultaneously to efficiently design a SCN. Facility location-allocation problem (FLAP) formulations attempt to simultaneously determine optimal locations for potential facilities and flows of products to customers to satisfy their demands and meet an organization's conflicting objectives [10], [11]. For example, Latha Shankar, Basavarajappa, Chen, and Kadadevaramath [12] proposed a swarm intelligence-based multi-objective hybrid particle swarm optimization

(MOHPSO) algorithm to solve the FLAP on a four-echelon SCN. The first objective was to minimize the total cost of the supply chain by determining the optimal number of suppliers, plants, and DCs. The second objective was to maximize the order fill rate by allocating customer zones to DCs under a minimum fill rate requirement constraint. The algorithm was able to generate Pareto optimal solutions showing the tradeoffs among total supply chain costs and order fill rates. Bagherinejad and Dehghani [13] formulated a SSCFLAP using a bi-objective binary integer linear programming (BILP) model and generated feasible solutions using a non-dominated sorting ant colony optimization (NSACO) algorithm. The first objective was to minimize total transit time and the second objective was to minimize total cost (i.e., fixed facility cost and shipping cost). The results showed that the proposed NSACO algorithm performed better than an alternative genetic algorithm in terms of deviation from an ideal point. However, the genetic algorithm outperformed the NSACO algorithm with respect to the number and the diversity of the Pareto solutions.

The review of the literature shows that the BAC problem has been considered only by a small number of practitioners when solving the SSCFLAP in the manufacturing supply chain. Among the few studies that have been conducted, there is a lack of evidence of prior work that has attempted to solve the SSCFLAP and balance the allocation of customers with respect to transit time in a two-echelon SCN. The potential advantages of including a BAC with respect to transit time are that it could (1) improve the flow of products among the supply chain entities, and (2) increase the probability that shipments will be made on time. These two effects could, in turn, lead to higher customer service levels. A BAC can also enhance performance, the quality of customer service, and the strategic position of the organization [9], [14].

III. Methodology

This research dealt with the SSCFLAP-BAC. The problem was studied using a two-echelon SCN with three sets of nodes, as depicted in Fig. 1. The first set of nodes in the SCN represents the manufacturing plants, the second set of nodes represents DCs, and the third set of nodes represents customers (e.g., regional retail chains or retail store locations). The product type considered in this research is large in size and may include aluminum rods, decking boards, drywall panels, and lumber, to name a few.

In the first echelon of the SCN, each plant is connected to one or multiple DCs with edge weights which represent unit shipping costs. There is also a set of edge weights representing unit shipping costs between DCs and customers. In the second echelon, each DC is connected to one or multiple customers

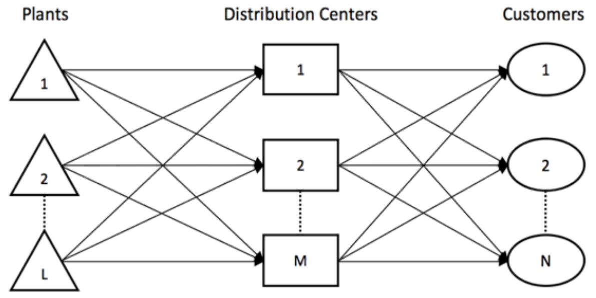

Fig. 1. A Two-Echelon Supply Chain Network

with edge weights which represent transit time (or shipping time). Transit time is defined as the time needed to ship an order from a DC to a customer. Finally, an initial fixed facility cost is associated with each plant and DC, which may include land acquisition, building construction, property taxes, and amortization of equipment and machines [15], [16].

A scenario that is representative of the problem considered in this research is when a large manufacturing firm reviews its current SCN and finds that its customer base has grown significantly and new sets of plants and DCs are needed to manage the growth. The firm expects that optimizing the SCN can simultaneously help reduce total costs and maintain or enhance responsiveness to customers in different competitive environments (i.e., easily adapt to change). Therefore, the firm's objectives when optimizing the SCN are to (1) minimize total cost (i.e., transportation and fixed facility costs), and (2) balance the allocation of customers.

A. *Problem Formulation*

The SSCFLAP-BAC was formulated as a mixed integer non-linear programming (MINLP) model using the model in [4] as a foundation. The following assumptions were made when developing the mathematical model of the SSCFLAP-BAC:

- The potential locations and the number of candidate plants and DCs are known. Therefore, plants and DCs are located on a discrete space.
- Customers have no specific choice for a DC, so customer demands can be fulfilled by any DC. However, customers can only be served by a single DC, which means that customer orders are consolidated in full truckloads before shipping them to the customers.
- Customer demands are known and remain unchanged during a given time period.
- The capacities of the plants and DCs are known.
- There is only one type of product in the SCN.
- The unit shipping costs between candidate plants and candidate DCs are known.
- The transit times between candidate DCs and customers are known.
- There are no losses or damages while handling or shipping product among the SCN entities (i.e., plants, DCs, and customers).

There are two objective functions in the model. The first objective function involves determining the optimal number of plants and DCs to be opened, and the quantity of product to be shipped among plants, DCs, and customers such that the total cost is minimized. The second objective function aims to minimize the sum of squares of the total transit time between DCs and customers. The lower the value of the balance level of transit time, the higher the degree of balance among the total transit times assigned to the opened DCs. Several constraints were defined in the model to ensure that (1) each customer is served only by a single DC; (2) the total customer demand allocated to each DC does not exceed its capacity; (3) the amount of product shipped from DCs to customers satisfies their demands; (4) the amount of product shipped from plants to DCs is equal to the amount of product required at each DC to satisfy customer demand; (5) the amount of product shipped from each plant to the DCs does not exceed the plant's capacity; (6) the number of DCs opened does not exceed the total DCs available; and (7) the number of plants opened does not exceed the total plants available. Additional constraints were added to the model to specify integer and binary decision variables.

B. *Non-Dominated Sorting Genetic Algorithm*

The non-dominated sorting genetic algorithm (NSGA-II) is a popular multiple-objective evolutionary algorithm (MOEA) [17]. The NSGA-II is capable of searching for a solution set in a large solution space without getting trapped in local optima, and it is also able to converge to the true Pareto optimal. In this research, the NSGA-II was modified and implemented to obtain feasible solutions to the formulated mathematical model. In particular, the original NSGA-II was modified to incorporate hybrid procedures to encode, decode, and repair chromosomes.

1) *Encoding Chromosomes*

The SSCFLAP-BAC can be characterized as a non-linear transportation problem, which is a type of network problem. One way to represent the network problem is to use a tree-based method to construct a network tree. The Prüfer number has been proven to successfully solve the transportation problem because it has the (dominant) characteristic of being able to represent all possible trees and it only requires $L + M - 2$ digits to distinctively represent all possible transportation trees with L plants and M depots. Each digit is represented as an integer between 1 and $L + M$. Therefore, the Prüfer number was used to encode the chromosomes in the first echelon of the SCN depicted in Fig. 2 because DCs can be allocated to many plants to have their demands fulfilled [18], [19].

An important aspect of the SSCFLAP-BAC is the single source constraint, which applies to the second echelon of the SCN (i.e., between DCs and customers). However, the Prüfer number does not guarantee that the single source constraint will be satisfied because it can generate a transportation tree that connects more than one source node to a destination node. Hence, a suitable genetic representation for the second echelon is integer encoding. In integer encoding, each gene in the chromosome represents a customer, each value of the gene (i.e., allele) represents a DC that serves that customer, and the length of the chromosome is equal to the total number of customers. Therefore, integer encoding ensures that each customer can only be served by a single DC. Moreover, the alleles also indicate the DCs that will be opened [15].

Fig. 2 depicts the hybrid encoding representation of a chromosome for a two-echelon SCN with four plants, three DCs, and five customers. All four plants in the first echelon are opened. DC1 is allocated to plants 3 and 4, whereas DC2 is allocated to plants 1, 2, and 4. Since DC3 is closed, plant 2 assigns zero flow of product to DC3. In the second echelon, customers 1, 2, and 5 are allocated to DC1 and customers 3 and 4 are allocated to DC2. This means that DC3 is closed and only DC1 and DC2 are opened.

2) *Decoding and Repairing Chromosomes*

The first step before decoding a chromosome is to check its feasibility. Incorporating feasibility checking and repairing procedures in the chromosome decoding process allows the NSGA-II to find good solutions for complex or large size problems [19]. In this research, feasibility checking and a repairing procedure for the chromosomes generated for the second echelon of the SCN were developed to ensure that solutions are feasible after the decoding process.

The decoding procedure is executed in reverse order. A chromosome in the second echelon of the SCN is decoded first to determine a set of DCs to be opened and to allocate customers to DCs. The chromosome in the first echelon is decoded next to allocate the opened DCs to plants and to determine a set of plants to be opened to satisfy the demands of all opened DCs. The Prüfer number can generate an infeasible chromosome in the first echelon that does not represent a transportation tree (i.e., the total number of edges connected to the source and destination nodes are unequal). Therefore, the chromosome needs to be repaired until the Prüfer number represents a valid transportation tree.

3) *Crossover*

In a genetic algorithm, the crossover operator is used to enhance the exploration of new solutions by defining how substrings from two parent chromosomes are exchanged to create offspring. The following three crossover operators were tested in this research through a computational study to identify the most suitable crossover operator to use:

- General two-point, segment-based crossover,
- Modified two-point, segment-based crossover with random binary mask in the second segment and the general two-point crossover in the first segment, and
- Modified two-point, segment-based crossover with random binary mask in both segments.

As mentioned before, each chromosome consists of two segments. Each chromosome segment encodes the structure of the first and second echelons of the SCN, respectively. The three crossover operators were evaluated in a computational study to determine the best suitable option for different

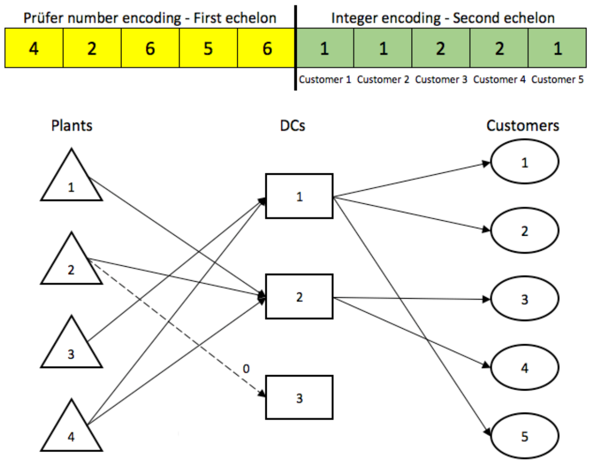

Fig. 2. Hybrid Encoding Representation of a Chromosome

problem instance sizes. In the computational study, the population size was set to 100 chromosomes, the probability of crossover was set to 0.6, the probability of mutation was set to 0.1, and the number of replicates was set to five. Two different generation numbers (i.e., number of iterations) were used: 500 and 1,000.

4) Mutation

In a GA, mutation helps to preserve the diversity in the chromosome population and is performed by modifying some genes in a chromosome [20]. Inversion mutation was applied to the first segment of a chromosome by randomly selecting two positions in the chromosome and inverting the substring within the range of the two positions [21], [22]. Swap mutation was applied to the second segment of a chromosome. The swap mutation operator randomly picks two genes from the second segment of the parent chromosome and swaps their positions to generate an offspring [15].

C. Generating Data for Problem Instances

Data were generated for small, medium, and large problem instance sizes to be used in different computational experiments. These data were set based on prior work conducted by [15], [23], and [24]. DCs and plants all have different capacities. The fixed costs of plants were generated using the economical scale formula $f_i = U[0,90] + U[100,110]\sqrt{b_i}$, where b_i denotes the capacity of plant i [25].

Since real transit times were not available, a dataset from a case study [26] comprised of 21 customers and seven DCs was used as a basis to generate transit times (in hours) between DCs and customers. More specifically, the dataset from the case study was used to fit a first-order regression model using unit shipping cost as the explanatory variable. A general regression analysis was conducted using the Minitab-16 software to determine whether or not a linear relationship exists between unit shipping cost and transit time. The regression equation from the results of this analysis is *Transit_Time = -33.1472 + 12.029 * Unit_Shipping*, where *Transit_Time* represents the transit time between DCs and a customer and *Unit_Shipping* represents the unit shipping cost between DCs and a customer.

D. Fine Tuning the Parameters of the Enhanced NSGA-II

The performance of the enhanced NSGA-II is driven by four critical parameters, i.e., the probability of crossover, the probability of mutation, the population size, and the number of generations (or iterations). Consequently, the values of the objective functions of the SSCFLAP-BAC are highly sensitive to how these four parameters of the NSGA-II are set.

Before conducting factorial experiments for the different problem instance sizes of the SSCFLAP-BAC, the response surface methodology (RSM) with central composite design (CCD) was used to fine tune the values of the four main parameters of the NSGA-II. RSM with CCD has been used extensively in problems "in which a response of interest is influenced by several variables and the objective is to optimize this response" [27]. This method helps in determining the optimal values of the four parameters that minimize the response [28].

The SSCFLAP-BAC studied in this research has two objective functions. The response selected for each treatment combination in the RSM experiment was the best response among the two objective function values in the first non-dominated front or Pareto optimal set. A response was selected by first normalizing the two objective function values in each solution of the Pareto optimal set into dimensionless values because they have different units (i.e., cost and time). The two normalized objective function values were summed together with an equal weight of 0.5. Since the objective of this research was to minimize both objective functions, the response selected was the lowest sum of the normalized objective function values [29].

E. Experimental Design

A 2^3 full factorial design was used in the designed experiment. There were five responses of interest:

- **Total Cost.** Includes the transportation costs between plants, DCs, and customers, and the fixed facility cost of opening plants and DCs.
- **Balance Level of Transit Time.** This is the total sum of squares of the total transit time assigned to the opened DCs.
- **Average Total Transit Time.** This is the average of the total transit times assigned to all opened DCs. This response is used to calculate the balance level of the transit time (i.e., the second objective function).
- **Number of Opened DCs.** The number of opened DCs impacts the fixed facility cost of opening DCs and, consequently, affects the total cost. The number of opened DCs also impacts the average total transit time which, in turn, affects the balance level of transit time.
- **Number of Opened Plants.** The number of opened plants impacts the fixed facility cost of opening plants and, consequently, affects the total cost.

The three main experimental factors of interest were:

- **Customer Demand.** Customer demand determines the amount of product that must be shipped to customers from DCs.
- **Unit Shipping Cost.** This is the cost to ship one unit of product from DCs to customers, or from plants to DCs.
- **Capacity.** The capacity of DCs and plants determines their sizes, which is proportional to their associated fixed cost.

Each of the main experimental factors had two levels (i.e., low and high), which results in a total of eight treatment combinations. Each treatment combination had five replicates for a total of 40 computational runs. Each replicate was run using a different set of chromosomes as the initial population.

Prior to running the replicates for a specific treatment combination, the feasibility of the data was verified. For example, if a treatment combination had a low capacity level and a high demand level, it was verified that the said capacity could fulfill the required demand.

IV. Results and Discussion

This section presents and discusses the results of the computational studies that were performed to improve the performance of the NSGA-II and the results of the designed experiment. All computational experiments were implemented in XCode and run on a MacOS High Sierra with 8GB RAM and 2.5 GHz Intel Core i5 processor. The statistical analyses were performed with the statistical software Minitab-16.

A. *Generating Data for Problem Instances*

The decision as to which crossover operator to use for each problem instance size was based on the lowest value, the average of the averages value, and the average standard deviation for the total cost and balanced transit time (i.e., the two objective functions of the SSCFLAP-BAC). Based on these metrics, the results were as follows:

- The general two-point, segment-based crossover with 1,000 generations performed the best for the small problem instance.
- The modified two-point, segment-based crossover with random binary mask in both segments with 500 generations performed the best for the medium problem instance.
- The modified two-point, segment-based crossover with random binary mask in the second segment and the general two-point crossover in the first segment with 1,000 generations performed the best for the large problem instance.

B. *Fine Tuning the Parameters of the NSGA-II*

Table I shows the optimal values for the four NSGA-II parameters for the three problem instance sizes obtained through the RSM with CCD. Model adequacy checking was performed to ensure that the analysis of variance (ANOVA) assumptions (i.e., normality of the residuals, independence of observations within and between samples, and equal variance) of the second order model were satisfied before obtaining the optimal values of the four parameters.

TABLE I. Optimal Parameter Values for the Three Problem Instance Sizes

Problem Size	Probability of Crossover	Probability of Mutation	Pop. Size	No. of Generations
Small	0.8	0.03	148	1,250
Medium	0.24	0.16	196	1,463
Large	0.43	0.15	147	1,136

It is important to emphasize that the optimal parameter values shown in Table I are only applicable to the SSCFLAP-BAC and to the approach followed to construct the small, medium, and high problem instance sizes using the data described in III.C. Therefore, if either the problem type or the characteristics of the problem instance sizes change, this will require the use of different optimal parameter values to optimize or improve the quality of the responses.

C. *Factorial Experimental Design*

The level of significance α used to determine statistically significant effects in the factorial experiment was set at 0.05. Model adequacy checking was performed to ensure that the ANOVA assumptions were satisfied before analyzing the main factor effects. If any violation to the ANOVA assumptions was identified, a transformation was applied. If none of the transformations were able to make the residuals satisfy normality assumption, a one-way ANOVA and the non-parametric procedure Kruskal-Wallis test were used to support the analysis of factors effects on the response variables [27], [30]. Before the results of each response variable for the three problem instances are presented and discussed, it is important to note the following:

- When analyzing the factor effects on the response variables *average total transit time*, *balance level of transit time*, and *number of opened DCs*, the main factor *unit shipping cost* represents the unit shipping cost between DCs and customers and the main factor *capacity* represents the capacity of DCs.
- When analyzing the factor effects on the response variable *number of opened plants*, the main factor *unit shipping cost* represents the unit shipping cost between plants and DCs and the main factor *capacity* represents the capacity of plants.
- When analyzing the factors effects on the response variable *total cost*, the main factor *unit shipping cost* includes both the unit shipping costs between plants and DCs and between DCs and customers, and the main factor *capacity* includes both the capacity of plants and the capacity of DCs.

1) *Total Cost*

The results of the ANOVA for the response variable total cost for the three problem instances seem to indicate that when demand increases, the total cost increases. Also, when unit shipping cost increases, the total cost increases because the total shipping cost is calculated by multiplying demand by the unit shipping cost. Finally, when the capacity of DCs and plants increases, the total cost also increases. There are also significant interactions between main factors and responses, which reveal that total cost increases when any of the three main factors increases.

2) *Average Total Transit Time*

The results of the ANOVA for the response variable average total transit time for the three problem instances seem to indicate that when demand increases, the number of opened DCs also increases which, in turn, decreases the average total transit time because transit times are more spread out among opened DCs. However, magnitude-wise, the effect is very small compared to the effect of unit shipping cost. In contrast, the average total transit time increases significantly when unit shipping cost increases because transit time increases as unit shipping cost increases. Increasing the capacity of DCs does not significantly affect the average total transit time.

3) *Balance Level of Transit Time*

The results of the ANOVA for the response variable balance level of transit time seem to indicate that, for small and large problem instances, the balance level of transit time increases when demand increases because more DCs are opened. Opening more DCs increases the variability in transit time, thus affecting the calculation of the sum of squares. In contrast, the balance level of transit time decreases when demand increases for medium problem instances because the transit times assigned to DCs are more balanced (i.e., customers are more spread out).

The results also showed that the balance level of transit time increases in all three problem instances when the unit shipping cost increases because unit shipping cost is proportional to transit time. The balance level of transit time also increases for small problem instances when the capacity of the DCs increases. This means that more customers are allocated to some of the opened DCs, which in turn increases the variability in transit time. For medium and large problem instances, an increase in the capacity of the DCs does not significantly affect the balance level of transit time because the number of opened DCs is not affected. There is a significant interaction between the main factors demand and unit shipping cost. When demand is either high or low and the unit shipping cost increases, the balance level of transit time increases. Hence, the main factor unit shipping cost has the largest effect (i.e., magnitude-wise) on the balance level of transit time.

4) *Number of Opened DCs*

The results of the ANOVA for the response variable number of opened DCs for the three problem instances seem to indicate that the number of opened DCs increases when demand increases. When unit shipping cost increases, the number of opened DCs increases. Since the transit time is proportional to the unit shipping cost, more DCs were opened to help in maintaining the balance level of transit time.

For small problem instances, the number of opened DCs decreases when the capacity of the DCs increases because more customers can be allocated to DCs. For medium and large problem instances, an increase in the capacity of the DCs does not affect the number of opened DCs given that the numbers of opened DCs were already high.

5) *Number of Opened Plants*

The results of the ANOVA for the response variable number of opened plants for the three problem instances seem to indicate that the number of opened plants also increases when demand increases. In contrast, an increase in the unit shipping cost does not affect the number of opened plants.

The main factor capacity of plants does not influence the number of opened plants for the any of the three problem instances. However, there is an interaction effect between the main factors demand and capacity of plants for the small problem instances, as depicted in Fig. 3. When demand is low, increasing the capacity of plants does not change the number of opened plants (i.e., a single plant can satisfy the demand). In contrast, increasing the capacity of plants decreases the number of opened plants when demand is high.

V. Conclusions

This research aimed at developing a methodology to generate feasible solutions to the multi-objective, single-source capacitated facility location-allocation problem (SSCFLAP) with a balanced allocation of customers (BAC) for a two-echelon supply chain network (SCN). The characteristics of the SSCFLAP-BAC and the assumptions considered when modeling the problem make the solution methodology applicable to regional retail chains that distribute product types that are large in size, including aluminum rods, decking boards, drywall panels, and lumber, to name a few.

As anticipated, the main factor that has the largest effect on the total cost of the SCN is customer demand because it is the main cost driver in the calculation of the total shipping costs. The main factor that has the largest effect on the balance level of transit time and the average total transit time is unit shipping cost because this main factor is proportional to transit time. Therefore, as the number of customers that are located farther away from the DCs increases, so do the balance level of transit time and the average total transit time. This implies that it is harder to balance the total transit time assigned to the opened DCs when customers are located farther away from the DCs. Consequently, when unit shipping cost increases, the number of opened DCs also increases to help in maintaining the balance level of transit time. An increase in customer demand has different effects on the balance level of transit time depending upon the size of the problem instance. The difference is mainly influenced by the number of opened DCs and the number of customers in each problem instance size. The number of opened plants is not influenced by unit shipping cost, because this main factor has no influence on the location and allocation decisions between DCs and plants.

A. *Research Limitations*

This research has some limitations that should be noted. Due to the limited prior work that has attempted to solve the SSCFLAP and balance the allocation of customers with respect to transit time in a two-echelon SCN, data for some of the parameters required to solve this problem were not readily available and were generated by the researcher. Also, a single type of product was assumed and a minimum balance level of transit time was not specified as one of the constraints.

B. *Opportunities for Future Work*

The scope of this research could be expanded to test additional scenarios that include different numbers of customers and facilities. Moreover, a more complex supply chain network could be studied that includes multiple levels (e.g., suppliers and/or third party logistics) with multiple types of products.

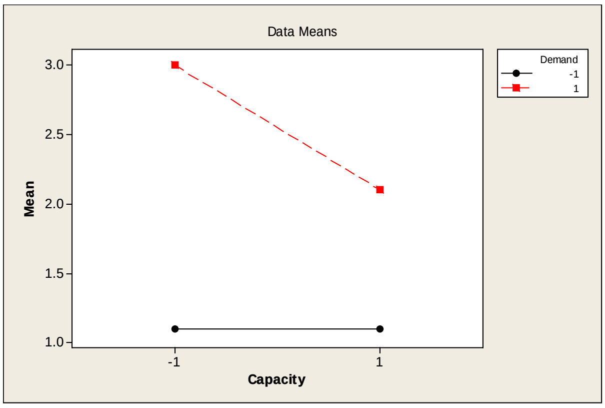

Fig. 3. Demand and Capacity Interaction Plot for Number of Opened Plants in Small Problem Instance

In this research, it was assumed that customer demand should be fulfilled by a single DC with a full truckload. Therefore, this assumption could be extended to include routing or shared truckload among customers if the capacity of the truck was not filled. Also, no loss or delay during shipment was considered (i.e., the transit time between customers and DCs was fixed). Incorporating variability in transit time could improve the analysis on the balance level of transit time. Finally, different metaheuristic algorithms (other than the NSGA-II) could be used to solve the proposed mathematical model to compare their performance.

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