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Web Semantic-Based MOOP Algorithm for Facilitating Allocation Problems in the Supply Chain Domain

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ABSTRACT

The facility allocation of the supply chain is critical since it directly influences cost efficiency, customer service, supply chain responsiveness, risk reduction, network optimization, and overall competitiveness. When enterprises deploy their facilities wisely, they may achieve operational excellence, exceed customer expectations, and obtain a competitive advantage in today's volatile business climate. Due to this reason, a multi-objective facility allocation problem is introduced in this research with cooperative-based multi-level backup coverage considering distance-based facility attractiveness. The facility of the coverage is further described as two different layers of the coverage process, where demand can be covered as full, partial, and no coverage by their respective facilities. The main objectives of this facility allocation problem are to maximize the coverage of the facility to maximize overall facility coverage in the supply chain network and simultaneously minimize the overall cost.

KEYWORDS

Cluster Network, Facility Allocation, Heuristic Optimization, Multi Objective Optimization Problem, Semantic Web, Supply Chain

1. INTRODUCTION

The facility allocation problem in the supply chain domain is a complex optimization problem that involves determining the best locations to place facilities such as warehouses, distribution centers, manufacturing plants, and retail stores (Melo et al., 2009). The facility allocation problem usually

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involves several competing goals, including reducing expenses, increasing service levels, and optimising inventory. It isn't easy to find a trade-off between these goals (Govindan et al., 2017). Hence specialised optimisation approaches are needed. With several tiers of suppliers, intermediary facilities, and end users, modern supply chains can be complicated (Pham & Yenradee, 2017). In such intricate networks, facility placement must take interdependencies and flows between different nodes under consideration (Aldrighetti et al., 2021). Such kind of importance of the facility allocation problem in the supply chain network has a long-term impact on investment. Therefore, this research is focused on the facility allocation problem in supply chain networks. Multi-objective Optimization Facility allocation often involves:

- Balancing multiple conflicting objectives, such as minimizing transportation costs.
- Minimizing inventory holding costs.
- Maximizing customer service levels.

Achieving the right trade-offs among these objectives can be complex. Compared to conventional single-objective approaches, the suggested multi-objective algorithm offers a more thorough and flexible solution to facility allocation problems (Tiwari & Garg, 2022). It enables organizations to make well-informed decisions that balance conflicting aims, deal with complexity, and navigate uncertainties in the supply chain domain by taking numerous objectives under perspective (C & P, 2022), (Sissodia et al., 2022).

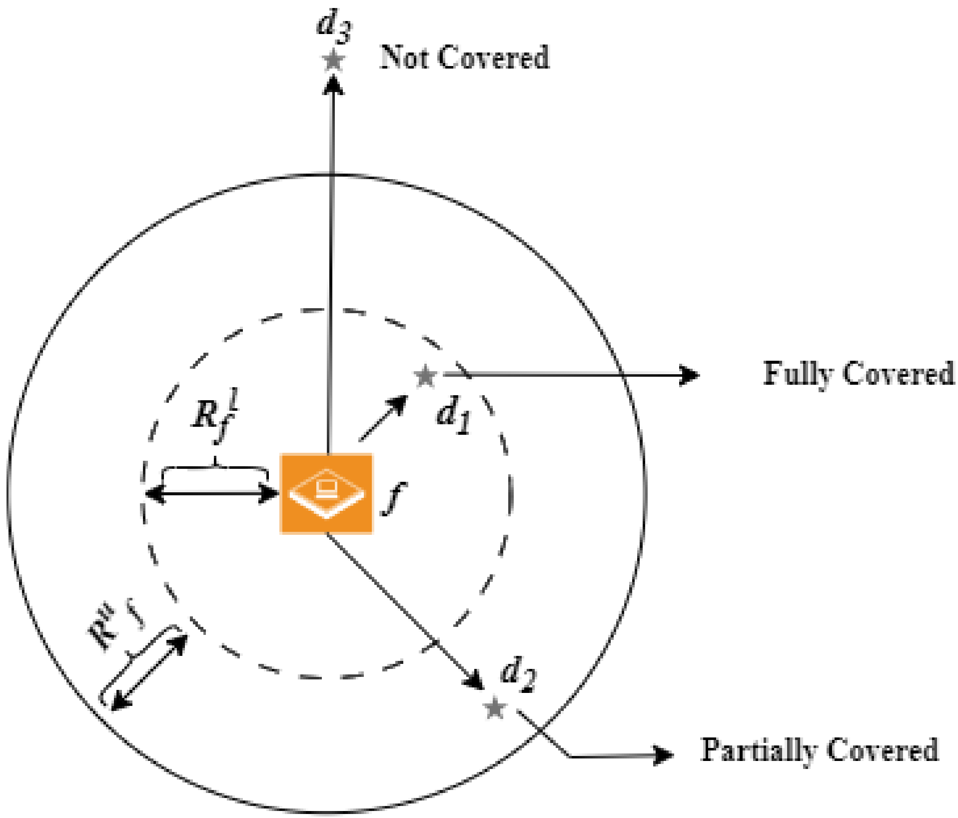
The main challenge in the facility allocation problem is the solutions of optimal locations are conflicting in nature.The facility allocation problem's main difficulty is that the best sites for each facility have contradictory solutions. The competitive selection of the facility, where new facilities must compete with old facilities to serve the same demand, is one of the primary causes of this contradictory solution (Yakavenka et al., 2020). This competitive site model with attractive facilities has to be taken into account. According to the competitive location model, there is an intense desire for the closest facilities to guarantee the transportation component. Unfortunately, when facility attractiveness is assessed, the nearest facility might not be the most attractive (Nayeri et al., 2020). The market size, product accessibility, pricing, and other elements contribute to the facility's attractiveness. These factors may lead to demand choosing a different facility over the closest one to meet its needs (Eskandarpour et al., 2017). As a result, it is essential to take into account and evaluate the facility's attractiveness and distance at the same time. The facility's coverage standards were thus introduced. Considerable losses in a specific supply chain's utility and finances, which impact the entire supply chain network, may come from the lack of proper facility availability (S.-C. Wang & Chen, 2017a). The facility's attractiveness consists of multiple factors, such as the size of the market, availability of the product, pricing of the product so on (J. Wang et al., 2020).Numerous elements, including the size of the market, the accessibility of the product, the price of the product, and others, contribute to the facility's attractiveness (Amin-Tahmasbi et al., 2023).We take into account three accurate constraint parameters: facility coverage (C_{fd}), overall cost (F_f), which includes setup and transportation expenses, and distance decreasing function (t_{fd}).Our proposed algorithm included adequate facilities' availability to minimise the considerable losses in the entire supply chain network. More availability of the facilities can lead to significant losses in utility and finances of a specific supply chain, affecting the overall supply chain network (Taghikhah et al., 2019).

The coverage criteria have been introduced several times in previous research on facility allocation problems based on different levels of coverage. The 1-coverage model is presented (S.-C. Wang & Chen, 2017a), where a single number of facilities always facilitates the demands. But when considering more realistic factors in facility allocation problems such as enormous demand and attractiveness of the facility, the uncertain possibility of the facility in 1-coverage failed to fulfil the ultimate solution to overcome such kind of problem. To overcome the 1-coverage problem, the introduced k-coverage model considers the n-facility allocation problem (S.-C. Wang & Chen, 2021). In the k-coverage model, the same demand points are covered by various facilities. In this approach, the facility number is used to decide the value of k-coverage. For example, if the value of k = 4, demand will be covered by 4 different facilities. By implementing this k-coverage model, the facility and demands gain a more reliable system. However, k-coverage has a drawback when cost factors are taken into account. Because in the k-coverage model, a constant number of facilities will be pre-assigned to the demand point without making the proper decision of the actual needs, which provides unnecessary coverage to the demand point. Due to this kind of over-coverage problem, the k-coverage approach directly impacts the overall cost for the facility. When optimising a comprehensive set of goals and empowering companies to go above and beyond for their customers, the proposed algorithm promotes operational excellence when incorporated into facility allocation processes (Elgendy et al., 2021). Organisations may assure economic, customer-focused, and strategically competitive facility allocations that stimulate success and growth in the supply chain domain by striking the correct balance between multiple factors. Everyone ensured cost effectiveness and continuous customer service in the supply chain network by introducing the multi-level backup coverage system for competitive facility allocation problems (Stylianou et al., 2022), (Bisht & Vampugani, 2022), where the dynamic number of facilities will be selected and provide the facility coverage as per the actual demand needs. This research considers the multiple objective optimization problems to construct a sustainable supply chain network system based on operational excellence and exceeding customer expectations. The first objective is built to maximize the coverage of the facility and simultaneously minimize the overall cost in the supply chain network as the second objective (Chander et al., 2022), (J. Li & Su, 2022).

To address the k-coverage model drawback in terms of uncertainties or changes in the supply chain environment, we proposed cooperative-based multi-level backup coverage since, in cooperative-based multi-level backup coverage, demands are always covered by dynamic numbers of facilities where the number of facilities must be more than one. So, the cooperative-based multi-level backup coverage solves the inadequate availability of the facilities by considering over-coverage and over-cost problems in the supply chain network. Therefore, when any lousy situation happens in a particular facility, other facilities will cover demands to maintain the sustainability of the entire supply chain network. More on facility coverage can be categorized into two types on the basics of covering capacity. The first type of coverage is binary coverage (full coverage denoted as 1 and no coverage denoted as 0,binary coverage model covered all the demand (0,1)), and the other is partial coverage. The binary coverage model facility will cover all demand points inside the coverage area (TOREGAS & ReVELLE, 1972). And for partial coverage facility creates double layers of coverage level (S.-C. Wang et al., 2018) from the facility's exact location. Two layers of coverage in the supply chain network, and the algorithm handles demand coverage in each layer and optimizes the allocation accordingly. The facility provides two layers of coverage level for partial range using its precise location. If a demand is contained within the first layer of coverage, it will be regarded as fully covered by the relevant facility under the partial coverage model. Demands will be referred to as partially covered by the facility is located on the second layer. Demands are regarded as not being covered by the facility when they are located outside the second layer of coverage. Figure 1 depicts the circumstances discussed previously. In this case, we take into account three demands $\left(d_1, d_2\ and\ d_3\right)$, of which d_1 is entirely provided by facility f, d_2 is partially covered by facility f, and d_3 is not covered by facility $\left(f\right)$ and one facility $\left(f\right)$. We designated the facility's coverage region as R_f^l, fully covered, and R_f^u, partially covered.

As for the solution process to find out the competitive location of facilities in the supply chain network, a multi-objective optimization problem must be introduced instated of single-objective optimization (Resat & Unsal, 2019). The limitations of a single-objective competitive facility location problem highlight the need for a multi-objective approach. It mentions that the closest facility may only sometimes be the most attractive option, especially when considering factors like competitiveness

Figure 1. Illustrated partial coverage scenario



and attractiveness (Jenkins et al., 2020). Therefore, a multi-objective facility location problem is necessary. It is important to note that multi-objective optimization in supply chain management can be complex due to the interconnectedness of various factors.

The decision-makers preferences, the problem's complexity, and the optimised goals' particulars influence the approach used (Moadab et al., 2023). The purpose is to choose a set of solutions from the Pareto-optimal set, considering the trade-offs between conflicting objectives that best fit the organization's goals and restrictions. Based on the various purposes, every key in the population is assessed. For each objective, values are assigned to the solutions (Elfarouk et al., 2022). The group of non-dominated solutions is known as the Pareto front. These options give decision-makers various options since they show the trade-off between different goals. In addition, uncertainty, dynamic factors, and practical limits must frequently be considered in real-world supply chain optimization (Ahmadini et al., 2021).

Therefore, collaborating with operations research or optimisation professionals can guarantee efficient issue formulation and precise outcomes. In supply chain management, a multi-objective optimisation problem entails simultaneously optimising several competing objectives. These goals often include cutting costs, improving customer service, lowering lead times, optimising inventory levels, and improving sustainability in the supply chain domain. Finding a collection of solutions that reflects the trade-off between various objectives is the goal of multi-objective optimisation. The Pareto-optimal or efficient frontier is these solutions. Each answer on the efficient frontier is the optimal trade-off between the goals, where achieving one goal would necessitate giving up another

(Petchrompo et al., 2022). Each solution on the efficient frontier represents the best compromise between the objectives, where improving one objective would require sacrificing another.

Generally, the multi-objective optimization problem is solved by different types of heuristic methods and the meta-heuristic method (Daqaq et al., 2021). The meta-heuristic method consists of different algorithms such as biology-inspired genetic algorithm, NSGA-II (Non-dominated Sorting Genetic Algorithm-II), PSO (Particle Swarm Optimization), artificial immune algorithm, etc. (Ismail et al., 2020), (Dhal et al., 2019), (Picek & Jakobovic, 2021). On the other side, heuristic method consists of exhaustive search, local search, dynamic programming, and so on (Demirović et al., 2022). Competitively, the meta-heuristic methods are more complex in terms of computation than heuristic methods (Parouha & Verma, 2021). Conversely, an exhaustive search takes a huge computation time duration with a huge data storage capacity. To overcome such kind of barrier, we introduced and proposed our heuristic-based algorithm per the problem model to obtain a Pareto-optimal.

The practical implications are to maintain the dynamicity of the supply chain network, a cost-effective, sustainable supply chain network by improving the supply chain's uninterrupted and uncertain factors. The MOOP method, based on web semantics, gives useful options for facility allocation in the context of supply chains. Businesses can improve decision-making, operational efficiency, customer happiness, and strategic advantage by optimising for various objectives and using web semantics. These improvements all contribute to the overall performance of operations in the supply chain.

1. This research is developing a multi-level backup coverage system for competitive facility allocation problems in the supply chain network, where the dynamic number of facilities will be selected and provide the facility coverage as per the actual demand needs.
2. The second significant contribution of this research is designing the multiple objective optimization problems to construct a sustainable supply chain network system where the first objective is built to maximize the coverage of the facility and simultaneously minimize the overall cost in the supply chain network as the second objective.
3. Third contribution of this research is constructing the heuristic-based algorithm as the proposed solution approach and the computation performance analysis between the proposed heuristic-based algorithm with exhaustive search methods.

As the future scope of studies, we can consider a meta-heuristic approach to solve the facility allocation problem and compare the computation efficiency with the proposed heuristic-based algorithm.

This research paper's remaining sections are arranged as follows: Section 2 discusses the literature review. Section 3 describes the proposed methodology. Section 4 implements the experimental result, and Section 5 concludes the research paper.

2. LITERATURE REVIEW

The supply chain "facility allocation problem" refers to the decision-making process of determining the optimal allocation of facilities within a supply chain network. It involves selecting the locations for warehouses, distribution centers, production plants, and retail outlets to meet customer demand efficiently and effectively (Mahmoudi et al., 2022). The facility allocation problem aims to find the optimal placement of facilities that minimizes costs, maximizes service levels, and improves overall supply chain performance (Amin-Tahmasbi et al., 2023). The problem considers various factors such as facility coverage, facility attractiveness in terms of transportation distance, transportation costs, product availability, inventory costs, facility capacities, customer demand patterns, and service requirements (Jalal et al., 2022), (Chauhan et al., 2019), (Zahraee et al., 2020), (Che et al., 2022). Thus, the facility allocation problem is a complex optimization problem involving multiple objectives and constraints. As previous mention, facility coverage and attractiveness of a facility have a direct impact on facility allocation problems. Moreover, it illustrates that coverage of a facility can also be defined as distance-based coverage of the facility (S.-C. Wang & Chen, 2021). Therefore, coverage of a facility in a location-allocation problem can be defined in many ways, such as location set coverage problem, also known as LSCP, where every demand must be covered by the facility (Rahman et al., 2021). If the main objective of facility location is to maximize the coverage of the facility, then this kind of problem is known as a maximum coverage location problem or MCLP (W. Wang et al., 2021). More maximum coverage location problems can also be defined as a maximum coverage facility location problem of MCFLP (Han et al., 2021) when the facility's location comes into the account. Coverage problems are defined as a binary form, which decides whether the facility will cover demand or not. Such a problem is known as a binary coverage problem (W. Wang et al., 2021). Later, a partial coverage problem was introduced in the facility allocation problem, where demands can also get partial coverage from the facility (MCLP-P). To make the coverage location problem more sustainable, some special types of coverage were introduced, such as fuzzy maximal covering location problem (FMCLP) (Arana-Jiménez et al., 2020), maximal expected coverage location problem (MEXCLP) (Grot et al., 2022), backup coverage problem (BACOP) (Ghaderi & Momeni, 2021), k-coverage problem (Erbeyoğlu & Bilge, 2020) and so on. At the very beginning, competitive facility location was discussed for a linear market where the main rivals are pricing and placement strategies "Hotelling model" (Reisinger et al., 2023). The main challenge in competitive placement is new facilities must compete with existing ones for the same demand (Zhao et al., 2020). As per the fundamental definition according to competitive location problem, demands try to select the nearest facilities, but in the real case, sometimes demands choose farther facilities due to the attractiveness in terms of product pricing, market size, product availability, and so on (Celik Turkoglu & Erol Genevois, 2020), (Küçükaydın & Aras, 2020). For that reason, the multi-objective competitive location problem (MOCLP) was introduced with distance-based attractiveness (S.-C. Wang et al., 2022). The process of selecting the best solution values for numerous desired objectives is referred to as the multi-objective location model. The use of the multi-objective location problem is justified by simplifying the task because multi-objective optimization does not necessitate complex equations. Especially in the field of the supply chain, multi-objective optimization problems played an important role (Ehtesham Rasi & Sohanian, 2020). An example of a sustainable supply chain for biomass addresses the importance of multi-objective optimization (Gital Durmaz & Bilgen, 2020). Inventory location is the backbone of the supply chain, which is thoroughly discussed as a multi-objective location–inventory problem (Rabbani et al., 2021). In the supply chain network, multiple distribution channels are located, which is also solved by the multi-objective location optimization problem (Torabzadeh et al., 2022).

As previously mentioned, the fundamental way to solve any multi-objective optimization problem is in two ways: the meta-heuristic approaches (Dwivedi et al., 2020) and heuristic approaches (Mohammed & Duffuaa, 2020). By enhancing the integration of data, compatibility, and processes for decision-making, semantic web applications have the potential to fundamentally transform the supply chain domain. By integrating information coming from many sources and revenue, semantic web apps are useful in demand projections. Semantic technologies can aid in shared decision-making by offering interactive representations and descriptions of several Pareto-optimal options. It could employ semantics and conceptual graphs to represent facilities, resources, constraints, objectives, and each other in facility allocation. This can retrieve pertinent data about resources, facilities, conditions, and targets during the optimisation process (Deveci et al., 2022). Numerous data sources can be integrated using semantic technologies, providing current knowledge to direct the optimisation procedure. Ultimately, this can help decision-makers make the best decisions for facility allocation by producing higher-quality answers and enabling more effective investigation of the Pareto-optimal set (J. Li & Su, 2022), (Bisht & Vampugani, 2022).

Because of semantic-based methodologies, resource allocation went from a challenging optimisation problem to becoming a more informed and effective decision-making process (Akram et al., 2022), (Malik et al., 2023). The organisation profited from higher client satisfaction due to quicker shipment of orders, improved warehouse management, and decreased operational expenses (Gaurav et al., 2023).

i. Additionally, depending on real-time data, it automatically modified the distribution of resources, optimising the use of the resources accessible while preserving efficiency (Z. Xu et al., 2023).
ii. The system reduced errors and loss of products and maintained accuracy by avoiding inappropriate goods placements and maintaining suitable storage conditions.
iii. Pareto-optimal approach representations enabled decision-makers to comprehend how distinct priorities trade-off with each other.

Management of supply chains can optimize levels of stock and reduce transportation costs by combining the information with multi-objective optimization algorithms and meta-heuristic techniques. In meta-heuristic approaches, different types of algorithms are presented with their diverse solution procured. Most of the solution procedures are developed by biological influence. One of the biological influences approaches is well-known as the evolutionary approach (N.-R. Xu et al., 2016). Under this evolutionary approach, many algorithms exist, such as genetic algorithm (Sang, 2021), clonal selection algorithm (L. Li et al., 2019), non-dominated sorting genetic algorithm (NSGA) (Brahami et al., 2022), NSGA-II (Ridwan et al., 2020) and many more. Besides the meta-heuristic approaches, heuristic approaches are impressive in solving multi-objective optimization problems. Some heuristic approaches are exhaustive search, local search, and dynamic programming (Queiroga et al., 2021), (Cobos et al., 2019).

The key benefit of using a heuristic method over the meta-heuristic is that it provides an immediate solution that is simple to comprehend. Heuristic algorithms are also useful because they provide quick, less expensive, and workable short-term answers to scheduling and planning issues (S.-C. Wang & Chen, 2017b). But unfortunately, there are some computation limitations in the exhaustive search heuristic method (S.-C. Wang et al., 2018); thus, we introduced a newly proposed heuristic method that can overcome the computation limitation over exhaustive search. The solution set of multi-objective optimization problems is called the Pareto-optimal solution.

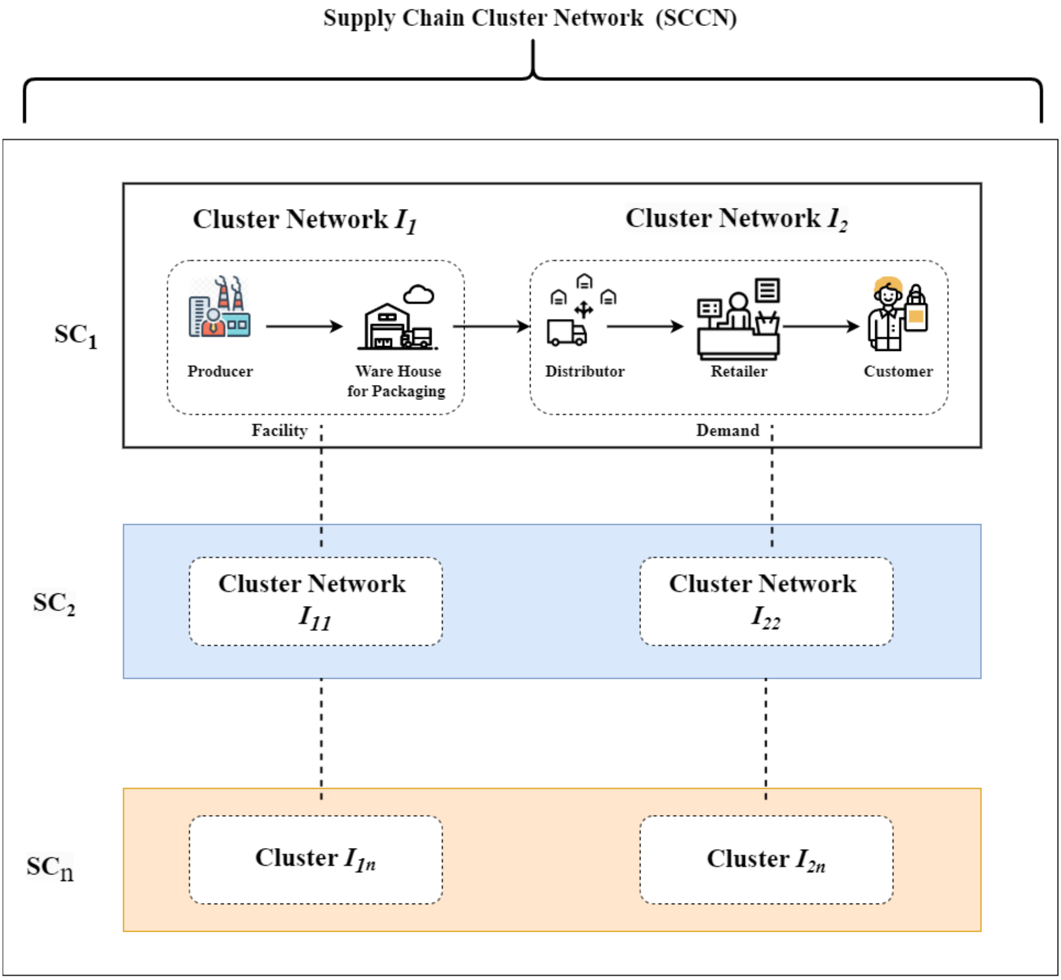
3. PROPOSED METHOD

Our proposed supply chain cluster network consists of five numbers of actors. Those are producer, warehouse for packaging and storing, distributor, retailer, and customer. As per the production facility and demand in consumption criteria, we separated the individual actors into two clusters. Cluster one or called facilities (F) consists of a producer and warehouse for packaging and storing. And cluster two or called demands (D) consists of the distributor, retailer, and customer, which is demonstrated in Figure 2 and numerical abbreviations demonstrated in table 1. In a supply chain network, each facility can provide multi-type services to their respective demands in a supply chain.

We, consider supply chain cluster network $\left(SCCN\right)$ is the summation of x numbers of supply chain, Where, $SCCN=\left(F_n, D_m\right)$.

i. There are n potential facilities and m demands located on a particular georgical location, known as region of interest (RoI).

Figure 2. Supply chain cluster network model



ii. Each potential facility deployed in RoI, where f ($f \in F$, $f = 1, 2, \ldots, |F| = n$) holds two level of coverage facility (R_f^l and R_f^u), and demand d ($d \in D$, $d = 1, 2, \ldots, |D| = m$) receives facility coverage (C_{fd}) from assigned facility in location f.

iii. Facility deployed in location f provides full coverage $C_{fd} = 1$ to demand d, where the distance between f and d must be $t_{fd} \le R_f^l$, when coverage $0 < C_{fd} < 1$, where $R_f^l < t_{fd} \le R_f^u$ called partial coverage, and when $C_{fd} = 0$ none, where $t_{fd} > R_f^u$ known as not covered.

iv. We introduced cooperative-based multi-level backup coverage in place of k-coverage in this research. In cooperative-based multi-level backup coverage demands will be covered by a dynamic number of facilities as per the exact requirements, and each demand will be covered by more than one facility. By implementing multi-level coverage, the entire supply chain network will be more sustainable in terms of reliability and cost. Because in k-coverage model a constant number of facilities be pre-assigned to the demand point as per the k value. Due to this cause, facilities are providing unnecessary coverage to the demand which increasing the total cost of the supply chain network. In Figure 3 described k-coverage where two demands are covered by three numbers of facilities $(k = 3)$. In this example demand d_1 is covered by facility f_1, f_2 and f_3 beside demand d_2 is covered by facility f_4 f_5 and f_6. In Figure (4) multi-level backup coverage is demonstrated where, demand d_1 covered by f_1 and f_2 at the same time d_2 is covered by f_2, f_3, f_4 and f_5 as multi-level coverage.

v. All demands should be covered/served within the region of interest by at least two facilities as a backup facility. More on each demand permitted to get service from any required necessary number of facilities.

vi. Covering criteria between facilities and demand will be depends upon facilities attractiveness and distance between the demand to facility.

The purpose of the problem is to select a minimum number of facilities to cover all demands which is based on the minimum sum of all distances between each demand and selected facilities as well as set up costs of the facilities and transportation cost of selected facilities and maximize the sum of facility coverage for each demand, simultaneously. Each demand is allowed to receive a various number of facilities as dynamic backup coverage consideration. To obtain the optimal solution to this proposed problem, we introduced a multi-objective optimization problem (MOOP). As per the problem statement, the fundamental problem for the supply chain network or cluster network is maximizing the cumulative sum of facility coverage to cover all demands inside the region of interest. Minimizing the overall cost (transportation cost and setup cost) by reducing the distance between facility to demand and implementing a cooperative-based multi-level backup coverage strategy.

This integrated approach aims to enhance the supply chain's efficiency, cost-effectiveness, and resilience, ensuring optimal coverage and resource utilization while maintaining a robust and adaptable network in response to varying demands and potential disruptions.

Figure 3. k-Coverage

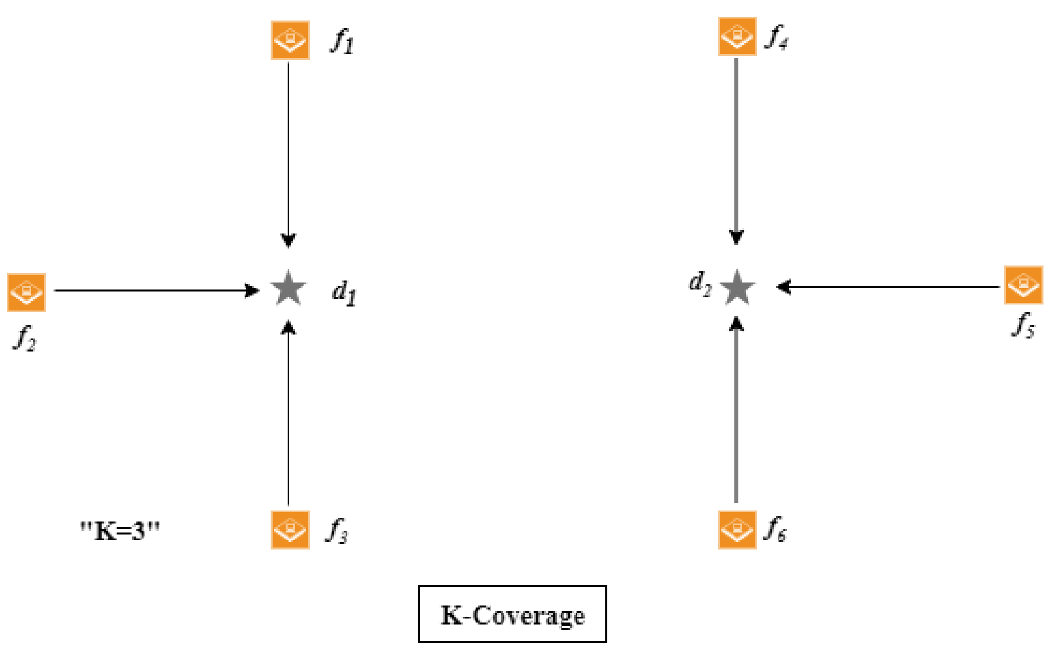


Figure 4. Multi-level backup coverage

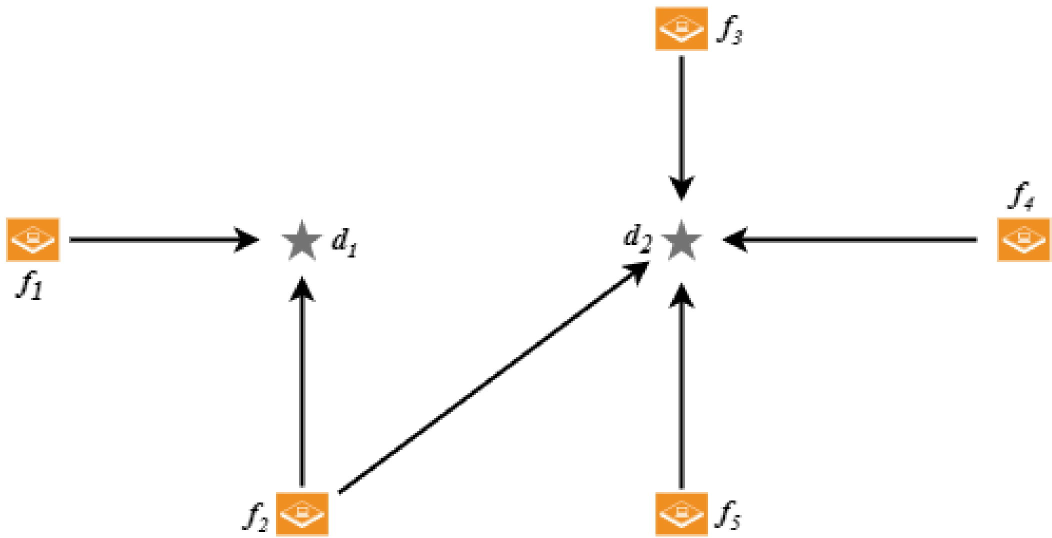


Table 1. Numerical notations abbreviations

No	Notation	Abbreviation
1	t_{fd}	distance decreasing function
2	C_{fd}	facility coverage
3	R_f^u	Upper bound limitation of facility coverage
5	R_f^l	lower bound limitation of facility coverage
6	$d \in D$	Number of demands in supply chain
7	$f \in F$	Number of facilities in supply chain
8	F_f	overall cost (including transportation and setup costs)
10	CN	supply chain network or cluster network
11	F_n	Number of facilities in supply chain network
12	D_m	Number of demands in supply chain network
13	y_f	Facility location binary decision variable
14	x_{fd}	Facility coverage binary decision variable

Demand d_1 receives full facility coverage (C_{fd})from the selected facility when $0 \leq t_{fd} \leq R_f^{l}$; and d_2 is partially covered by the facility where, $R_f^{l} < t_{fd} < R_f^{u}$ at the last demand is not covered by the facility because $t_{fd} \geq R_f^{u}$.

As per the distance increasing factor between facility and demand the coverage level of facility is exponentially decreasing. Thus, $f\left(t_{fd}\right)$ is represented as distance decreasing function of facility coverage for facility f to demand d. The abovementioned scenario is described in Figure 5.

$$C_{fd} = \begin{cases} 1, & \text{if} 0 \leq t_{fd} \leq R_f^{l}; \\ f\left(t_{fd}\right), & \text{if } R_f^{l} < t_{fd} < R_f^{u}; \\ 0, & \text{if } t_{fd} \geq R_f^{u}. \end{cases}$$

The mathematical formulation of facility coverage was introduced and mathematically proved by (S.-C. Wang & Chen, 2017a). As per our problem, we reconstruct the same facility coverage formulation (C_{fd}) as,

$$C_{fd} = \frac{\text{Max}\left\{R_f^l - t_{fd}, 0\right\}}{\text{Max}\left\{R_f^u - R_f^l, R_f^u - t_{fd}, \mu\right\}}$$

3.1 Model Development and Problem Formulation

In this section, we developed our problem formulation model in the mathematical formulation. Furthermore, this section formulated our two main objectives as a multi-objective problem. At the same time, we also constructed our multi-level backup coverage formulation as a problem constraint. Mathematical formulations are described below,

- $y_f = 1$ be the facility once deployed at the candidate location f, else $y_f = 0$.
- $x_{fd} = 1$ be the demand d covered by facility deployed at location f, else $x_{fd} = 0$ as per the binary decision variable.
- F_f : overall cost (including transportation and setup costs) at the candidate location f.

$$\max \sum_{d \in D} \sum_{f \in F} C_{fd} x_{fd} \tag{1}$$

$$\min \sum_{f \in F} F_f y_f + \sum t_{fd} x_{fd} \tag{2}$$

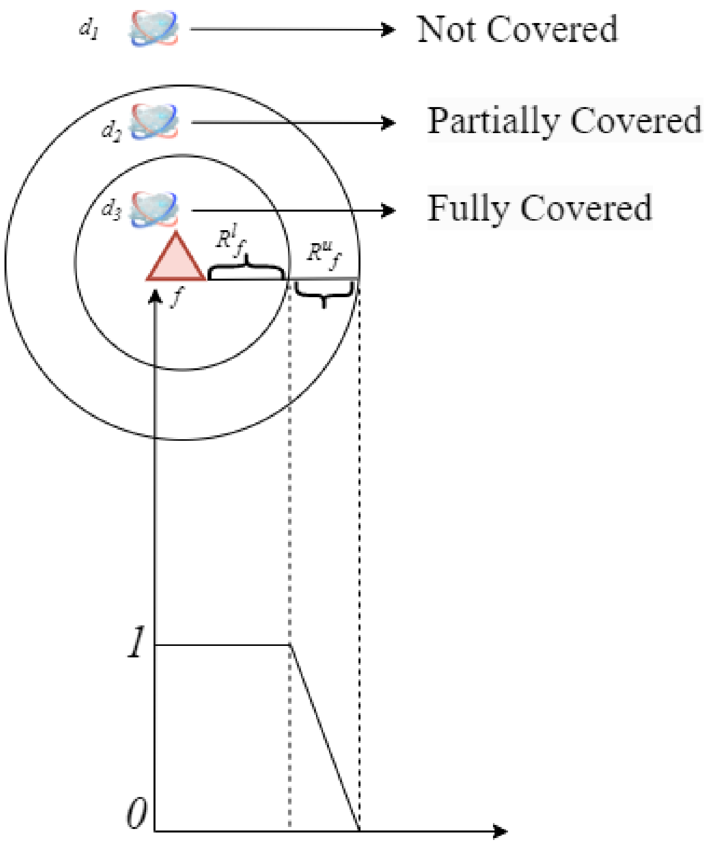
subject to

$$y_f \geq x_{fd} \ \forall d \in D, \ f \in F \tag{3}$$

$$\sum_f x_{fd} > 1 \tag{4}$$

$$y_f \in \left\{0,1\right\} \ \forall f \in F \tag{5}$$

Figure 5. Partial coverage with distance-based decreasing coverage function



$$x_{fd} \in \{0,1\} \; \forall d \in D,\; f \in F \tag{6}$$

- First objective (1): maximize the sum of the facility coverage for each demand received.
- Second objective (2): minimize the sum of overall costs for each facility assigned to deploy in location f.
- Constraint (3): each demand should be covered/served by the deployed facility.
- Constraint (4): each demand must be covered/served by more than 1 facility as multi-level coverage.
- Constraints (5) and (6): enforce the decision variables x_{fd} and y_f to be binary.

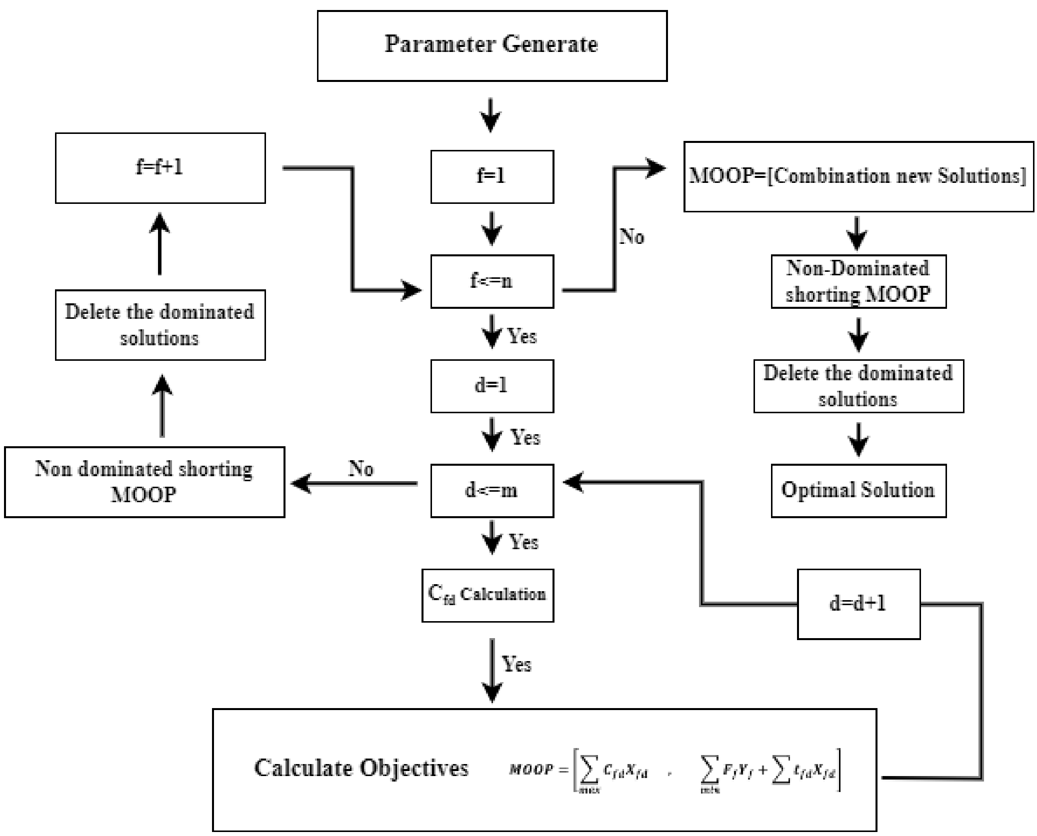
4. CLARIFICATION OF SOLUTION PROCEDURE

In the previous section, we constructed the problem formulation as per the problem description. The constructed problem is introduced as a multi-objective optimization problem (MOOP) because of its conflicted nature. Thus, the optimization problem is anticipated with pairs solutions because there is no existence of a single global optimal solution. The solution pairs are also represented as Pareto-optimal solutions, where some solution sets are dominated by the coexisting solution set. Therefore, the heuristic-based proposed solution process is designed and developed influenced by (S.-C. Wang & Chen, 2017b) as the multi-objective optimization problem. The objectives of the proposed problem are to maximize the coverage of the solution and minimize the overall cost by reducing the distance between the facility and demand. According to the problem, there is m number of potential facilities and n number of demands situated in a region of interest, where every demand is covered by more than one number of facilities. As per the computation complexity in the solution procedure, we introduced the heuristic-based algorithm as the proposed algorithm. The working flow of the proposed algorithm is described as follows in Figure 6.

4.1 Heuristic-Based Algorithm Steps

The implementation of heuristic-based algorithm details and given specific steps used in supply chain cluster network domain to construct a sustainable supply chain network system. These steps provide a general framework that are adopted into the proposed scenarios. Compared to other cutting-edge techniques, the MOOP algorithm performs better regarding coverage, cost-effectiveness, competitiveness, trade-off analysis, adaptability, and decision-making insights. The MOOP technique is particularly efficient in dealing with the complexity of facility allocation because it can concurrently consider numerous goals and provide a broad range of solutions. The advantages associated with coverage, cost-effectiveness, and competitiveness help decision-makers allocate resources and locate facilities more comprehensively and strategically.

Figure 6. Heuristic based algorithm flow chart diagram



With the aid of MATLAB commands, we performed random parameter generation based on the issue's construction to simulate the problem. These crucial variables are the number of demands in the supply chain $\left(d\right)$, the number of facilities in the supply chain $\left(f\right)$, the overall cost (including transportation and setup costs) F_f, and the upper bound and lower bound limitations of facility coverage (R_f^u) and (R_f^l).

Steps 1: As per the problem, we generated parameters. These are the number of facilities, number of demands, Fixed cost (F_f) and traveling distance $\left(t_{fd}\right)$. Fixed cost and traveling distance we created randomly, where we were given a lower bound and upper bound limitation.

Step 2: After creating the necessary parameters, we calculated the coverage of the individual facilities $\left(C_{fd}\right)$ as per the demands.

Step 3: After calculating the coverage of the individual facilities, we created the binary decision variable conditions that consider the number of facilities and demands. In this step, we implement our first constraint where we assign all demands that must be covered by more than one facility. This binary decision variable constrain is represented as, $\sum_{\mathrm{f}} \mathrm{x}_{\mathrm{fd}} > 1$.

Step 4: After creating binary decision variable conditions, we calculated the objectives for corresponding demand. And after completion of the objective's calculation, we search and choose those objectives one values are more than or equal to one. The objectives for corresponding demand are equation 1 $\max \sum_{\mathrm{d}\in\mathrm{D}} \sum_{\mathrm{f}\in\mathrm{F}} \mathrm{C}_{\mathrm{fd}} \mathrm{x}_{\mathrm{fd}}$ and equation 2 $\min \sum_{\mathrm{f}\in\mathrm{F}} \mathrm{F}_{\mathrm{f}} \mathrm{y}_{\mathrm{f}} + \sum \mathrm{t}_{\mathrm{fd}} \mathrm{x}_{\mathrm{fd}}$.

Step 5: After doing the shorting (for objective one values must more than equal to one) we combined the objectives results with their respective binary decision variable conditions.

Step 6: After the combination of all objectives, we did the non-dominating searching and shorting. Next, we deleted dominated results in objectives with their corresponding binary decision variable condition. And keep the combined nondominated solution.

Step7: After getting the new combined nondominated solution we did the final non-dominating searching and shorting we get the optimal solution set as objectives with their binary decision variable.

5. EXPERIMENTAL RESULTS

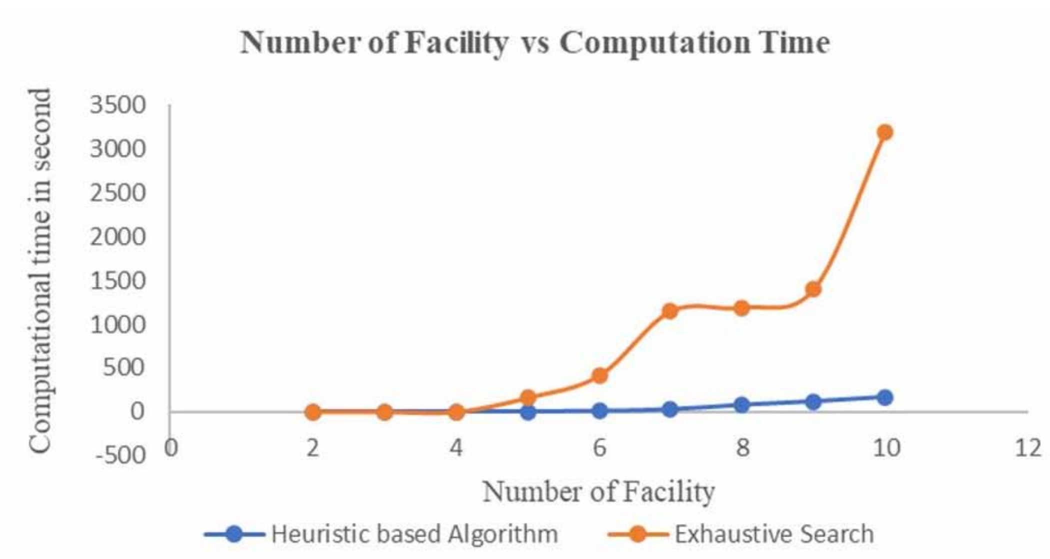
The numerical experiments for proposed heuristic-based algorithm and exhaustive search methods are presented in this section. As per the problem we randomly generated all required parameters. To construct the problem coding and simulated the experiment we used MATLAB R2021b computing environment on Lenovo ThinkPad computer equipped with an Intel(R) Core (TM) i5-6200U CPU running at 2.30GHz and 8.00 GB of RAM.

As per table 2, we showed the comparison of computational time between the proposed heuristic-based algorithm with exhaustive search approach for a different combination of demands with their respective number of facilities. We set the computation run-time limitation up to 3600 second. In this abovementioned table NA indicates the computation time is crossing the limitation of 3600 seconds. In Figure 7 we plotted the graph between computation time in y-axis varies with number of facilities in x-axis. In this situation we assigned the number of total demands is two. After the close observation from the Figure 7 we can analysis the computation time for five number of facilities the time is suddenly arises exponentially up to eight demands. And after 9 combination of facilities the computation time is increased with a huge time difference. From this analysis we can conclude that the computation efficiency is more in proposed heuristic algorithm comparing to exhaustive search.

Table 2. Computation time comparison table between proposed heuristic-based algorithm with exhaustive search method for different combinations of facility and demand

Facility	Demand	Heuristic	Exhaustive	Facility	Demand	Heuristic	Exhaustive
2	2	0.03163	0.075357	6	2	7.228411	416.757613
	3	0.035216	0.074724		3	9.66642	1086.09926
	4	0.041953	0.948257		4	10.96787	NA
	5	0.062918	0.105493		5	49.68516	NA
3	2	0.097183	0.115413	7	2	26.311944	1149.1742
	3	0.097475	0.120262		3	32.382395	NA
	4	0.131261	0.216184		4	194.41286	NA
	5	0.177037	0.476596		5	486.193504	NA
4	2	0.095974	0.123193	8	2	78.193504	1187.30
	3	0.130886	0.346871		3	112.0265	NA
	4	0.213233	11.97944		4	825.6294	NA
	5	0.715853	146.4288		5	1743.1419	NA
5	2	1.10535	162.173632	9	2	116.271781	1402.8527
	3	1.327543	314.62995		3	162.7152	NA
	4	1.929607	574.61	10	2	166.137355	3193.5207
	5	103.86	2847.0149		3	169.7725	NA

Figure 7. Computation time and comparison between proposed heuristic-based algorithm and exhaustive search



In Figure 8 we plotted the Pareto-optimal solution points for exhaustive method, where we show the graphical representation of all possible solution set which is consist of 17,576 solutions set. And in Figure 9 at showed all non-dominated solution points consist of 23 solutions set. And the computation time for exhaustive search is 314.62995 second. In these two graphical representations we represent our objective 1 as coverage of the facility in x-axis and objective 2 as cost along y-axis. In Figure 10 we show the graphical representation of all possible solution combination consist with 104 solutions set. And in Figure 11 illustrate all non-dominated solution points consist with 23 solutions set at the right-hand side with the 1.327543 second of computation time. Above mentioned experimental result is taken where 5 facilities are serving 3 demands. If we compare the Figures 9 and 11, we can conclude that the number and coordinate of nondominated solution set are exact same in proposed heuristic-based algorithm and exhaustive search approach. But the consumption of time for computation is very high in exhaustive algorithm over proposed algorithm. It means that the proposed heuristic-based algorithm is more efficient over exhaustive search method.

6. CONCLUSION

In this study, we introduced a facility allocation problem for the supply chain network. This allocation problem also considers the distance-based attractiveness with cooperative-based multi-level backup coverage. As per the benefits of this coverage model, the supply chain network will become more sustainable in terms of reliability and cost-effectiveness. More facility coverage is defined as two levels of the coverage process, where the respective facilities can partially and fully cover demands. According to the problem objectives, a multi-objective optimization problem is developed and formulated. More prissily, the main objectives of this multi-objective facility allocation optimization problem are to maximize the coverage of the individual facility to maximize the overall coverage of the supply chain network and minimize the overall cost of the supply chain network by reducing the distance between the facility location and demand location in terms of transportation cost and reducing the over-coverage problem in terms of setup cost. To make the overall supply chain network more sustainable, we also introduced cooperative-based multi-level backup coverage, where every demand will be covered by more than one facility simultaneously to avoid any inadequate moments. This research aims to ensure that the number of potential facilities must cover each demand.

We conclude from the experimental result of these two solution approaches that the proposed heuristic-based algorithm is more efficient after observing the solution quality and computational time compared with the exhaustive search method. Furthermore, the heuristic algorithm demonstrated

Figure 8. All possible solution sets by exhaustive search

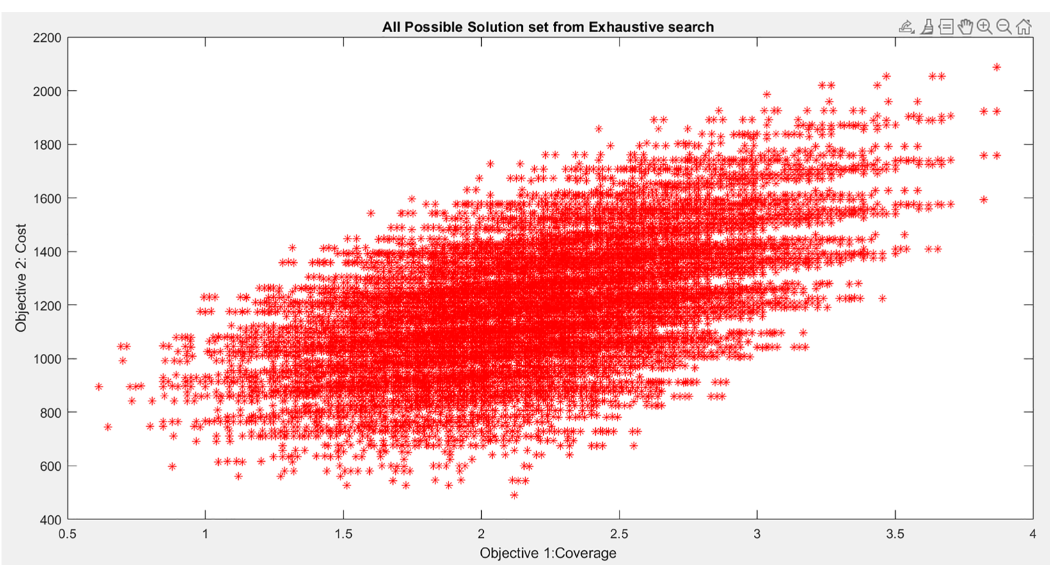


Figure 9. Non-dominated solution set from exhaustive search

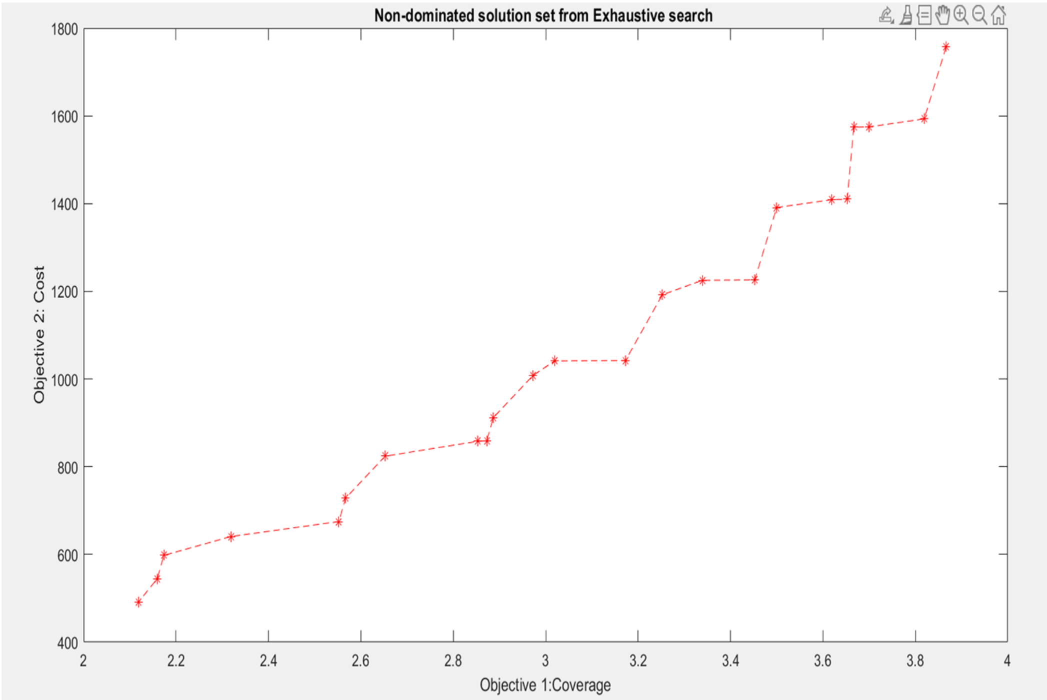
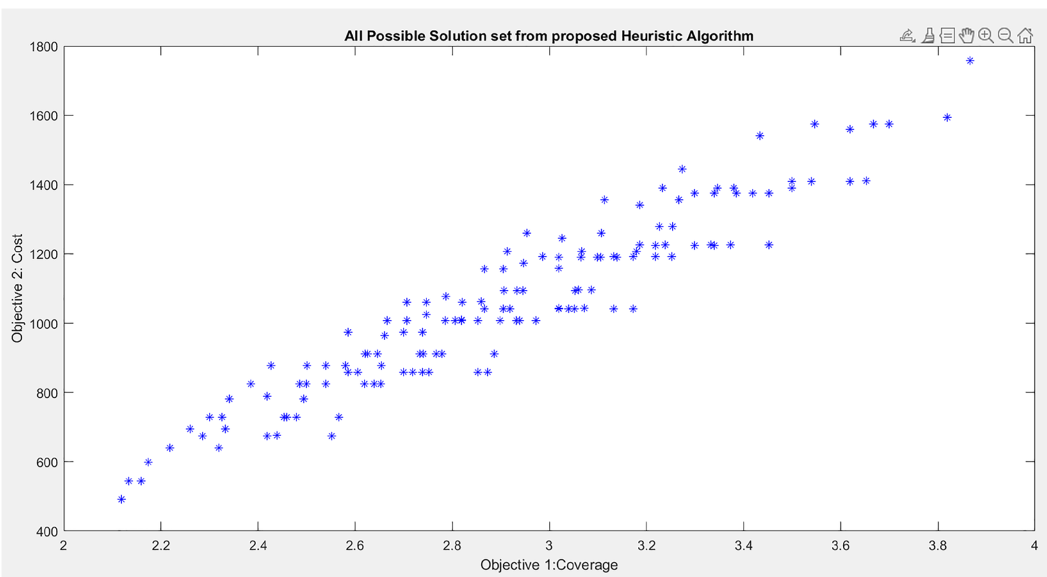
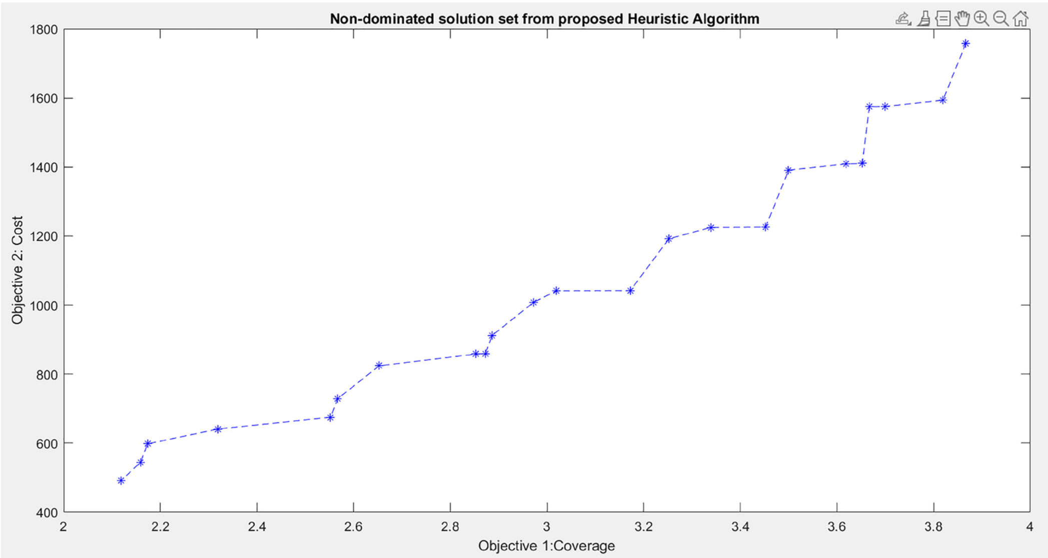


Figure 10. All possible solution sets from proposed heuristic-based algorithm



remarkable scalability, making it a viable choice for handling more extensive and complex problem instances. This finding indicates its potential to be applied in real-world scenarios in supply chain facility allocation problems, where time and computational resources are limited. The heuristic strategy

Figure 11. Non-dominated solution set from proposed Heuristic Algorithm



also demonstrated improved robustness without sacrificing the quality of the answer, outperforming the exhaustive search method. The facility allocation problem can be solved using a meta-heuristic approach in the future, and the computing efficiency of the suggested heuristic-based algorithm can be compared.

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