

WORKING PAPER SERIES
WP 2025-003
August 2025



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Haibo Wang
Texas A&M International University

**Bahram Alidaee**The University of Mississippi

www.tamiu.edu/cswht

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# Variable Neighborhood Descent Methods for Large-Scale Single-Assignment Multi-Level Facility Location Problem

Haibo Wang<sup>1</sup>

A. R. Sanchez, Jr. School of Business, Texas A&M International University, Laredo, Texas, USA

Bahram Alidaee

School of Business Administration, The University of Mississippi, University, Mississippi, USA

### **Abstract**

This paper addresses the single-assignment uncapacitated multi-level facility location (MFL) problem, which has numerous applications, including tactical and strategic supply chain management. We consider four- and five-level facilities (4-LFL and 5-LFL). Although the MFL has been addressed in the literature in various settings, solutions to large-scale, realistic problems are still lacking. This paper considers several variants of the variable neighborhood descent (VND) method, including BVND, PVND, CVND, and UVND, for the problem. In each case, a multi-start strategy with strong diversification components is provided. Extensive computational experiments are presented to compare the methods for large-scale problems involving up to 10,000 customers, 150 distribution centers, 50 warehouses, and 30 plants in the case of 4-LFL; and 8,000 customers, 150 distribution centers, 50 warehouses, 50 plants, and 100 suppliers in the case of 5-LFL. Sensitivity analyses, supported by appropriate statistical methods, validate the effectiveness of the heuristics' results.

**Keywords:** Multi-level Facility Location Problem, Variable Neighborhood Descent Methods, Large-Scale Optimization

### 1. Introduction

This paper focuses on multi-level facility location (MFL) problems. In the literature, MFL is referred to by various terminologies, including multi-echelon facility location, multi-stage facility location, hierarchical facility location, multi-layer facility location, and *k*-level facility location (*k*-LFL). Here, we interchangeably refer to these problems as MFL and *k*-LFL, with *k* equal to 4 and 5. The problem has far-reaching applications in various settings, including tactical and strategic supply chain configuration and transportation planning (Muriel and Simchi-Levi 2003; Melo, Nickel, and Saldanha-da-Gama 2009; Ortiz-Astorquiza, Contreras, and Laporte 2018; Kumar et al. 2020; Janjevic, Merchán, and Winkenbach 2021; Li, Li, and Jiang 2021; Kang, Shen, and Xu 2022; Borajee, Tavakkoli-Moghaddam, and Madani-Saatchi 2023; Ouyang et al. 2023; Chen and Chen 2025; Amiri-Aref and Doostmohammadi 2025; Wandelt, Wang, and X. Sun 2025). For example, Amiri-Aref and Doostmohammadi (2025) emphasize the integration of strategic decisions regarding the number and location of retailers, collection center facilities, as well as

<sup>&</sup>lt;sup>1</sup> Address correspondence to Haibo Wang, Ph.D., Division of International Business and Technology Studies, A. R. Sanchez, Jr. School of Business, Texas A&M International University, 5201 University Boulevard, Laredo, Texas, USA. Email: <a href="https://hwang@tamiu.edu">hwang@tamiu.edu</a>

decisions related to manufacturing, remanufacturing, and recycling, inventory levels, and fleet sizes across the supply chain network.

A comprehensive review by Farahani et al. (2014) indicates the model's remarkable adaptability. The model has been used to solve public welfare problems, such as determining the optimal sites for new healthcare clinics or positioning emergency medical services for the fastest response times. At the same time, the model can handle complex logistical and infrastructure planning, from organizing municipal solid waste management systems to optimizing the layout of production and distribution networks. Its utility even extends into designing more efficient computer and telecommunication systems. Recent applications in services have been reported in Ahmadi-Javid, Seyedi, and Syam (2017), Gendron, Khuong, and Semet (2017), Rostami et al. (2018), Mogale, Cheikhrouhou, and Tiwari (2020), Majumdar et al. (2023), Kar and Jenamani (2024, 2025), Kumar and Kumar (2024), Ariningsih et al. (2025), and Sebatjane (2025). In a survey of 50 years of research in *Computers & Operations Research*, Guan et al. (2025) also emphasize the application of MFL in various settings in operations research.

In a recent survey of facility location in healthcare, Ahmadi-Javid, Seyedi, and Syam (2017) emphasize that health systems are hierarchical, resulting in various types of services that differ in cost and complexity. From local clinics to major hospitals, their placement is critical. Ariningsih et al. (2025) conducted a multi-echelon analysis of the pharmaceutical distribution network and waste management. Tsao, Balo, and Lee (2024) emphasize the importance of making strategic MFL decisions that will enhance supply chain resilience against natural disasters. Janinhoff et al. (2024) and Janjevic, Merchán, and Winkenbach (2021) focus on multi-facility locations of parcel lockers for last-mile delivery to solve the final, and often most difficult, logistical puzzle of getting a package to a customer.

Although hub-location analysis differs from the hierarchical model mentioned in this paper, it is also considered a multi-echelon approach. It can benefit from our work here, and vice versa. For example, Wandelt, Wang, and Sun (2025) and Ouyang et al. (2023) emphasize the multi-echelon location analysis of the e-commerce last-mile delivery system.

The remainder of this article is structured as follows. We first define the MFL model of this study, followed by a literature review, and a discussion of the contribution of this paper. Next, we describe the variable neighborhood descent (VND) search process for the problem and provide several variants of the VND, including Basic Variable Neighborhood Descent (BVND), Pipe Variable Neighborhood Descent (PVND), Cycle Variable Neighborhood Descent (CVND), and Union Variable Neighborhood Descent (UVND). Extensive computational experiments are conducted for 4- and 5-LFL on large-scale problems. Sensitivity analyses, supported by appropriate statistical methods, are used to validate the effectiveness of the heuristics' results. Managerial implications are then presented; and finally, the article concludes and provides suggestions for further research.

### 2. Problem Definition

The single-assignment MFL, known as *k*-LFL, is defined as follows. This paper considers 4- and 5-level facilities, i.e., 4-LFL and 5-LFL. In the 4-LFL, we have Levels 1 through 4, while in the 5-LFL, we have Levels 1 through 5. The following notations are used to explain the problem:

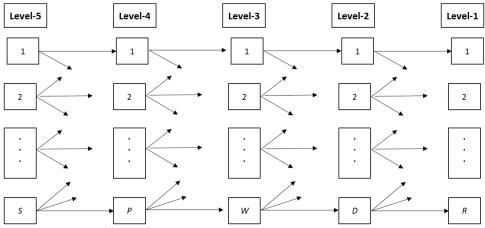
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R: Number of retail stores (Level 1)
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- D: Number of distribution centers (Level 2)
- W: Number of warehouses (Level 3)
- P: Number of plants (Level 4)
- S: Number of suppliers (Level 5)
- r: A retail store, r=1,...,R
- d: A distribution center, d=1,...,D
- w: A warehouse, w=1, ..., W
- p: A plant, p=1,..., P
- s: A supplier, s=1,..., S

(s,p,w,d,r), a feasible solution for a retailer r=1,...,R

Considering 5-LFL, each retail store  $r \in Level\ 1$  must be served via a single-assignment product (a bundle of products), starting from  $Level\ 5$  and finally reaching r. In that, a bundle of products flows from  $Level\ (k+1)$  to  $Level\ k$  (for  $k=1,\ldots,4$ ); however, an element in  $Level\ k$  can receive products only from a set of elements in facilities in  $Level\ (k+1)$  (for  $k=1,\ldots,4$ ).

Furthermore, each retail store  $r \in Level \ 1$ , besides being interested in receiving a bundle of products from an eligible  $Level \ 2$  facility, it may also only be interested in receiving products from an eligible set of facilities in  $Level \ 4$  (i.e., an eligible facility  $p \in Level \ 4$ ). This may occur in reality, as retailers are often interested in products from specific facilities (e.g.,  $Level \ 4$  plants, facilities). A general topology of such a complex network of facilities is illustrated in Figure 1. A schedule for transporting a bundle of products to a retail store  $r \in Level \ 1$  is illustrated by path (s,p,w,d,r) in Figure 1.



**Figure 1.** Topology of a 5-LFL.

Due to many real factors such as resource limitations and market considerations, we impose upper bounds on the number of facilities selected in each level k (k=2,...,5). Transporting products through such a complex network incurs some costs. Opening a facility at Level k (for k=2,...,5) involves a one-time fixed cost, while moving a bundle of products from Level (k+1) to Level k (for k=1,...,5) incurs a cost each time it is moved. The objective is to serve all retailers (i.e., elements

of the Level 1 facility) while minimizing total costs. We defined the problem for k=5; however, it can similarly be defined for k=4.

This problem has numerous applications in supply chain management. It is similar to the problem discussed in Ortiz-Astorquiza, Contreras, and Laporte (2018, 2019), except that we also consider the interests of retailers with products from a specific set of facilities in *Level 4*. Ortiz-Astorquiza, Contreras, and Laporte (2018) provided a comprehensive review of the MFL. Ortiz-Astorquiza, Contreras, and Laporte (2019) obtained an exact solution to the problem for k equal to 2 and 3, solving medium-sized problems. Here, we consider a very large-scale multi-start heuristic based on several variants of the VND meta-heuristic for k equal to 4 and 5. In the next section, we present the literature review, followed by a discussion of this paper's contribution.

### 3. Literature Review

Below, we review the literature on single-assignment MFL problems.

The single-assignment uncapacitated multi-level facility location (UMFL) problem generalizes the fundamental single-assignment uncapacitated single-level facility location (UFL) problem. The UFL problem has been extensively researched over many decades (e.g., Laporte, Nickel, and Saldanha da-Gama 2019).

An early study of the MFL problem was conducted by Kaufman, Eede, and Hansen (1977), who introduced the two-level so-called warehouse and plant location problem. Ortiz-Astorquiza, Contreras, and Laporte (2018) and Kumar et al. (2020) noted that most research on MFL has focused on two- or three-level cases, which is also discussed in Gendron, Khuong, and Semet (2017), Malik, Contreras, and Vidyarthi (2022), Sluijk et al. (2023), Fokouop et al. (2024), Gendron, Khuong, and Semet (2024), and Marianov and Eiselt (2024). We refer to a comprehensive review of general MFL problems by Ortiz-Astorquiza, Contreras, and Laporte (2018), including single-assignment cases.

Chardaire, Lutton, and Sutter (1999) formulated a telecommunication problem as a single-assignment two-level model and provided upper and lower bounds for the problem. Previously, Tragantalerngsak, Holt, and Rönnqvist (1997) also formulated a transportation problem as a single-assignment two-echelon model and applied a Lagrangian heuristic. Yaman (2009) considers a three-level single-assignment transportation problem with loading and unloading as a three-level facility location in the context of a hub network and presents a mixed-integer programming model.

Gendron, Khuong, and Semet (2015) implemented a multilayer variable neighborhood search (VNS) to solve a two-level, single-assignment facility location problem. Gendron, Khuong, and Semet (2016) presented a Lagrangian branch-and-bound approach for the optimal solution to the two-level uncapacitated single-assignment problem. Gendron, Khuong, and Semet (2017) also considered the two-level uncapacitated single assignment problem. The authors present six mixed-integer formulations and compare them experimentally.

Hammami, Frein, and Bahli (2017) examined the impact of lead time on a single-assignment, multi-echelon facility location in the supply chain. They concluded that manufacturing and distribution sites should be located near the demand zone (i.e., retailers) and local suppliers should be selected, despite their higher costs.

Ortiz-Astorquiza, Contreras, and Laporte (2018, 2019) studied the UMFL with single-assignment constraints. Path-based and arc-based integer programming approaches are given. An

optimal solution approach based on Benders' reformulation is provided, which solves medium-sized two- and three-level problems.

Ramshani et al. (2019) considered the single-assignment two-level uncapacitated facility location problem with uncertain disruption. The authors developed two mathematical models and a tabu search as a solution approach.

Myung and Yu (2020) analyzed a freight transportation model with a multi-echelon structure that bundles products. They mentioned that the transportation of product bundling can be viewed as a special case of single-assignment; however, additional efforts and costs are associated with the bundling and unbundling of products. The authors developed a heuristic based on the network flow algorithm.

De Oliveira et al. (2021) examined how well a specific "divide-and-conquer" algorithm works for a dynamic facility location problem. Their study looked at a two-level system without capacity limits, testing the algorithm's performance when customers must be assigned to just one facility and when they can be assigned to many.

Wang et al. (2023) addressed a single-item, multi-echelon location inventory and provided a  $\varepsilon$  – optimal approach using Lagrangian relaxation. Although the hub facility location is hierarchical and shares a significant similarity with the MFL considered in the current study, they are not identical. Our approaches can benefit hub location analysis and vice versa. For a comprehensive review of articles from an air transportation perspective, refer to O'Kelly, Sun, and Wandelt (2025), which includes a review of single-assignment models.

In a recent survey of facility location in healthcare applications, Ahmadi-Javid, Seyedi, and Syam (2017) noted that healthcare systems are hierarchical. They formulated the multistage single-assignment p-median problem. The authors identified several gaps in the MFL within healthcare systems, utilizing both modeling and computational approaches. In the context of a closed-loop supply chain design, Amiri-Aref and Doostmohammadi (2025) developed a mathematical model to determine the best locations and the ideal number of facilities that serve as retail stores and return centers. They also provide two algorithms, Relax-and-Fix and Fix-and-Optimise, to solve the problem.

### 4. Contribution of This Paper

As the literature suggests, for single-assignment MFL, most algorithms are based on two-level (in rare cases, three-level) facility location problems. Even in these cases, small to medium-sized problems are being considered. Real-world problems are large-scale, often involving more layers (e.g., supply chain design problems), and within each layer, potentially more facilities are considered (Zandi Atashbar, Labadie, and Prins 2018). Note that even in the simplest case, the UFLP is NP-hard (nondeterministic polynomial time hard). MFL problems are more complex and require sophisticated algorithms for large-scale cases. The problems considered in this study are not only larger in scale, but they also involve additional constraints related to the literature, as explained above. To address these shortcomings, we consider the VND meta-heuristic, a variant of the VNS meta-heuristic, for large-scale 4- and 5-LFL problems. Although there are many variants of VND, the most representative are BVND, PVND, CVND, and UVND (Duarte et al. 2018). The detailed explanation of these four variants for 5-LFL is explained in the next section. Again, tuning the algorithms for 4-LFL is straightforward.

A brief overview of recent applications of the four variants of VND (BVND, PVND, CVND, and UVND) algorithms is provided below. As mentioned earlier, Duarte et al. (2018) provide an excellent discussion of these VND variants and their applications.

Erzin, Mladenovic, and Plotnikov (2017) provided a hybrid genetic algorithm and VND for min-power symmetric connectivity. In this VND, three neighborhood structures were considered. Liu et al. (2021) also provided a hybrid VND genetic-particle swarm algorithm for the flexible job-shop. The VND is integrated into the standard genetic algorithm (GA) framework as an improvement process. Mjirda et al. (2017) employed a sequential VND for the traveling salesman problem. The authors used the four variants we also consider here as the moves in their procedures. Osorio-Mora, Escobar, and Toth (2023) proposed an iterated hybrid simulated annealing and VND for a variant of the vehicle routing problem (VRP), known as the latency VRP. Matijević et al. (2024) considered a general VNS for symmetric vehicle routing. The BVND variant was integrated as an improvement process into multi-start local search and several well-known meta-heuristics. Tadaros, Sifaleras, and Migdalas (2024) considered a hierarchical multi-echelon VRP, integrating a general VNS that employs BVND to solve the problem. Daquin et al. (2021) applied two VND variants, BVND and UVND, as an improvement to the general VNS and used them to cross-dock truck assignments. They employed the Best Improvement (BI) and First Improvement (FI) processes in the algorithms. Janinhoff et al. (2024) surveyed out-of-home delivery in last-mile logistics, including VND applications. Siew, Sze, and Goh (2025) considered VND variants, including the four variants we consider here, as an improvement process in the Whale Optimization Algorithm (WOA). Surprisingly, variants of the VNS are absent from the application in MFL problems.

### 5. Four Variants of VND Meta-heuristic for MFL

An optimization problem may be defined by a feasible solution X, and an objective function  $f: X \to Real$  where Real is the set of real numbers. The problem is to find a solution,  $x * \in X$  that optimizes (maximizes or minimizes, depending on the problem) the function f. Without loss of generality, we focus on minimization, noting that maximization is equivalent to minimizing -f.

Members of the set X may be defined differently depending on the problem considered. Often,  $x \in X$  is a binary vector, or a vector of real numbers.

Below, we provide several definitions for 5-LFL; however, similar definitions may be given for 4-LFL. In many cases, the set of solutions is defined on a network, as we do here. Earlier, we explained that a feasible solution (schedule) for a customer  $r \in Level\ 1$  is defined by a path (s,p,w,d,r) in the network shown in Figure 1. We show this individual solution by  $x_r = (s,p,w,d,r)$ . Generally, many feasible solutions for a retailer r create a set of solutions denoted by  $X_r$ . Now, we can define the set of feasible solutions for the problem as  $X = \{X_r\}$  for  $r=1,\ldots,R$ .

Given a feasible solution,  $x_r \in X_r$  for a retail store  $r \in Level \ 1$ , let  $x'_r \in X_r$  when k (for k=1,...,4) eligible elements from the set  $\{s,p,w,d\}$  are changed. The set of all such  $x'_r \in X_r$  is called the set of k-neighborhoods of  $x_r$ , denoted by  $N_k(x_r)$ . For a retail store r,  $N_k(x_r)$  includes 4 (one-element change), 6 (two-element change), 4 (three-element change), and 1 (four-element change), also called neighborhood types, for k=1, 2, 3, and 4, respectively, for a total of 15 neighborhood types. Furthermore,  $\mathbb{N}(k) = \bigcup_{r=1}^R N_k(x_r)$  is referred to as the set of k-neighborhood structures for the problem. Let  $x_{loc} \in \mathbb{N}(k)$  be such that  $f(x_{loc}) \leq f(x)$  for all  $x \in \mathbb{N}(k)$ ,  $x_{loc}$ 

gives us the best possible outcome. Let  $\mathbb{N} = \bigcup_{k=1}^{max_k} N(k)$ , and  $x * \in \mathbb{N}$  be such that  $f(x^*) \le f(x)$  for all  $x \in \mathbb{N}$ ,  $x^*$  is a *global optimal* solution for the problem.

Over the last several decades, researchers have formulated a wide range of real-world problems as optimization problems and solved them using various methods. Since these problems are NP-hard and finding a solution to realistic, large-scale problems is difficult, researchers often use heuristics, specifically meta-heuristics. Duarte et al. (2018) noted that over the last several decades, more than 50 variants of meta-heuristics have been developed. In general, such heuristics can be categorized into Adaptive Heuristics (AH), Large Neighborhood Search (LNS), Adaptive Large Neighborhood Search (ALNS), and various combinations of these methods (Rahimi and Rahmani 2024).

AH is a heuristic that modifies its configuration as the search progresses and, thus, changes its behavior (Gouda and Herman 1991; Sevaux, Sörensen, and Pillay 2018; Yaakoubi and Dimitrakopoulos 2025). First introduced by Shaw (1998), LNS is a metaheuristic built on a surprisingly straightforward principle: to find a better solution, it may be necessary to break an existing good one selectively. The core idea isn't to construct a solution from scratch, but to operate through a cyclical process of partial destruction and subsequent reconstruction. At each search step, the algorithm typically pairs one of each. It first applies a destructive method to take the current solution apart, creating a partial, incomplete version. Then, using a constructive method, it rebuilds from that point, ideally charting a path to an improved overall outcome. Often, the selection of constructive and destructive processes is implemented probabilistically. ALNS, initially developed by Ropke and Pisinger (2006), builds upon LNS by probabilistically selecting the pair of constructive and destructive processes based on information from previous performances.

In general, the basic idea of AH involves dynamic neighborhood changes to reach better solutions when a simpler neighborhood is stuck in a local optimum. This dynamism expands the search to diverse areas of the search space for better solutions. Refer to Sevaux, Sörensen, and Pillay (2018) for a general discussion of AH models, Ahuja et al. (2002) for a survey of very large-scale neighborhood search algorithms, and Mara et al. (2022) for a survey of ALNS applications.

A popular adaptive meta-heuristic is the VNS, proposed by Mladenović and Hansen (1997). The VNS relies on several local search processes across several neighborhood structures. The General VNS is a type of ALNS and, thus, often depends on the pair of *constructive* and *destructive* processes in a solution. However, several variants of the VNS have been proposed in the literature, including VND, Reduced VNS (RVNS), Basic VNS (BVNS), General VNS (GVNS), Skewed VNS (SVNS), and Variable Neighborhood Decomposition Search (VNDS); refer to Duarte et al. (2018) for a basic discussion of these methods. Among these variants, VND is one of the most applied by researchers; it is effective and straightforward to implement and does not rely on constructive and destructive phases. Over the years, many variants of VND have been proposed, see for example, Erzin, Mladenovic, and Plotnikov (2017), Mjirda et al. (2017), Duarte et al. (2018), Daquin et al. (2021), Matijević et al. (2024), de Armas and Moreno-Perez (2025), and Siew, Sze, and Goh (2025).

In the VND algorithms, a list of neighborhood structures is provided sequentially, usually in the order of sophistication (starting from the smallest to the largest neighborhood structures). Within these variants, Basic VND (BVND), Pipe VND (PVND), Cyclic VND (CVND), and Union VND (UVND) are the most representative, according to Duarte et al. (2018). These methods differ in the order in which the neighborhood structures are implemented and the depth to which they are

implemented. This means that when an improvement in a neighborhood is detected, it is important to determine which neighborhood to explore next and how deeply it should be investigated.

It is believed that the larger the neighborhood, the better the quality of the locally optimal solutions. However, using a larger neighborhood incurs high CPU time costs (Ahuja et al. 2002). Thus, when applied to large-scale problems, it is crucial to balance CPU time and explore larger areas of the neighborhood to find better solutions. A general description of these algorithms is given below, focusing on where to explore next after an improvement is detected in the process (Duarte et al. 2018).

After finding a way to improve the solution:

- BVND This strategy returns to the beginning and reapplies its first search method on the newly improved solution.
- PVND This strategy uses the same search method that just succeeded.
- CVND This strategy proceeds to the next search method in its predefined list.
- UVND This strategy treats all search methods as one big "toolbox." After finding an improvement with one tool, it continues searching using any tools from its entire collection, without a strict order.

As mentioned, the neighborhood structures are presented in order of sophistication. Thus, the BVND process is fully explored each time the least sophisticated (simplest) neighborhood structure is reached. In the PVND, each neighborhood structure is fully explored before proceeding to the next structure. In the CVND, however, as soon as an improvement is detected, the search continues to the next structure. In the case of UVND, all structures are combined into a single large structure and appropriately explored.

An important factor to consider when implementing a local search within a specific neighborhood is the order in which the search process is executed. This is especially important when dealing with very large-scale problems. In these cases, the order of implementation is effective in reaching actionable results. This provides an opportunity to explore a more diverse area of the solution space. It has been experimentally demonstrated that a random order of implementations yields significantly better results than always choosing a specific order (Alidaee and Wang 2017). Choosing a random order each time to explore the neighborhood structure can be time-consuming. However, selecting a sequence each time can significantly reduce this time, as discussed in Wang and Alidaee (2023) and several references in that study. We explore this factor in more detail later in the paper when describing the pseudocode of the algorithms.

In the following subsection, we provide the pseudocode of the algorithms for 5-LFL, which can be easily tuned for 4-LFL.

### 5.1 Pseudocode of the Four Algorithms for 5-LFL

Considering 5-LFL, given a schedule  $x_r = (s, p, w, d, r)$  for a retail store r, with all neighborhood structures  $N_k(x_r)$  for k=1,...,4, and k possible changes among s, p, w, and d. We also refer to this as a k-flip move (or exchange). Thus, for k=1, 2, 3, and 4, the number of elements in  $N_k(x_r)$ , respectively, is n=4, 6, 4, and 1, totaling 15 neighborhood moves.

As previously mentioned, a critical issue in designing heuristics is the choice of neighborhood structure and the order in which they are implemented. The order of implementation for a local search within each neighborhood structure is also an important factor. Furthermore, in

optimization problems, neighborhood structures are often defined based on the mathematical programming formulation of the problem. However, a graphical neighborhood structure is considered here.

In the case of 4-LFL, we have three neighborhood structures  $\mathbb{N}(k)$  for k=1,2, and 3. For  $\mathbb{N}(k)$  and k=1 and 2, each includes three neighborhood types, while for k=3, there is one, for a total of seven neighborhood types, as illustrated in Figure 2. In the case of 5-LFL, we have four neighborhood structures  $\mathbb{N}(k)$  for k=1,2,3, and 4. For  $\mathbb{N}(k)$  and k=1 and 3, each includes four neighborhood types, and for k=2, it includes six neighborhood types, while for k=4, it includes one, for a total of 15 neighborhood types, as illustrated in Figure 3. These figures are shown in Appendix A.

To implement the *k*-flip move processes, for a given value of *k*, several important issues should be considered:

- (a) Which retail stores, r, should be considered each time for a possible k-flip move implementation? We use a sequence Lr(1), ..., Lr(R) of R numbers to select the next retail store.
- (b) Given a schedule for a retail store, r, which combination of k elements from the set  $N_k(x_r)$  should be considered for k-flip moves? For this, we use a sequence, q(1),...,q(n), for example, for k=2, we use a sequence of n=6 numbers q(1),...,q(6), indicating an order of six elements in  $N_2(x_r)$ . Thus, for k=2, each element  $q(.) \in N_k(x_r)$  is a pair of nodes.
- (c) Given a schedule for a retail store, r, a neighborhood structure,  $N_k(x_r)$  for some value of k, and an element  $q(.) \in N_k(x_r)$ , which element of q(.) should be considered next for a k-flip move? For example, for (s,p,w,d,r) and k=2, let  $q(.) = \{d,p\}$ . For this, we consider sequences Ld(1),...,Ld(D), and Lp(1),...,Lp(P), respective, D and P numbers. Thus, along these two sequences, we flip two nodes  $d' \neq d$  and  $p' \neq p$  for a possible 2-flip move. Similarly, we can implement k-flip moves for different values of k.

Algorithm-0 is a basic k-flip local search strategy appropriately used in other algorithms.

**Algorithm-0:** Simple *k-flip* Neighborhood Search Process (5-FLP)

**Initialization:** Set of numbers *R*, *D*, *W*, *P*, and *S*.

A value for k (1,...,4), and the set of neighborhood structures  $\mathbb{N}(k)$ . A feasible schedule (s,p,w,d,r) for each retail store r=1,...,R.

*Improvement*=True

While (Improvement) Do

*Improvement*=False

Randomly select an order of numbers 1,...,n, i.e., q(1),...,q(n), of elements in  $\mathbb{N}(k)$ 

For (h=q(1),...,q(n))

Randomly select sequences, *Lr, Ls, Lp, Lw,* and *Ld,* of numbers *R, S, P, W,* and *D,* respectively. If a *h-flip* is improving along appropriate sequences *Lr, Ls, Lp, Lw,* and *Ld,* implement the move, and set *improvement*=True

**End For** 

Update the best-known solution

End While

Algorithm-0 exhaustively implements the process of *k*-flips until no more moves are possible. In Algorithm-0-k, however, the algorithm returns when an improvement is detected.

**Algorithm-0-k(.)** for k=2,3,4, is the same as Algorithm-0 except that as soon as an improvement is found for any of the h values, RETURN the result.

```
Algorithm-1 (Multi-start k-flip): Multi-start Neighborhood Search Process (5-FLP)
Initialization: Set of neighborhood structures, \mathbb{N}(k), for a value of k=1,\ldots,4. Set of integer numbers R, D,
W, P, and S. Max-Local (number of multiple starts), j=1
While (j \le Max-Local) Do
  Randomly select sequences, Lr, Ls, Lp, Lw, and Ld
  Call Algorithm-0 for k
  Keep track of the best solution found throughout
End While
Algorithm-2: BVND Multi-start Neighborhood Search Process (5-FLP)
Initialization: Set of neighborhood structures, \Box (k), (for k=1,...,4)
Call Algorithm-1(.) with k=1
Improvement=True
While (Improvement) Do
  Improvement=False
  Step 1. Call Algorithm-0(.) with k=1.
  For (k=2,...,4) Do
     Call Algorithm-0-k(.) with k, if an improvement is detected, implement the change,
     improvement=True, and go to Step 1, otherwise continue
  End For
  Update the best-known solution
End While
```

Note that in **Step 1** of Algorithm-2, the 1-flip Algorithm-0(.) is exhaustively implemented; however, the same algorithm for k=2, 3, and 4 returns to **Step 1** as soon as an improvement is detected, i.e., Algorithm-0-k(.). Also, note that Algorithm-1(.) with k=1 is the multi-start 1-flip local search strategy. The result of this algorithm is used as a starting solution for the BVND, PVND, CVND, and UVND algorithms.

The choice of different sequences in the algorithms is crucial. Using different sequences allows diversification into a large area of the solution space as the search progresses. It is also easy to start different solutions in the multi-start strategy. Any method for selecting new sequences each time is acceptable. However, a clever implementation of the sequence selection process can significantly reduce CPU time. Two such innovative approaches are adapted from applications in sequencing problems, such as the Traveling Salesman Problem (TSP). One is based on the socalled *l*-Opt local search strategy applied to the TSP and many other sequencing problems (see Alidaee and Wang 2017). The other is the Random-Key strategy (see Wang and Alidaee 2023), adapted from the Random-Key application in the TSP (Bean 1994). There are both advantages and disadvantages to using these two strategies. Using the *l*-Opt strategy may be more time-consuming, but it takes less memory space. However, the opposite is true for the use of the Random-Keys application. To address very large-scale problems, we employed the l-Opt strategy to minimize space usage. Refer to Alidaee and Wang (2017) for a detailed implementation of the *l*-Opt strategy, and Wang and Alidaee (2023) for details on the Random-Key strategy supplication. Note that the value of r in the l-Opt strategy is effective in results when solving problems. We used a limited 4-Opt strategy in our implementation, adapted from Glover (1996) for TSP applications.

As explained earlier, there are different ways to define neighborhood structures. Often, they are determined based on mathematical programming formulations of the problem. However, this study uses graphical structures, as shown in Figure 2 for 4-FLP and Figure 3 for 5-FLP.

We previously noted variations of the VND methods differ in the order and depth in which the neighborhood structures are implemented. This can create many variants, some of which could be very time-consuming. However, four popular variants are BVND, PVND, CVND, and UVND. Even within each of these variants, there are many ways to implement the process. After applying several approaches (see the computational experiments section), it was revealed that implementing a multi-start strategy similar to Algorithm 1 significantly reduces CPU time. At the same time, the quality of the results of Algorithms 2 through 5 also remains high.

A k-flip local search can be exhaustively implemented for each neighborhood structure  $\mathbb{N}(k)$ . Generally, implementing local searches for larger values of k is more time-consuming. However, it is also believed that larger values of k can diversify to broader areas of the solution space and possibly create better solutions. Thus, it is important to balance CPU time and achieving better solutions. Here, we used a multi-start strategy, Algorithm-1, which incorporates the 1-flip strategy. The results of this algorithm are used as a starting solution in Algorithms 2 through 5.

Algorithm-2 is written for BVND; however, it can easily be tuned for other VND variants. Algorithms 3, 4, and 5 are designed for PVND, CVND, and UVND. Note that in PVND, before the search moves from one neighborhood structure to another, an exhaustive 1-flip local search is completed. However, in CVND, the search is explored in the next neighborhood structure after each local improvement is detected. Also note that in the UVND, it is important to specify the order of the local improvement process within the *big* neighborhood structures. The union of all neighborhoods includes different types of possible moves: 1, 2, 3, or 4 moves. Here, we randomly chose the order to check the improvement of moves in the *big* neighborhood structure. The UVND has similarities with CVND. In CVND, we have an order in which we implement neighborhood structures; however, in UVND, we treat all neighborhood structures the same and randomly implement the improvement process. Also, note that most researchers use the so-called Best Improvement (BI) or First Improvement (FI) (Daquin et al. 2021; Matijević et al. 2024) process in UVND; however, we use the Next Improvement process here.

```
Algorithm-3: PVND Multi-start Neighborhood Search Process (5-FLP)

Initialization: Set of neighborhood structures, \mathbb{N}(k), (for k=1,...,4)

Call Algorithm-1(.) with k=1

Improvement=True

While (Improvement) Do

Improvement=False

For (k=1,...,4) Do

Call Algorithm-0(.) with k, if an improvement is detected, implement the change.

Improvement=True

End For

Update the best-known solution

End While
```

Note that Algorithm-3 does not return immediately after finding an improvement in Algorithm-0(.) with k. It exhaustively continues the search in the same neighborhood structure, then returns and restarts Algorithm-0(.) with k+1.

```
Algorithm-4: CVND Multi-start Neighborhood Search Process (5-FLP)

Initialization: Set of neighborhood structures, N(k), (for k=1,...,4)

Call Algorithm-1(.) with k=1

Improvement=True

While (Improvement) Do

Improvement=False
For (k=1,...,4) Do

Call Algorithm-0-k(.) with k, if an improvement is detected, implement the change Improvement=True,

End For

Update the best-known solution

End While
```

Note that, in CVND, Algorithm-0-k(.) is used in the inner loop, as each time a local search is detected, we return to the next neighborhood. Additionally, the inner loop is consistently implemented with the same order: k = 1, 2, 3, 4. You may obtain different results for each order if other orders are used. However, CPU time will increase.

```
Algorithm 5: UVND Multi-start Neighborhood Search Process, (5-FLP)
Initialization: Set of neighborhood structures, \mathbb{N}(big) = \mathbb{N}(1) \cup \mathbb{N}(2) \cup \mathbb{N}(3) \cup \mathbb{N}(4)
Call Algorithm-1(.) with k=1
Improvement=True
While (Improvement) Do
  Improvement=False
  Randomly select an order of four neighborhood structures, M(j), j=1,...,4, in \mathbb{N}(big)
  For (k=M(1),...,M(4)) Do
     Select an order of numbers 1, ..., n, (i.e., q(1), ..., q(n)), where n is the number of elements in \mathbb{N}(k).
     For (h=q(1),...,q(n)) Do
       Call Algorithm-0-k(.) with k, if an improvement is detected, implement the change,
       Improvement=True, and go to Start a new neighborhood, otherwise continue
     End For
     Start a new neighborhood
  End For
  Update the best-known solution
End While
```

In UVND, the loop running via k goes through all neighborhood structures, and the loop running via k goes through each element of  $\mathbb{N}(k)$ . As soon as an improvement is detected, it proceeds to the next neighborhood. It should be clear that the orders used in the implementation processes can significantly affect the outcomes in UVND and other algorithms regarding solution values and CPU time. Thus, there are many ways to create an effective variant of VND.

### 6. Experimental Design and Results

### 6.1 Data Generation

There is no benchmark available for the problems considered in this paper. The only benchmark that shares some characteristics with our problems is provided by Ortiz-Astorquiza, Contreras, and

Laporte (2019). However, there are only two with four-level facilities. These two problems also lack some data that cannot be used in our computational experiment. Thus, we randomly generated problem instances and solved them using the algorithms. All algorithms were implemented in Fortran and executed in order on a Cray Cluster 140 with Intel Haswell Xeon processors.

We generated problems of varying sizes with different densities for matrices and fixed cost levels. Table B1 in Appendix B shows the parameters with which the data is generated. For each problem size with High, Medium, and Low densities, and Large, Medium, and Small fixed costs, we generated three instances and solved them using B-VND, P-VND, C-VND, and U-VND algorithms. Results for 4-LFL are shown in Table 1, and for 5-LFL are shown in Table 2. Note that problem IDs for 4-LFL are shown by (R-D-W-P-Density-Fixed Cost-#). For example, (2000-150-50-30-Hdens-LgFx-1) means R=2000, D=150, W=50, and P=30, with High Density, Large Fixed Cost, and problem # 1. Similarly, problem IDs for 5-LFL are shown by (R-D-W-P-S-Density-Fixed Cost-#). For example, (2000-150-50-50-100-Hdens-LgFx-1) means R=2000, D=150, W=50, P=50, S=100, High Density, Large Fixed Cost, and problem number 1. Three instances of each problem were generated and solved using B-VND, P-VND, C-VND, and U-VND. The objective function in each case, as well as the CPU time to reach the best solution, is given.

### 6.2 Computational Results

As discussed earlier, each VND variant can be implemented in many different ways. However, it is important to strike a balance between CPU time and high-quality solutions. This is especially important when dealing with large-scale problems. The multi-start strategy offers an opportunity to start a new solution each time, leading to different end solutions and, potentially, a higher-quality solution. To balance CPU time with the final solution, we applied a multi-start strategy on Algorithm-1 with k=1, a speedy process. Then, we used the best result of this process as a starting solution for each variant of the VND process. Tables 1 and 2 show the results.

### 6.3 Sensitivity Analyses of Algorithms

To determine which of our algorithms performs better across different tasks, we employed rank-based statistical methods, which are well-suited for these evaluations. Instead of getting overwhelmed by the precise numerical outcomes, these tests focus on the relative ordering of algorithm performance for each problem. Of course, care was taken to ensure these comparisons were meaningful. This includes running sufficient experiments and being thoughtful about our significance thresholds. It is especially important to account for making multiple comparisons at once, so we report not just the raw significance values (p-values) but also effect sizes, where appropriate, to provide a clearer picture of the results.

Our first step was to get a bird's-eye view of the overall performance. For this, we used Friedman's test, a non-parametric method that serves a similar purpose to a repeated measures ANOVA. It works by ranking the algorithms on each dataset and then checking if the average ranks are too different to be explained by random chance. A significant result from Friedman's test suggests that at least one algorithm behaves differently but does not specify which ones.

When the Friedman test indicated a meaningful difference, we needed to dig deeper to identify the specific pairs of algorithms that were outperforming others. The Nemenyi test is designed for this situation, comparing all algorithms against each other while carefully controlling the error rate

Table 1a. Computational results of four VND processes on 4-LFL instances of 2000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants										
Problem ID	Objective Function					Time to Bes	st (Seconds)			
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
2000-150-50-30-Hdend-LgFx-1	82516	86936	86799	82526	97.03	91.99	92.08	100.99		
2000-150-50-30-Hdend-LgFx-2	93339	93795	93672	93283	348.10	348.56	346.97	350.82		
2000-150-50-30-Hdend-LgFx-3	104994	114192	113427	105810	168.18	150.51	147.30	166.85		
2000-150-50-30-Hdend-MedFx-1	87044	91414	90685	87105	47.25	38.94	31.96	42.92		
2000-150-50-30-Hdend-MedFx-2	77593	78426	77962	77798	44.65	46.59	38.42	48.01		
2000-150-50-30-Hdend-MedFx-3	84139	84258	84285	84139	335.55	334.96	328.18	344.14		
2000-150-50-30-Hdend-SmFx-1	95006	95295	95236	94980	236.52	235.87	221.99	254.58		
2000-150-50-30-Hdend-SmFx-2	88092	90839	90091	88084	225.18	172.04	181.31	217.52		
2000-150-50-30-Hdend-SmFx-3	79293	81267	79732	79287	232.29	221.69	216.82	221.03		
2000-150-50-30-Ldend-LgFx-1	48260	49314	49400	48260	114.10	113.42	113.44	114.19		
2000-150-50-30-Ldend-LgFx-2	53515	53675	53516	53677	17.08	16.73	16.53	16.81		
2000-150-50-30-Ldend-LgFx-3	49092	49289	49180	49092	6.59	6.30	6.33	6.93		
2000-150-50-30-Ldend-MedFx-1	43313	44401	44109	43295	8.46	7.57	7.54	8.28		
2000-150-50-30-Ldend-MedFx-2	44200	46591	46503	44160	109.07	108.09	108.01	108.94		
2000-150-50-30-Ldend-MedFx-3	42525	42774	42773	42518	40.83	40.38	40.15	40.83		
2000-150-50-30-Ldend-SmFx-1	37037	37132	37179	37031	86.99	86.87	86.80	86.90		
2000-150-50-30-Ldend-SmFx-2	41712	42716	42203	41712	142.56	141.24	141.83	141.75		
2000-150-50-30-Ldend-SmFx-3	43197	43268	43190	43188	154.14	153.66	153.80	153.78		
2000-150-50-30-Mdend-LgFx-1	87964	88780	88322	87951	264.56	261.60	260.82	266.42		
2000-150-50-30-Mdend-LgFx-2	86041	87853	86522	86557	265.45	264.17	263.81	267.34		
2000-150-50-30-Mdend-LgFx-3	96397	103287	100513	96410	87.37	79.96	79.25	84.27		
2000-150-50-30-Mdend-MedFx-1	78867	80260	78863	78159	88.88	83.26	88.22	87.10		
2000-150-50-30-Mdend-MedFx-2	76912	84061	83021	76928	232.99	227.44	227.16	229.98		
2000-150-50-30-Mdend-MedFx-3	69865	76446	76090	69916	162.71	158.24	158.42	162.97		
2000-150-50-30-Mdend-SmFx-1	63630	63711	63626	63646	155.42	151.46	152.40	154.65		
2000-150-50-30-Mdend-SmFx-2	83593	84916	83572	83605	50.19	33.47	43.52	40.19		
2000-150-50-30-Mdend-SmFx-3	71192	76370	75316	71162	268.24	265.92	263.91	266.17		

**Table 1b.** Computational results of four VND processes on 4-LFL instances of 4000 retailers.

Problem ID		Objective	Function			Time to Bes	st (Seconds)	
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND
4000-150-50-30-Hdend-LgFx-1	163782	167375	166115	163851	1072.31	1061.14	1062.49	1065.11
4000-150-50-30-Hdend-LgFx-2	144186	147013	146360	144151	226.74	225.45	204.67	225.98
4000-150-50-30-Hdend-LgFx-3	142331	145623	144457	142388	320.24	321.90	326.89	321.63
4000-150-50-30-Hdend-MedFx-1	179338	180803	179841	179462	1029.07	997.08	999.71	1003.84
4000-150-50-30-Hdend-MedFx-2	148549	148879	148540	148544	268.42	252.38	251.16	254.26
4000-150-50-30-Hdend-MedFx-3	168375	176749	173930	168375	1166.66	987.03	1054.70	1034.42
4000-150-50-30-Hdend-SmFx-1	129510	129906	129520	129487	569.84	542.02	546.21	566.37
4000-150-50-30-Hdend-SmFx-2	170884	174552	173076	170863	317.76	204.84	235.93	212.54
4000-150-50-30-Hdend-SmFx-3	135090	136289	135533	135097	222.43	176.78	183.69	187.66
4000-150-50-30-Ldend-LgFx-1	84948	88032	87999	84945	604.26	601.90	601.64	604.20
4000-150-50-30-Ldend-LgFx-2	81317	82363	82189	81342	139.10	137.22	136.63	138.73
4000-150-50-30-Ldend-LgFx-3	82540	82795	82644	82540	694.10	692.76	692.87	694.06
4000-150-50-30-Ldend-MedFx-1	76294	77101	76816	76181	472.91	472.02	470.85	472.08
4000-150-50-30-Ldend-MedFx-2	73613	74692	74580	73604	134.52	134.65	133.58	134.54
4000-150-50-30-Ldend-MedFx-3	81556	82755	82031	81505	752.50	750.80	751.65	751.20
4000-150-50-30-Ldend-SmFx-1	80637	81740	81145	80689	710.93	708.15	708.62	708.90
4000-150-50-30-Ldend-SmFx-2	73529	74665	74167	73521	522.74	519.80	520.05	521.80
4000-150-50-30-Ldend-SmFx-3	77185	79849	79605	77182	260.39	258.22	258.28	259.58
4000-150-50-30-Mdend-LgFx-1	148423	159622	158510	148396	478.79	458.22	460.49	464.91
4000-150-50-30-Mdend-LgFx-2	129456	135679	135126	127102	238.96	221.87	223.87	228.46
4000-150-50-30-Mdend-LgFx-3	152378	163307	160447	153006	1214.70	1181.89	1187.64	1193.33
4000-150-50-30-Mdend-MedFx-1	136152	138858	137970	136156	669.24	657.77	656.69	660.70
4000-150-50-30-Mdend-MedFx-2	160547	167382	165509	159933	710.64	704.40	694.18	709.02
4000-150-50-30-Mdend-MedFx-3	128098	145466	143543	128109	260.81	232.19	232.36	243.18
4000-150-50-30-Mdend-SmFx-1	123517	138277	136997	123519	309.29	271.82	280.25	289.08
4000-150-50-30-Mdend-SmFx-2	121252	126117	124998	121237	436.82	410.81	402.68	423.95
4000-150-50-30-Mdend-SmFx-3	118064	122915	121221	118063	619.87	598.78	604.78	606.84

**Table 1c.** Computational results of four VND processes on 4-LFL instances of 5000 retailers.

Problem ID		Objective	Function			Time to Bes	st (Seconds)	
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND
5000-150-50-30-Hdend-LgFx-1	165209	165790	165369	165228	311.40	292.38	293.05	302.70
5000-150-50-30-Hdend-LgFx-2	212370	214486	212124	211893	865.58	771.14	805.62	781.36
5000-150-50-30-Hdend-LgFx-3	147921	169689	169670	147936	555.54	546.31	550.74	561.90
5000-150-50-30-Hdend-MedFx-1	201505	202249	201523	201519	923.67	834.44	848.55	854.05
5000-150-50-30-Hdend-MedFx-2	168430	170054	168760	168430	1795.55	1729.24	1741.30	1758.29
5000-150-50-30-Hdend-MedFx-3	197495	198152	197498	197512	1118.70	1091.12	1096.34	1097.77
5000-150-50-30-Hdend-SmFx-1	135116	157476	157285	135116	1281.75	1237.76	1229.08	1297.30
5000-150-50-30-Hdend-SmFx-2	205700	209432	208485	205700	1075.55	995.81	985.64	1011.30
5000-150-50-30-Hdend-SmFx-3	203097	222019	218951	203101	781.38	556.89	605.73	650.90
5000-150-50-30-Ldend-LgFx-1	103976	103981	103976	103976	541.60	541.73	541.59	541.53
5000-150-50-30-Ldend-LgFx-2	106521	107654	106970	106481	719.53	715.77	714.87	718.08
5000-150-50-30-Ldend-LgFx-3	99511	100092	99548	99451	508.95	508.38	507.21	508.10
5000-150-50-30-Ldend-MedFx-1	95877	97206	96822	95885	1012.71	1011.60	1011.04	1011.61
5000-150-50-30-Ldend-MedFx-2	88235	89074	88428	88244	801.17	798.02	797.06	798.93
5000-150-50-30-Ldend-MedFx-3	96004	97554	97350	96059	326.70	324.71	324.06	326.99
5000-150-50-30-Ldend-SmFx-1	90998	91652	91121	91072	775.48	774.02	772.99	774.25
5000-150-50-30-Ldend-SmFx-2	92268	92616	92387	92133	1054.15	1052.52	1051.58	1053.32
5000-150-50-30-Ldend-SmFx-3	86461	87546	87086	86490	553.43	551.13	550.27	552.15
5000-150-50-30-Mdend-LgFx-1	167206	183965	182350	167208	1250.08	1218.28	1227.12	1247.28
5000-150-50-30-Mdend-LgFx-2	183179	203938	200599	181107	424.98	382.73	385.31	414.35
5000-150-50-30-Mdend-LgFx-3	172385	180852	179326	172432	1062.48	1028.18	1034.57	1039.06
5000-150-50-30-Mdend-MedFx-1	177003	195466	191273	178034	1119.24	1062.35	1069.11	1072.15
5000-150-50-30-Mdend-MedFx-2	169550	180337	178808	169566	1318.56	1250.66	1272.73	1269.32
5000-150-50-30-Mdend-MedFx-3	193137	201951	200787	192227	414.68	325.98	323.76	358.58
5000-150-50-30-Mdend-SmFx-1	167334	173544	172463	167497	815.40	770.28	773.20	787.58
5000-150-50-30-Mdend-SmFx-2	155656	176255	174320	155625	1566.87	1485.99	1492.47	1533.44
5000-150-50-30-Mdend-SmFx-3	149553	161147	159245	149808	364.94	307.91	303.49	324.78

**Table 1d.** Computational results of four VND processes on 4-LFL instances of 8000 retailers.

Problem ID		Objective	Function			Time to Bes	st (Seconds)	
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND
8000-150-50-30-Hdend-LgFx-1	286710	287974	286970	286712	6151.77	6090.37	6092.19	6084.82
8000-150-50-30-Hdend-LgFx-2	308767	315077	311141	3091136	2943.53	2909.41	2874.83	2965.03
8000-150-50-30-Hdend-LgFx-3	247574	255382	255250	247581	1518.00	1507.69	1504.14	1534.80
8000-150-50-30-Hdend-MedFx-1	290102	295803	293067	290112	740.91	541.49	559.88	582.32
8000-150-50-30-Hdend-MedFx-2	290469	299441	297337	290606	1200.70	1020.87	1123.96	1003.45
8000-150-50-30-Hdend-MedFx-3	328326	329411	328329	328357	962.72	567.95	758.02	579.47
8000-150-50-30-Hdend-SmFx-1	272208	295780	293111	272221	1000.10	404.84	493.88	569.34
8000-150-50-30-Hdend-SmFx-2	246276	246590	246354	246276	1114.02	1061.67	1070.72	1096.07
8000-150-50-30-Hdend-SmFx-3	381493	385195	382142	381510	1478.04	1262.27	1288.34	1286.01
8000-150-50-30-Ldend-LgFx-1	158772	160923	160715	158830	857.10	846.35	845.96	855.38
8000-150-50-30-Ldend-LgFx-2	143288	143440	143445	143288	1147.32	1146.80	1146.13	1147.54
8000-150-50-30-Ldend-LgFx-3	158978	160708	160287	158942	613.94	603.96	607.36	608.72
8000-150-50-30-Ldend-MedFx-1	143892	145651	145237	144002	3381.92	3375.60	3372.98	3380.55
8000-150-50-30-Ldend-MedFx-2	144136	147494	147337	144093	724.30	715.60	713.60	722.83
8000-150-50-30-Ldend-MedFx-3	152146	152564	152217	152115	244.76	240.96	238.78	242.61
8000-150-50-30-Ldend-SmFx-1	133503	135270	134117	133575	1046.20	1039.95	1040.04	1043.17
8000-150-50-30-Ldend-SmFx-2	140496	143090	142734	140408	778.90	775.29	774.28	775.85
8000-150-50-30-Ldend-SmFx-3	142819	146484	145582	142738	1457.02	1442.55	1443.12	1454.80
8000-150-50-30-Mdend-LgFx-1	222168	247649	243531	223419	4175.72	4084.95	4097.18	4134.04
8000-150-50-30-Mdend-LgFx-2	279576	296747	294166	279657	6167.65	6080.30	6078.07	6115.31
8000-150-50-30-Mdend-LgFx-3	285159	299181	297137	285138	2710.06	2613.99	2618.81	2654.68
8000-150-50-30-Mdend-MedFx-1	284920	298920	296919	284763	1118.66	970.73	996.28	1016.65
8000-150-50-30-Mdend-MedFx-2	320007	341952	335765	319652	5150.24	4871.87	4926.04	4931.52
8000-150-50-30-Mdend-MedFx-3	256300	259117	257165	257062	1038.47	963.42	970.94	975.63
8000-150-50-30-Mdend-SmFx-1	239190	243659	241833	239265	502.92	401.59	419.89	423.74
8000-150-50-30-Mdend-SmFx-2	270643	285783	281573	270628	2032.92	1867.06	1898.94	1898.20
8000-150-50-30-Mdend-SmFx-3	255149	264036	260899	255142	4774.45	4634.19	4687.79	4657.68

**Table 1e.** Computational results of four VND processes on 4-LFL instances of 9000 retailers.

Problem ID		Objective	Function			Time to Bes	st (Seconds)	
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND
9000-150-50-30-Hdend-LgFx-1	390442	411536	406318	390132	659.46	314.92	374.93	383.77
9000-150-50-30-Hdend-LgFx-2	318904	340494	339534	319112	473.23	328.34	323.12	485.47
9000-150-50-30-Hdend-LgFx-3	367271	390719	387381	385050	1773.64	1576.77	1597.60	1565.60
9000-150-50-30-Hdend-MedFx-1	349182	372814	368714	349224	6672.44	6228.07	6400.78	6308.50
9000-150-50-30-Hdend-MedFx-2	347940	356658	347862	346429	3544.22	3033.01	3297.32	3099.96
9000-150-50-30-Hdend-MedFx-3	364524	378008	372895	364516	2949.52	2585.90	2613.23	2728.91
9000-150-50-30-Hdend-SmFx-1	246377	273784	273392	246377	1034.88	860.35	853.36	991.70
9000-150-50-30-Hdend-SmFx-2	275550	278316	276224	275550	4276.80	4105.87	4124.20	4165.33
9000-150-50-30-Hdend-SmFx-3	343131	363371	351337	343118	2657.10	2114.36	2242.05	2075.53
9000-150-50-30-Ldend-LgFx-1	161461	165181	164801	161312	747.61	737.44	737.95	745.46
9000-150-50-30-Ldend-LgFx-2	184900	185579	185122	184850	482.22	475.51	474.14	476.39
9000-150-50-30-Ldend-LgFx-3	166494	174804	174409	166464	1698.78	1682.08	1681.02	1692.64
9000-150-50-30-Ldend-MedFx-1	175197	175960	175653	174880	287.13	279.18	275.92	281.53
9000-150-50-30-Ldend-MedFx-2	151682	153011	151811	151724	2322.94	2318.39	2315.97	2317.93
9000-150-50-30-Ldend-MedFx-3	160917	164013	163042	160970	3667.90	3657.80	3657.32	3662.78
9000-150-50-30-Ldend-SmFx-1	149633	153113	152299	149669	3851.04	3838.30	3839.81	3843.20
9000-150-50-30-Ldend-SmFx-2	148940	154249	153723	148877	2571.52	2560.97	2557.90	2575.92
9000-150-50-30-Ldend-SmFx-3	163000	166762	166024	162976	1018.69	1003.78	1003.06	1013.05
9000-150-50-30-Mdend-LgFx-1	302000	347963	344931	301974	4782.90	4588.68	4637.00	4680.38
9000-150-50-30-Mdend-LgFx-2	310059	327107	324182	310220	708.31	597.94	593.89	634.69
9000-150-50-30-Mdend-LgFx-3	334976	351967	348056	335199	2614.49	2511.94	2509.76	2531.13
9000-150-50-30-Mdend-MedFx-1	278898	303181	301665	279041	3753.53	3590.35	3608.75	3667.71
9000-150-50-30-Mdend-MedFx-2	257541	263062	262050	257544	1474.90	1377.54	1378.82	1391.96
9000-150-50-30-Mdend-MedFx-3	290489	359204	356493	298982	5992.55	5768.64	5767.68	5880.00
9000-150-50-30-Mdend-SmFx-1	265834	285834	281615	266086	1783.06	1589.02	1646.48	1637.20
9000-150-50-30-Mdend-SmFx-2	282574	309572	305118	282607	1253.98	1102.05	1125.95	1157.28
9000-150-50-30-Mdend-SmFx-3	342723	361822	357501	342703	4649.82	4249.38	4384.29	4311.06

**Table 1f.** Computational results of four VND processes on 4-LFL instances of 10000 retailers.

Problem ID		Objective Function Time to Best (Second						
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND
10000-150-50-30-Hdend-LgFx-1	321566	323926	322505	321815	639.67	551.23	497.39	578.27
10000-150-50-30-Hdend-LgFx-2	379082	383488	383735	379594	1690.76	1320.62	1313.88	1348.39
10000-150-50-30-Hdend-LgFx-3	320632	352198	351363	319578	1406.69	1263.92	1221.20	1381.74
10000-150-50-30-Hdend-MedFx-1	361291	370279	369371	361294	2303.12	2204.46	2190.18	2262.41
10000-150-50-30-Hdend-MedFx-2	335514	339266	337369	335348	2765.08	2551.57	2614.85	2625.55
10000-150-50-30-Hdend-MedFx-3	321362	333568	327664	321329	921.41	729.91	813.82	791.89
10000-150-50-30-Hdend-SmFx-1	332991	345289	339160	333045	4372.67	4054.38	4104.60	4066.57
10000-150-50-30-Hdend-SmFx-2	359455	370686	361198	359384	5858.61	5321.47	5482.52	5397.01
10000-150-50-30-Hdend-SmFx-3	330040	337091	334763	330040	2824.08	2591.13	2652.53	2610.52
10000-150-50-30-Ldend-LgFx-1	208777	209883	209766	208743	3899.71	3891.78	3889.88	3896.27
10000-150-50-30-Ldend-LgFx-2	179812	180655	180744	179846	546.14	538.99	534.02	542.51
10000-150-50-30-Ldend-LgFx-3	195325	198598	198030	195322	3219.56	3207.65	3206.80	3212.88
10000-150-50-30-Ldend-MedFx-1	167132	168517	168252	167118	3514.88	3502.36	3500.17	3510.79
10000-150-50-30-Ldend-MedFx-2	191287	195498	193375	191238	3860.14	3843.09	3839.75	3850.53
10000-150-50-30-Ldend-MedFx-3	187463	193603	193471	187488	910.96	895.64	894.97	908.78
10000-150-50-30-Ldend-SmFx-1	180076	184180	185628	180094	3182.96	3173.86	3159.89	3179.92
10000-150-50-30-Ldend-SmFx-2	166020	173044	172237	166057	3895.22	3864.76	3863.71	3883.09
10000-150-50-30-Ldend-SmFx-3	171613	175725	172520	171893	2312.89	2299.34	2298.64	2299.03
10000-150-50-30-Mdend-LgFx-1	362394	372857	368330	362641	4808.75	4684.20	4721.71	4737.26
10000-150-50-30-Mdend-LgFx-2	328630	340188	336855	328355	190.70	81.60	82.57	110.69
10000-150-50-30-Mdend-LgFx-3	362394	372857	368330	362641	4380.88	4248.51	4287.62	4302.37
10000-150-50-30-Mdend-MedFx-1	369488	377681	374475	369511	1060.09	782.66	798.33	808.85
10000-150-50-30-Mdend-MedFx-2	332321	334136	332321	332321	8630.42	8529.22	8551.88	8530.94
10000-150-50-30-Mdend-MedFx-3	362587	368086	364583	362516	7527.28	7279.72	7295.86	7301.94
10000-150-50-30-Mdend-SmFx-1	308897	319490	316897	308894	5385.31	5228.19	5225.23	5262.53
10000-150-50-30-Mdend-SmFx-2	343946	345068	343957	343961	6257.47	6040.22	6019.37	6054.05
10000-150-50-30-Mdend-SmFx-3	370793	388874	381709	370787	1034.55	512.71	586.47	576.04

**Table 2a.** Computational results of four VND processes on 5-LFL instances of 2000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants, S=# Suppliers										
Problem ID		Objective	Function			Time to Bo	est (Seconds)			
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
2000-150-50-50-100-Hdend-LgFx-1	127180	129392	133848	127020	1532.10	1819.50	2328.41	2697.78		
2000-150-50-50-100-Hdend-LgFx-2	131016	147501	156709	130646	1048.17	1233.28	2138.57	1891.16		
2000-150-50-50-100-Hdend-LgFx-3	129708	130546	139464	127778	725.87	2495.46	5133.46	4187.80		
2000-150-50-50-100-Hdend-MedFx-1	119217	119399	125171	119172	1374.84	2702.95	2142.58	4721.81		
2000-150-50-50-100-Hdend-MedFx-2	104083	105558	114242	102157	1693.83	1874.25	1833.02	2233.02		
2000-150-50-50-100-Hdend-MedFx-3	108347	105161	123306	102029	1619.39	3080.19	2080.40	3854.57		
2000-150-50-50-100-Hdend-SmFx-1	88575	90635	110244	87920	989.47	1135.67	1978.85	2397.26		
2000-150-50-50-100-Hdend-SmFx-2	103840	106741	119004	105105	1231.82	1501.53	1884.11	2628.80		
2000-150-50-50-100-Hdend-SmFx-3	84333	82403	85694	82589	864.18	1025.16	2691.49	1676.86		
2000-150-50-50-100-Ldend-LgFx-1	123531	128472	128979	111671	331.52	234.22	507.87	1138.07		
2000-150-50-50-100-Ldend-LgFx-2	127847	130257	133605	127971	638.95	616.27	676.31	793.06		
2000-150-50-50-100-Ldend-LgFx-3	128693	128809	131974	125444	463.33	506.85	588.02	1010.13		
2000-150-50-50-100-Ldend-MedFx-1	102544	103234	115655	96479	493.41	819.55	777.84	1223.59		
2000-150-50-50-100-Ldend-MedFx-2	102246	102280	119321	102241	367.36	924.08	819.71	1367.53		
2000-150-50-50-100-Ldend-MedFx-3	100115	100740	112246	90659	288.88	660.87	573.91	772.63		
2000-150-50-50-100-Ldend-SmFx-1	103094	107937	112919	104700	557.78	936.14	665.24	1212.30		
2000-150-50-50-100-Ldend-SmFx-2	86687	90362	114823	85569	923.04	1330.40	1022.91	1797.37		
2000-150-50-50-100-Ldend-SmFx-3	87611	88629	93278	82495	504.37	748.80	702.74	910.61		
2000-150-50-50-100-Mdend-LgFx-1	133450	134299	142980	134235	1050.54	927.73	1296.05	2541.49		
2000-150-50-50-100-Mdend-LgFx-2	130008	140061	141766	129883	765.22	827.62	1210.80	1094.91		
2000-150-50-50-100-Mdend-LgFx-3	141132	142844	148292	141220	1223.29	1487.47	1498.24	2290.16		
2000-150-50-50-100-Mdend-MedFx-1	107333	109648	116862	106968	1161.83	2052.24	1418.20	2751.46		
2000-150-50-50-100-Mdend-MedFx-2	115833	115557	117425	109747	536.47	673.40	983.72	822.49		
2000-150-50-50-100-Mdend-MedFx-3	119481	108682	126895	115650	741.21	1290.15	1455.34	2400.86		
2000-150-50-50-100-Mdend-SmFx-1	91442	93979	111419	90700	1143.57	1824.61	1423.73	2659.35		
2000-150-50-50-100-Mdend-SmFx-2	89198	91327	103848	86695	309.41	625.61	643.16	886.67		
2000-150-50-50-100-Mdend-SmFx-3	80569	84387	101457	81435	578.40	1337.62	1148.89	1465.98		

**Table 2b.** Computational results of four VND processes on 5-LFL instances of 3000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants, S=# Suppliers										
Problem ID		Objective	Function			Time to Bo	est (Seconds)	)		
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
3000-150-50-50-100-Hdend-LgFx-1	177143	181279	188765	177171	1730.51	2774.29	2855.76	3317.83		
3000-150-50-50-100-Hdend-LgFx-2	185687	181059	216072	185317	2557.96	3712.22	3452.67	4547.93		
3000-150-50-50-100-Hdend-LgFx-3	226165	229090	234020	209822	1575.09	1718.28	2555.89	6453.75		
3000-150-50-50-100-Hdend-MedFx-1	155601	143283	174113	151073	3102.29	5227.15	3224.85	8061.98		
3000-150-50-50-100-Hdend-MedFx-2	162708	181873	206139	170701	1801.24	4322.82	3228.67	6592.10		
3000-150-50-50-100-Hdend-MedFx-3	165688	168593	175312	165719	2594.15	3338.00	3202.92	5285.76		
3000-150-50-50-100-Hdend-SmFx-1	148823	154034	161306	141953	2054.82	2787.82	5039.54	5244.57		
3000-150-50-50-100-Hdend-SmFx-2	125141	127389	137693	125123	1748.31	2596.58	3565.00	4622.17		
3000-150-50-50-100-Hdend-SmFx-3	119312	120421	139086	118029	2051.55	2954.15	3483.59	4265.77		
3000-150-50-50-100-Ldend-LgFx-1	169606	181739	188606	169814	1155.88	1211.17	1245.18	1586.68		
3000-150-50-50-100-Ldend-LgFx-2	183923	181877	196333	172949	1596.45	1958.97	2159.86	2237.93		
3000-150-50-50-100-Ldend-LgFx-3	165942	169482	191824	165498	1603.40	2130.76	1663.86	2826.26		
3000-150-50-50-100-Ldend-MedFx-1	143168	133492	158848	129467	994.58	1947.49	975.56	2355.73		
3000-150-50-50-100-Ldend-MedFx-2	152122	150776	154927	138277	608.50	1178.65	728.49	1612.80		
3000-150-50-50-100-Ldend-MedFx-3	139154	140911	154228	134399	1636.26	1975.74	1460.27	2385.93		
3000-150-50-50-100-Ldend-SmFx-1	149072	151165	154243	144555	1489.77	2823.59	1566.15	4249.35		
3000-150-50-50-100-Ldend-SmFx-2	131108	137822	151672	131870	797.18	1442.17	851.93	1994.85		
3000-150-50-50-100-Ldend-SmFx-3	123340	129105	163749	118981	814.33	1595.61	983.17	1933.13		
3000-150-50-50-100-Mdend-LgFx-1	201766	202385	219455	201890	1147.99	1695.32	1743.13	2189.42		
3000-150-50-50-100-Mdend-LgFx-2	200961	202491	211892	201378	2878.33	3390.62	3622.60	4608.55		
3000-150-50-50-100-Mdend-LgFx-3	210361	209517	220199	210284	1136.45	2181.45	2158.88	2948.50		
3000-150-50-50-100-Mdend-MedFx-1	157920	153900	162390	157980	1308.13	2323.04	1405.11	2309.58		
3000-150-50-50-100-Mdend-MedFx-2	186210	190493	203165	170739	1748.24	2765.20	1384.80	3176.68		
3000-150-50-50-100-Mdend-MedFx-3	137290	139402	172374	135231	1314.72	2252.12	2039.26	3187.55		
3000-150-50-50-100-Mdend-SmFx-1	126919	128570	138260	125620	2388.45	3446.25	2865.53	4990.77		
3000-150-50-50-100-Mdend-SmFx-2	147877	149180	149946	148057	734.46	1124.48	1752.31	3194.35		
3000-150-50-50-100-Mdend-SmFx-3	148726	154574	161357	147700	1921.16	3371.77	1957.44	4269.02		

**Table 2c.** Computational results of four VND processes on 5-LFL instances of 4000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants, S=# Suppliers										
Problem ID		Objective	Function			Time to Bo	est (Seconds	)		
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
4000-150-50-50-100-Hdend-LgFx-1	250322	255850	293675	245746	4784.90	5895.74	5270.13	8884.54		
4000-150-50-50-100-Hdend-LgFx-2	249491	252572	264465	249410	3299.39	4922.62	5532.07	4923.97		
4000-150-50-50-100-Hdend-LgFx-3	312969	300518	293565	301348	3644.90	5780.33	6871.76	6377.05		
4000-150-50-50-100-Hdend-MedFx-1	241640	235244	252694	229504	5714.65	12607.79	7976.43	15501.11		
4000-150-50-50-100-Hdend-MedFx-2	195071	199395	228603	194101	2018.72	6839.02	4256.44	8104.99		
4000-150-50-50-100-Hdend-MedFx-3	240578	251823	259403	239200	5801.16	9854.55	7012.48	12639.69		
4000-150-50-50-100-Hdend-SmFx-1	159181	167744	194203	159469	3210.56	5498.01	3838.97	9474.06		
4000-150-50-50-100-Hdend-SmFx-2	222856	227498	234632	221096	3180.44	5331.01	5627.42	7754.41		
4000-150-50-50-100-Hdend-SmFx-3	190958	191280	193857	181928	3453.02	5982.70	5133.84	10205.69		
4000-150-50-50-100-Ldend-LgFx-1	187355	188975	212454	187193	807.58	947.11	1122.42	1474.65		
4000-150-50-50-100-Ldend-LgFx-2	200560	204187	224145	200237	1452.09	2205.28	2472.19	2479.21		
4000-150-50-50-100-Ldend-LgFx-3	209885	213684	232702	210091	1827.84	2285.93	1577.39	2560.29		
4000-150-50-50-100-Ldend-MedFx-1	192514	197223	236585	183226	2156.44	2937.75	2830.92	3437.66		
4000-150-50-50-100-Ldend-MedFx-2	220348	200020	234815	190991	2063.87	2955.56	2439.38	3674.91		
4000-150-50-50-100-Ldend-MedFx-3	206992	201915	236051	192946	2895.13	4523.59	2737.84	5101.41		
4000-150-50-50-100-Ldend-SmFx-1	164835	167148	190134	162773	2762.72	4170.86	2754.89	4547.10		
4000-150-50-50-100-Ldend-SmFx-2	164886	168507	192300	164179	1015.01	2294.03	1326.23	3166.26		
4000-150-50-50-100-Ldend-SmFx-3	174047	171087	190750	171942	3171.29	4197.75	2680.87	5961.77		
4000-150-50-50-100-Mdend-LgFx-1	207110	209461	217585	207206	2822.33	2887.98	3620.69	3908.46		
4000-150-50-50-100-Mdend-LgFx-2	259007	259314	262621	257541	2311.42	2392.37	2963.21	3560.05		
4000-150-50-50-100-Mdend-LgFx-3	205937	207658	256148	202064	1974.51	3472.08	2630.59	4477.17		
4000-150-50-50-100-Mdend-MedFx-1	227464	223909	259425	212093	4851.74	10925.84	3933.99	12634.54		
4000-150-50-50-100-Mdend-MedFx-2	199662	197979	237652	189764	2623.72	3993.71	3472.93	5343.94		
4000-150-50-50-100-Mdend-MedFx-3	237735	221130	273895	230915	1570.35	4076.80	2939.10	2555.40		
4000-150-50-50-100-Mdend-SmFx-1	158717	162377	206016	159200	2670.78	4978.39	2834.21	7641.99		
4000-150-50-50-100-Mdend-SmFx-2	150733	145308	175914	141209	1957.93	2910.38	2509.98	4787.07		
4000-150-50-50-100-Mdend-SmFx-3	178686	181847	200345	179126	3147.32	4336.45	3606.06	6628.40		

**Table 2d.** Computational results of four VND processes on 5-LFL instances of 5000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants, S=# Suppliers										
Problem ID		Objective	Function			Time to Be	est (Seconds	)		
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
5000-150-50-50-100-Hdend-LgFx-1	268947	276512	297434	268887	3761.39	5433.48	6809.43	5335.40		
5000-150-50-50-100-Hdend-LgFx-2	279601	287671	307109	276429	5806.98	6224.42	8866.12	10636.43		
5000-150-50-50-100-Hdend-LgFx-3	245074	245245	250646	244790	2581.77	3593.95	5116.11	4985.79		
5000-150-50-50-100-Hdend-MedFx-1	271725	273315	330750	271971	9682.94	21701.61	8731.48	21718.32		
5000-150-50-50-100-Hdend-MedFx-2	278547	281093	290523	278039	8337.45	11630.52	4723.23	15719.49		
5000-150-50-50-100-Hdend-MedFx-3	221034	202497	335217	192316	4435.51	11194.44	4382.31	12814.57		
5000-150-50-50-100-Hdend-SmFx-1	206043	219826	263292	206468	3488.80	5877.63	4492.62	7620.25		
5000-150-50-50-100-Hdend-SmFx-2	228559	241498	245041	228941	4958.44	9709.47	4698.77	11913.70		
5000-150-50-50-100-Hdend-SmFx-3	226301	242429	270806	218908	5892.36	11834.95	7856.14	16263.07		
5000-150-50-50-100-Ldend-LgFx-1	279697	289762	294586	272549	2505.48	2329.37	3252.98	3903.00		
5000-150-50-50-100-Ldend-LgFx-2	293944	282869	306636	293751	4002.84	4481.35	4636.14	5959.44		
5000-150-50-50-100-Ldend-LgFx-3	320792	327720	362256	285965	3418.14	4958.07	3255.28	6335.93		
5000-150-50-50-100-Ldend-MedFx-1	248485	251232	284234	244833	2791.12	4775.07	3204.98	5150.11		
5000-150-50-50-100-Ldend-MedFx-2	249046	232645	283852	225577	2787.85	4544.13	2813.65	5456.14		
5000-150-50-50-100-Ldend-MedFx-3	227814	212717	248618	231710	3023.70	4814.99	3081.34	4939.87		
5000-150-50-50-100-Ldend-SmFx-1	207160	212101	237825	200998	4006.85	5428.53	3834.05	6305.15		
5000-150-50-50-100-Ldend-SmFx-2	224958	226515	263278	223008	2582.18	5077.92	2149.58	5752.48		
5000-150-50-50-100-Ldend-SmFx-3	247893	247679	265141	240354	4673.47	5704.33	4289.94	5734.73		
5000-150-50-50-100-Mdend-LgFx-1	342111	346407	365131	339762	3910.67	13969.66	3288.19	14615.31		
5000-150-50-50-100-Mdend-LgFx-2	313128	316014	321843	313308	4836.85	6858.35	5865.27	8489.50		
5000-150-50-50-100-Mdend-LgFx-3	299188	296278	315600	298995	4342.93	5757.15	6738.68	5328.56		
5000-150-50-50-100-Mdend-MedFx-1	248908	240800	325411	227999	5879.65	9970.59	5492.00	10023.12		
5000-150-50-50-100-Mdend-MedFx-2	249029	258083	294296	255775	6179.88	9984.09	7496.14	12630.46		
5000-150-50-50-100-Mdend-MedFx-3	270201	273845	330514	242249	2049.76	3460.07	2739.98	5503.08		
5000-150-50-50-100-Mdend-SmFx-1	205491	209016	238292	196062	4182.37	5773.55	3916.20	7953.54		
5000-150-50-50-100-Mdend-SmFx-2	207958	215717	267263	208563	3457.46	7494.63	2792.22	9684.29		
5000-150-50-50-100-Mdend-SmFx-3	199180	212104	254877	198394	2604.59	4328.23	3750.37	5646.27		

**Table 2e.** Computational results of four VND processes on 5-LFL instances of 6000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants, S=# Suppliers										
Problem ID		Objective	Function			Time to Bes	st (Seconds)			
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
6000-150-50-50-100-Hdend-LgFx-1	293008	300028	319771	271939	7518.29	7752.59	8788.95	15675.96		
6000-150-50-50-100-Hdend-LgFx-2	393936	400790	433530	392230	6817.73	9325.12	7131.65	11823.88		
6000-150-50-50-100-Hdend-LgFx-3	331602	349018	354894	312272	6512.04	7133.33	8750.93	10520.74		
6000-150-50-50-100-Hdend-MedFx-1	309084	315475	339472	309267	13910.61	23165.08	10432.06	22768.38		
6000-150-50-50-100-Hdend-MedFx-2	321685	328873	370244	294956	5233.25	7595.34	5378.63	13408.95		
6000-150-50-50-100-Hdend-MedFx-3	306137	312871	344676	276489	11065.63	17483.96	10824.81	23178.23		
6000-150-50-50-100-Hdend-SmFx-1	298367	304797	320097	298511	4744.46	8680.57	9825.08	9010.65		
6000-150-50-50-100-Hdend-SmFx-2	276283	284867	309814	271278	9608.96	14602.37	11752.54	23380.67		
6000-150-50-50-100-Hdend-SmFx-3	233352	256432	294902	234922	5538.64	8062.13	12111.97	11105.01		
6000-150-50-50-100-Ldend-LgFx-1	297336	305185	320026	297697	4015.26	5390.77	2969.21	6951.39		
6000-150-50-50-100-Ldend-LgFx-2	320940	332249	389929	320309	3010.60	4941.23	3112.37	5173.45		
6000-150-50-50-100-Ldend-LgFx-3	383004	383836	419718	382987	854.67	4519.03	63.18	2642.41		
6000-150-50-50-100-Ldend-MedFx-1	271278	234922	297697	320309	9608.96	5538.64	4015.26	3010.60		
6000-150-50-50-100-Ldend-MedFx-2	248552	255533	349898	245610	5953.86	9490.38	6630.76	10870.23		
6000-150-50-50-100-Ldend-MedFx-3	286315	288274	323095	258663	2285.24	3177.12	2570.81	4689.73		
6000-150-50-50-100-Ldend-SmFx-1	239486	245162	292851	230756	4734.46	8507.50	2910.73	10239.04		
6000-150-50-50-100-Ldend-SmFx-2	271974	274030	315028	267892	5862.15	9991.21	5813.19	11675.50		
6000-150-50-50-100-Ldend-SmFx-3	266301	267334	301369	253206	2144.32	4919.35	2499.02	6916.76		
6000-150-50-50-100-Mdend-LgFx-1	360112	394691	403522	359874	3986.33	7790.15	4217.82	10627.67		
6000-150-50-50-100-Mdend-LgFx-2	377857	384473	399858	344081	3123.52	2665.16	4604.86	7212.37		
6000-150-50-50-100-Mdend-LgFx-3	321651	328403	366359	322146	5392.56	6033.74	5172.69	7447.67		
6000-150-50-50-100-Mdend-MedFx-1	324842	318890	346186	289247	5945.23	10348.75	7156.49	14427.86		
6000-150-50-50-100-Mdend-MedFx-2	318968	291904	330334	282535	8925.05	13132.62	8354.21	15052.72		
6000-150-50-50-100-Mdend-MedFx-3	307249	289231	313039	299443	5874.64	15787.05	4672.66	11380.20		
6000-150-50-50-100-Mdend-SmFx-1	289793	283423	305845	279657	7945.99	15302.42	8741.47	15444.77		
6000-150-50-50-100-Mdend-SmFx-2	216721	224010	300369	216542	5189.52	10202.04	5511.24	12777.54		
6000-150-50-50-100-Mdend-SmFx-3	303470	311863	325223	303353	6194.88	13501.47	4643.48	18602.30		

**Table 2f.** Computational results of four VND processes on 5-LFL instances of 8000 retailers.

R=# Retailers, D=# Dist Centers, W=# Warehouses, P=# Plants, S=# Suppliers										
Problem ID		Objective	Function			Time to Bes	st (Seconds)			
(R-D-W-P-Density-Fixed Cost Size-#)	BVND	PVND	CVND	UVND	BVND	PVND	CVND	UVND		
8000-150-50-50-100-Hdend-LgFx-1	460043	512460	580678	459786	5149.86	9977.25	7275.21	12243.60		
8000-150-50-50-100-Hdend-LgFx-2	387970	400420	489917	387969	8819.33	17220.76	10960.60	12918.66		
8000-150-50-50-100-Hdend-LgFx-3	481098	483133	495038	480988	6206.11	7531.56	10709.55	10433.51		
8000-150-50-50-100-Hdend-MedFx-1	403368	412470	474116	403122	16824.32	25967.07	15196.93	28814.66		
8000-150-50-50-100-Hdend-MedFx-2	309120	325281	480938	310566	16897.69	28653.49	17992.02	31458.59		
8000-150-50-50-100-Hdend-MedFx-3	348911	328797	388588	320849	6766.82	9356.48	10818.30	12112.75		
8000-150-50-50-100-Hdend-SmFx-1	322998	328336	439910	319933	7232.40	16204.02	8777.54	18275.64		
8000-150-50-50-100-Hdend-SmFx-2	356273	361349	382524	336157	9029.71	21010.80	11851.64	24648.14		
8000-150-50-50-100-Hdend-SmFx-3	329781	333136	354270	330067	9131.13	20176.41	9936.22	24549.03		
8000-150-50-50-100-Ldend-LgFx-1	436168	439563	462480	435383	6078.60	11017.90	4954.90	15366.45		
8000-150-50-50-100-Ldend-LgFx-2	338560	351882	380284	338346	3217.08	3795.77	3264.54	5143.09		
8000-150-50-50-100-Ldend-LgFx-3	404454	408439	443446	393934	6219.02	6657.13	6497.89	9748.62		
8000-150-50-50-100-Ldend-MedFx-1	398400	399903	428327	379651	9199.84	13199.69	9416.97	13769.74		
8000-150-50-50-100-Ldend-MedFx-2	376643	380956	410772	353777	8778.36	13618.16	6957.65	15815.32		
8000-150-50-50-100-Ldend-MedFx-3	462088	468267	506080	462155	7801.79	8852.34	6081.72	14368.71		
8000-150-50-50-100-Ldend-SmFx-1	294810	304183	368753	294360	8152.99	11967.96	7991.52	12275.05		
8000-150-50-50-100-Ldend-SmFx-2	346083	342947	387215	329934	7002.97	12752.58	5589.84	12973.57		
8000-150-50-50-100-Ldend-SmFx-3	337552	349742	407553	320960	5832.42	10282.20	3876.65	12390.54		
8000-150-50-50-100-Mdend-LgFx-1	544783	559126	636860	543943	9532.67	14818.14	10711.08	18589.10		
8000-150-50-50-100-Mdend-LgFx-2	422654	429948	460233	417468	6241.39	10765.83	5411.63	12349.77		
8000-150-50-50-100-Mdend-LgFx-3	441001	442948	443705	441232	5948.38	9164.54	8584.71	11328.28		
8000-150-50-50-100-Mdend-MedFx-1	400289	375619	406227	365818	2847.80	8144.00	4882.62	9706.31		
8000-150-50-50-100-Mdend-MedFx-2	429118	426793	487408	390742	8374.05	14886.71	8762.91	25737.91		
8000-150-50-50-100-Mdend-MedFx-3	411866	414954	425643	405364	9995.88	13812.95	9548.09	16999.94		
8000-150-50-50-100-Mdend-SmFx-1	396622	403721	424452	409841	11948.44	20194.12	11669.24	27102.25		
8000-150-50-50-100-Mdend-SmFx-2	334539	339190	363120	331733	11790.59	13732.46	11633.42	19720.01		
8000-150-50-50-100-Mdend-SmFx-3	332512	340180	417354	329292	16513.92	28054.14	12889.34	28668.03		

that can arise from so many simultaneous comparisons. In other cases, where we were more interested in direct head-to-head contests between two specific algorithms, the Wilcoxon signed-rank test was a better fit. This approach is useful because it considers the direction and magnitude of the performance differences. When running multiple Wilcoxon tests, we adjusted our significance levels using methods like the Bonferroni correction to avoid drawing faulty conclusions due to repeated testing.

Key statistics are reported in Tables 3, 4, 5, and 6 for the primary omnibus test, including the test statistics, degrees of freedom, and the p-value, so the overall findings are clear. Next, we specify exactly which pairs of algorithms showed statistically significant differences based on the follow-up methods we applied, making it easy to identify where the meaningful distinctions lie.

**Table 3.** Results of Friedman's Test, Nemenyi's Post-Hoc Test, and Pairwise Wilcoxon Test on the OFV of 4-LFL instances.

### Friedman's Test for BVND, PVND, CVND, and UVND

Number of complete experiments (blocks/rows): 162

Number of algorithms (groups/columns): 4 Friedman chi-squared statistics: 397.855

P-value: 6.454e-86

Note: The Friedman test was conducted to determine if there were any statistically significant differences in the median Objective Function Values (OFVs) achieved by the four algorithms (BVND, PVND, CVND, and UVND) across the 162 experiments. With a chi-squared statistic of 397.855 and an extremely low p-value (6.454e-86), far below the significance level of 0.05, the null hypothesis that all algorithms perform equally well (i.e., have similar median OFVs) was rejected. This indicates that at least one algorithm's typical OFV performance is statistically different from the others, necessitating post-hoc analysis to identify specific pairwise differences.

### --- Post-Hoc Analysis ---

Nemenyi's Post-Hoc Test Results (pairwise p-values):							
	BVND	PVND	CVND	UVND	_		
BVND		0	0	0.931			
PVND	0		1.02E-11	0			
CVND	0	1.02E-11		0			
UVND	0.931	0	0				

Note: Following the significant Friedman test, Nemenyi's post-hoc test was used for pairwise comparisons of algorithm performance based on their OFVs, with a significance level of 0.05. The results indicate that the OFVs achieved by algorithms BVND and UVND are not statistically distinguishable from each other (p = 0.931). However, all other pairwise comparisons yielded p-values less than 0.05, signifying statistically significant differences in their OFV performance. Specifically, PVND and CVND each have OFV distributions that are significantly different from each other, and both are significantly different from the BVND/UVND pair, suggesting three distinct tiers of OFV performance among the algorithms.

Pairwise Wilcoxon Test with Bonferroni Correction (p-values)						
	BVND	PVND	CVND	UVND		
BVND		1.48E-27	1.29E-26	1.00		
PVND	1.48E-27		3.39E-26	2.95E-26		
CVND	1.29E-26	3.39E-26		2.05E-25		
UVND	1.00	2.95E-26	2.05E-25			

Note: The pairwise Wilcoxon signed-rank tests, with a Bonferroni correction applied to maintain a family-wise error rate of 0.05, were also conducted to compare the OFV performance between each pair of algorithms. These results corroborated the findings from Nemenyi's test: no statistically significant difference in the OFVs produced by BVND and UVND (p = 1.00). Conversely, all other pairwise comparisons (BVND vs. PVND, BVND vs. CVND, PVND vs. CVND, PVND vs. UVND, and CVND vs. UVND) showed highly statistically significant differences in their OFV distributions (all adjusted p-values < 0.05, many << 0.001). This reinforces the conclusion that PVND and CVND perform differently from each other and that the BVND/UVND pair is statistically similar in terms of their resulting OFVs.

**Table 4.** Results of Friedman's Test, Nemenyi's Post-Hoc Test, and Pairwise Wilcoxon Test on the computing time of 4-LFL instances.

### Friedman's Test for BVND, PVND, CVND, and UVND

Number of complete experiments (blocks/rows): 162

Number of algorithms (groups/columns): 4 Friedman chi-squared statistic: 332.556

P-value: 8.926E-72

Note: The Friedman test was employed to assess whether there were statistically significant differences in the median computing times among the four algorithms (BVND, PVND, CVND, and UVND) across the 162 experiments. The test yielded a chi-squared statistic of 332.556 and a small p-value of 8.926E-72. Since this p-value is less than the pre-defined significance level ( $\alpha = 0.05$ ), the **null hypothesis** (**H**<sub>0</sub>), stating that all algorithms have the same median computing time, is **rejected**. This indicates strong evidence that at least one algorithm's computing time distribution differs significantly from the others, warranting post-hoc analysis to identify specific pairwise differences.

### --- Post-Hoc Analysis ---

Nemenyi's Post-Hoc Test Results (pairwise p-values):							
	BVND	PVND	CVND	UVND			
BVND		0	0	1.14E-10			
PVND	0		0.678	0			
CVND	0	0.678		5.22E-15			
UVND	1.14E-10	0	5.22E-15				

Note: Nemenyi's post-hoc test was conducted to perform pairwise comparisons of algorithm computing times following the significant Friedman test, using  $\alpha = 0.05$ . The results show that the computing times for PVND and CVND algorithms are not statistically distinguishable (p = 0.678). However, all other pairwise comparisons yielded p-values well below 0.05 (e.g., BVND vs. PVND, p=0.00; BVND vs. UVND, p=1.14e-10; PVND vs. UVND, p=0.00; and CVND vs. UVND, p=5.22e-15). This suggests that algorithms BVND and UVND each have computing times significantly different from all other algorithms. At the same time, PVND and CVND form a group with similar computing times.

Pairwise Wilcoxon Test with Bonferroni Correction (p-values)						
	BVND	PVND	CVND	UVND		
BVND		4.74E-27	3.34E-27	2.68E-20		
PVND	4.74E-27		1.13E-02	5.75E-24		
CVND	3.34E-27	1.13E-02		3.31E-10		
UVND	2.68E-20	5.75E-24	3.31E-10			

Note: A more detailed analysis, carefully adjusted for multiple comparisons to ensure reliability, examined the computing time differences between every pair of algorithms (BVND vs. PVND, BVND vs. CVND, etc.). This analysis found a real, meaningful difference in computing time between *all* pairs of algorithms. This means BVND's computing time differed from PVND's, CVND's, and UVND's. Similarly, PVND's computing time was different from CVND's (though this difference, while real, was less strongly evident than others), and UVND's and CVND's computing time was also different from UVND's.

The four algorithms present distinct performance profiles when considering solution quality (OFV) and computing speed on 4-LFL instances. Algorithms BVND and UVND achieve statistically similar solution qualities, but their computing times are significantly different from each other and from the other two algorithms. In contrast, PVND and CVND each deliver unique solution qualities, different from each other and also different from the BVND/UVND pair; their computing speeds are relatively close to one another (though a stricter test suggests a slight difference) but distinct from the speeds of BVND and UVND. This indicates clear trade-offs, with no single algorithm definitively outperforming others on both criteria based solely on statistical significance, necessitating an examination of actual performance values (mean OFVs and times) and problem-specific priorities to select the most suitable algorithm.

**Table 5.** Results of Friedman's Test, Nemenyi's Post-Hoc Test, and Pairwise Wilcoxon Test on the OFV of 5-LFL instances.

### Friedman's Test for BVND, PVND, CVND, and UVND

Number of complete experiments (blocks/rows): 162

Number of algorithms (groups/columns): 4 Friedman chi-squared statistic: 370.926

P-value: 4.387E-80

Note: The Friedman test was conducted to determine if there were any statistically significant differences in the median Objective Function Values (OFVs) achieved by the four algorithms (BVND, PVND, CVND, and UVND), specifically on the 162 5-LFL problem instances. The resulting high chi-squared statistic of 370.926 and an extremely low p-value (4.387E-80), well below the 0.05 significance level, led to the rejection of the null hypothesis that all algorithms produce similar median OFVs. This indicates significant variations in OFV performance among the algorithms when applied to the 5-LFL problem set, justifying further post-hoc analysis to identify which specific algorithms differ in their OFV results.

### --- Post-Hoc Analysis ---

Nemenyi's Post-Hoc Test Results (pairwise p-values):							
	BVND	PVND	CVND	UVND			
BVND		7.0E-06	0	3.0E-05			
PVND	7.0E-06		0	0			
CVND	0	0		0			
UVND	3.0E-05	0	0				

Note: Following the significant Friedman test, Nemenyi's post-hoc test was used to perform all pairwise comparisons of the algorithms' OFV performance on the 5-LFL problems, using an alpha of 0.05. The p-values for all comparisons (e.g., BVND vs. PVND, p=0.000007; PVND vs. CVND, p=0.0) were well below this threshold. This signifies that statistically significant differences in the OFVs achieved exist between every pair of algorithms. Consequently, for the 5-LFL problems, each algorithm—BVND, PVND, CVND, and UVND—demonstrates a level of OFV performance that is statistically distinct from all the others.

Pairwise Wilcoxon Test with Bonferroni Correction (p-values)						
	BVND	PVND	CVND	UVND		
BVND		8.48E-07	5.10E-27	1.43E-14		
PVND	8.48E-07		2.44E-27	6.03E-20		
CVND	5.10E-27	2.44E-27		6.73E-27		
UVND	1.43E-14	6.03E-20	6.73E-27			

Note: The pairwise Wilcoxon signed-rank tests, with a Bonferroni correction applied to control the family-wise error rate at 0.05, were also conducted to compare the OFV performance between each pair of algorithms on the 5-LFL problems. These results robustly confirmed Nemenyi's findings, as all Bonferroni-adjusted p-values (e.g., BVND vs. PVND, p=8.478E-07; CVND vs. UVND, p=6.726E-27) were exceptionally small and significantly below the 0.05 alpha level. This provides strong, conservative evidence that statistically significant differences in OFV exist between all pairs of the four algorithms, reinforcing that each algorithm achieves a unique distribution of OFVs when tackling the 5-LFL problem set.

**Table 6.** Results of Friedman's Test, Nemenyi's Post-Hoc Test, and Pairwise Wilcoxon Test on the computing time of 5-LFL instances.

### Friedman's Test for BVND, PVND, CVND, UVND

Number of complete experiments (blocks/rows): 162

Number of algorithms (groups/columns): 4 Friedman chi-squared statistics: 334.778

P-value: 2.948E-72

Note: The Friedman test was applied to assess whether there were statistically significant differences in the median computing times among the four algorithms (BVND, PVND, CVND, and UVND) when solving the 162 5-LFL problem instances. With a high chi-squared statistic of 334.778 and an exceptionally low p-value (2.941E-72), far below the 0.05 significance level, the null hypothesis that all algorithms exhibit similar median computing times was decisively rejected. This result strongly indicates significant variations in computational speed among the algorithms for the 5-LFL problem set, necessitating post-hoc analysis to pinpoint specific pairwise differences in their computing times.

**Table 6. (continued)** 

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 Post-	-Hoc	Ana	IVSIS	

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Nemenyi's Post-Hoc Test Results (pairwise p-values):						
	BVND	PVND	CVND	UVND		
BVND		0	1.70E-07	0		
PVND	0		5.51E-05	7.98E-14		
CVND	1.70E-07	5.51E-05		0		
UVND	0	7.98E-14	0			

Note: Following the Friedman test's indication of overall differences, Nemenyi's post-hoc test was employed to conduct all pairwise comparisons of the algorithms' computing times, specifically for the 5-LFL problems, using an alpha of 0.05. The p-values for all pairs (e.g., BVND vs. PVND, p < 1.0E-07; PVND vs. CVND, p = 5.51E-05) were well below this significance threshold. This outcome demonstrates that statistically significant differences in computing time exist between every single pair of algorithms. Therefore, for the 5-LFL problems, each algorithm—BVND, PVND, CVND, and UVND—operates at a statistically distinct speed from all the others.

Pairwise Wilcoxon Test with Bonferroni Correction (p-values)						
	BVND	PVND	CVND	UVND		
BVND		4.73E-26	1.47E-07	1.53E-26		
PVND	4.73E-26		9.78E-12	2.28E-22		
CVND	1.47E-07	9.78E-12		5.95E-24		
UVND	1.53E-26	2.28E-22	5.95E-24			

Note: The pairwise Wilcoxon signed-rank tests, adjusted with a Bonferroni correction to maintain a family-wise error rate of 0.05, were also utilized to compare the computing times between each pair of algorithms for the 5-LFL problem set. These more conservative tests strongly corroborated Nemenyi's findings, with all Bonferroni-adjusted p-values (e.g., BVND vs. CVND, p = 1.47E-07; CVND vs. UVND, p = 5.95E-24), which were extremely small and significantly below the 0.05 alpha level. This provides robust evidence that the computing time for each of the four algorithms is statistically distinguishable from that of every other algorithm when applied to the 5-LFL problems.

When we analyzed the results for the 5-LFL problem set, a distinct performance hierarchy emerged among the four algorithms tested: BVND, PVND, CVND, and UVND. Regarding solution quality, we found that each algorithm produced an Objective Function Value (OFV) statistically different from all the others. The same was true for how fast they ran. Each algorithm settled into a unique and statistically significant computing time when solving these problems. What this complete separation in performance suggests is a classic trade-off. This forces us to look beyond the statistics alone and examine the actual mean OFVs and run times to make a practical decision tailored to the specific demands of a 5-LFL challenge.

### 7. Managerial Implications

When we think about a company's supply chain, it is easy to picture a simple line from a single factory to a single store. The reality, especially for large retailers, is much more complicated. Their success often depends on designing a multi-level network, which might involve structuring operations across four or even five distinct layers. For a typical retail business, this could mean moving products from manufacturing plants to massive central warehouses, then out to regional distribution centers, and finally onto the shelves of local stores where customers shop. The real puzzle is figuring out the best place to put each facility and how big it should be, all while juggling transportation costs, holding inventory, and running the retail stores.

The sheer scale of this challenge becomes clear when you look at a giant like Walmart, which serves around 255 million customers weekly, managing over 100,000 different products from

thousands of suppliers across over 10,000 stores. Making that system work is not magic; it is the result of decades of careful decisions regarding where to place their plants, warehouses, and distribution centers. These strategic choices have been key in keeping transport costs low and ensuring products are delivered on time.

This complexity can go even deeper. A five-level system is common in e-commerce, where getting a package to someone's front door is everything. Amazon's network, for instance, seems to follow this model: goods move from suppliers to initial sorting hubs, then to enormous fulfillment centers, on to smaller regional sortation centers, and finally to local stations for last-mile delivery. Each step represents its unique puzzle with its own set of trade-offs.

Owning every piece of the puzzle is not the only path to success. While Amazon invests heavily in its distribution infrastructure, apparel companies like Zara and Benetton have succeeded with a different approach. They maintain agility by working with a wide network of small, independent manufacturers. This allows them to manage the first stage of their supply chain for rapid adaptation to changing fashion trends. Researchers like Soshko, Merkuryev, and Chakste (2007) have pointed out that selecting the correct facility location can lead to tangible benefits like lower transportation costs and better service.

### 8. Conclusion

This study focused on single-assignment MFL problems, specifically for 4- and 5-level locations. All customers (i.e., retail stores) at Level 1 must be served. Single-assignment from upper-level facilities to lower-level facilities is considered. Furthermore, each retail store also prefers products from a specific set of plants. The flow of a bundle of products from an upper-level facility to a lower-level facility incurs some costs each time it is moved. The selection of each facility also incurs a one-time fixed cost, and the number of facilities selected at each level is limited to an upper bound. We considered large-scale problems and provided four variants of VND meta-heuristics. Extensive computational experiments with heuristics are provided for randomly generated problems, and sensitivity analyses, supported by appropriate statistical methods, are used to validate the effectiveness of the heuristics' results.

Further research may be considered as follows:

- There are different methods to embed sequences within heuristics, as demonstrated by Alidaee and Wang (2017) and Wang and Alidaee (2019, 2023). In this study, we employed the *l-Opt* strategy adapted from a traveling salesman type application. However, it would be valuable to compare these approaches to determine which performs best for these problems.
- We also used hierarchical problems; however, retailers (also intermediate facilities) often order directly from upper-level facilities. This situation requires further attention, and we are addressing it for future research. In such cases, it is appropriate to consider a multimodal situation, which we are also considering.
- Each time a product bundle is transferred from one facility to the next, it incurs a cost. This cost is independent of the retail store, similar to the problem in Ortiz-Astorquiza, Contreras, and Laporte (2018). However, it makes sense to consider such costs when they depend on the retail store, similar to Ortiz-Astorquiza, Contreras, and Laporte (2019). In such cases,

- the number of variables significantly increases, and the use of computer storage also increases significantly.
- We did not include capacity constraints for the selected facilities. However, practical problems often require capacity consideration, including opening, closing, and expanding facilities. It makes sense to consider such situations for single-assignment problems, although for multi-assignment problems, such cases have been considered in the past (Melo, Nickel, and Saldanha da Gama 2006).

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## Appendix A

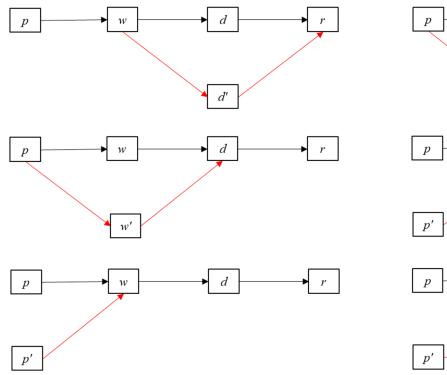


Figure 2(a) One-exchnahe, N(1), for 4-LFL

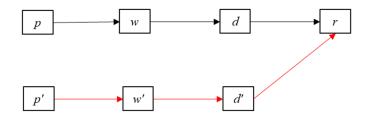


Figure 2(c) Three-exchnahe, N(3), for 4-LFL

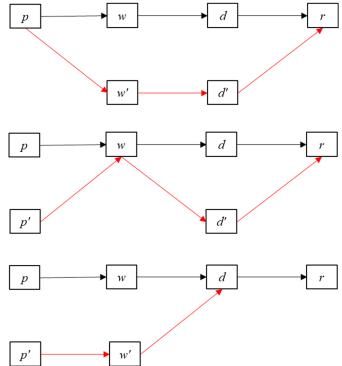


Figure 2(b) Two-exchnahe, N(2), for 4-LFL

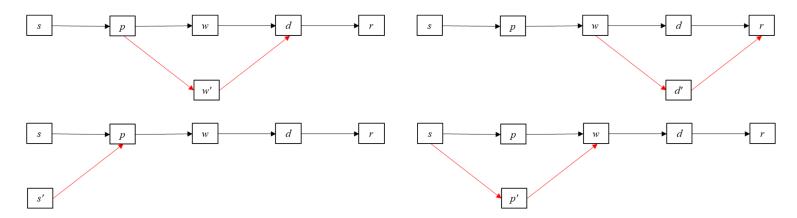


Figure 3(a) One-exchnahe, N(1), for 5-LFL

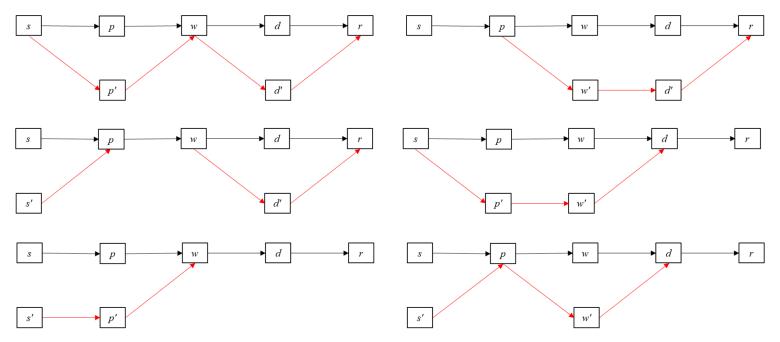


Figure 3(b) Two-exchnahe, N(2), for 5-LFL

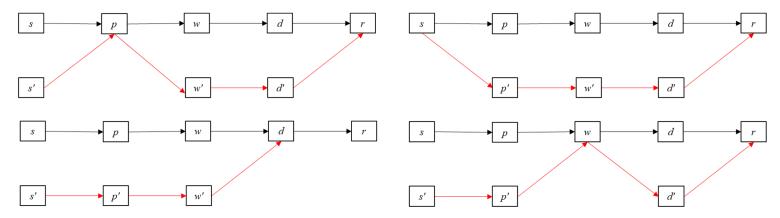


Figure 3(c) Three-exchnahe, N(3), for 5-LFL

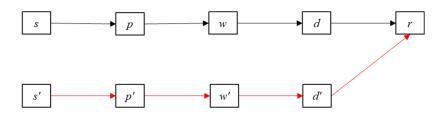


Figure 3(d) Four-exchnahe, N(3), for 5-LFL

### Appendix B

### **Table B1.** Parameters used for data generation.

### **Parameters:**

**R**, number of retail stores (Level 1), 2000, 3000, 4000, 5000, 6000, 8000, 9000, 10000

For 4-LFL, 2000, 4000, 5000, 8000, 9000, 10000

For 5-LFL, 2000, 3000, 4000, 5000,6000, 8000

D, number of distribution centers (Level 2), 150

W, number of warehouses (Level 3), 50

P, number of plants (Level 4), 30, 50

S, number of suppliers (Level 5), 100

r, a retail store

d, a distribution center

w, a warehouse

**p**, a plant

s, a supplier

**P-R, P by R binary matrix**, pr-th element 1 means plant p is eligible to ship products to a retail store r, 0 otherwise.

**D-R, D by R matrix**, positive dr-th element means distribution center d is eligible to ship products to retail store r with cost or distance equal to value of dr-th element, and 0 means ineligible.

W-D, W by D matrix, positive wd-th element means warehouse w is eligible to ship products to distribution center d with cost or distance equal to value of wd-th element, and 0 means ineligible.

**P-W, P by W matrix**, positive pw-th element means plant p is eligible to ship products to warehouse w with cost or distance equal to value of pw-th element, and 0 means ineligible.

S-P, S by P matrix, positive sp-th element means supplier s is eligible to ship products to plant p with cost or distance equal to the value of the sp-th element, and 0 means ineligible.

L DR (U DR), lower (upper) value for elements of cost matrix D-R, (L DR, U DR) = (5, 50)

L WD (U WD), lower (upper) value for elements of cost matrix W-D, (L WD, U WD) = (100, 500)

L PW (U PW), lower (upper) value for elements of cost matrix P-W, (L PW, U PW) = (5, 500)

L SP (U SP), lower (upper) value for elements of cost matrix S-P, (L SP, U SP) = (5, 150)

Ldense, low density, for 4-FLP 20%, for 5-FLP 40%

Mdense, medium density, for 4-FLP 40%, for 5-FLP 50%

Hdense, high density, for 4-FLP 60%, for 5-FLP 60%

L FD (U FD), lower (upper) value for distribution center fixed costs

L\_FW (U\_FW), lower (upper) value for warehouse fixed costs

L FP (U FP), lower (upper) value for plant fixed costs

L\_FS (U\_FS), lower (upper) value for supplier fixed costs

### Table B1. (continued)

SmFx, small fixed costs. (L\_FD, U\_FD) = (50, 100), (L\_FW, U\_FW) = (100, 200), (L\_FP, U\_FP) = (200, 400), (L\_FS, U\_FS) = (20, 100)

MedFx, medium fixed costs, (L\_FD, U\_FD) = (100, 200), (L\_FW, U\_FW) = (200, 400), (L\_FP, U\_FP) = (400, 800), (L\_FS, U\_FS) = (50, 200)

LgFx, Large fixed costs, (L\_FD, U\_FD) = (200, 400), (L\_FW, U\_FW) = (400, 800), (L\_FP, U\_FP) = (800, 1600), (L\_FS, U\_FS) = (200, 400)

UB D, upper bound for number of distribution centers to be opened, density\*D

UB\_W, upper bound for number of warehouse centers to be opened, density\*W

**UB** P, upper bound for number of plants to be opened, density\*P

**UB** S, upper bound for number of suppliers to be opened (considered), density\*S

Max Local, the number of multi-start. For low-density 70, medium-density 50, and high-density 30

### Variables:

**D** Upper, number of distribution centers opened

W Upper, the number of warehouses opened

P\_Upper, number of plants opened

S Upper, the number of suppliers opened

(p, w, d, r), schedule of receiving a bundle of products to retailer r, via plant p, warehouse w, and distribution center d in 4-FLP

(s, p, w, d, r), schedule of receiving a bundle of products to retail store r, via supplier s, plant p, warehouse w, and distribution center d in 5-FLP

### **Objective function:**

Find a schedule of shipments satisfying all retailers, minimizing the total cost of shipment, and opening facilities