Efficient Allocation of Customers to Facilities in the Multi-Objective Sustainable Location Problem

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Abstract: This paper aims to evaluate the impact of customer allocation on the facility location in the multi-objective location problem for sustainable logistics. After a new practical multi-objective location model considering vehicle carbon emissions is introduced, the NSGA-II and SEAMO2 algorithms are employed to solve the model. Within the framework of each algorithm, three different allocation rules derived from the optimization of customer allocation based on distance, cost, and emissions are separately applied to perform the customer-to-facility assignment so as to evaluate their impacts. The results of extensive computational experiments show that the allocation rules have nearly no influence on the solution quality, and the allocation rule based on the distance has an absolute advantage of computation time. These findings will greatly help to simplify the location-allocation analysis in the multi-objective location problems.

Keywords: sustainable logistics; multi-objective location problem; location-allocation analysis; NSGA-II; SEAMO2; CPLEX optimizer

1. Introduction

Location decision on logistics facilities plays a critical role in the strategic design of supply chain networks to ensure efficient and effective goods movement. It determines where goods are stored, what quantity of goods is held in inventory, how goods are shipped from raw material sites to component fabrication or assembly plants, as well as how the finished products are delivered to customers. On the other hand, location projects of logistics facilities are generally viewed as long-term investments due to the high costs associated with facility construction. It is often difficult for business owners to reverse their original decisions even if some inputs of decisions change over a long period of time. Inadequate locations of logistics facilities will result in excessive costs throughout their service lives, no matter how well the transportation option, inventory management, and information sharing mechanism are optimized in response to the changing conditions [1].

Traditionally, the facility location problem (FLP) was formulated as a single objective model to minimize the total costs, which is usually expressed as the sum of shipping and opening costs. This modeling approach, however, is facing challenges in addressing the need for real-world complexities. With increasing environmental concerns, thinking objective functions other than economic costs, e.g., environmental impacts, are becoming a must [2,3]. Companies would benefit from using multi-objective optimization (MOO) techniques when designing their logistics networks. Instead of a single solution (often optimized on costs), the MOO techniques can offer the decision-maker a choice of tradeoff solutions. It may be quite possible, for example, to greatly reduce greenhouse gas (GHG) emissions while incurring a slight increase in economic costs. However, such compromise solutions can be easily missed by the traditional single-objective optimization.
As we know, the FLP is always concerned with the allocation of customers to facilities. In other words, it involves making decisions at two levels: (1) Determining which facilities should be selected from a set of candidate sites, and (2) determining which facility each customer should be assigned to. Level 1 is usually regarded as the strategic decision because it is often difficult to change even in the intermediate term due to the high costs of facility construction. Once logistics facilities are in place, however, it is a common practice to periodically reassess the allocation of customers at Level 2, which belongs to the tactical decision. Since the assignment of customers to facilities at Level 2 is an essential part for making the strategic decision at Level 1, it will be of great significance to investigate the impact of the allocation of customers on the location of facilities.

The main purpose of this study is to evaluate the impact of customer allocation on the facility location in the multi-objective location context and the scientific contributions of this study are three-fold. First, it proposes a new practical multi-objective location model for sustainable logistics in which the objectives are to minimize economic costs and carbon emissions simultaneously. Second, two well-known multi-objective genetic algorithms, including non-dominated sorting genetic algorithm II (NSGA-II) and simple evolutionary algorithm for multi-objective optimization 2 (SEAMO2), are hybridized with the CPLEX optimizer to solve the model. Third, three allocation rules derived from the optimization of customer allocation based on distance, cost, and emissions are used to perform the assignment of customers so as to evaluate their impacts.

The remainder of this paper is constructed as follows. Section 2 reviews the literature closely related to this study. Section 3 introduces our multi-objective sustainable location model. Section 4 describes two genetic algorithms, as well as the implementation of three allocation rules. Section 5 reports the results of computational experiments, and finally, conclusions are made in Section 6.

2. Literature Review

The study on the FLP can be traced back to 1909, when Alfred Weber considered how to position a single depot for minimizing the total distance between the depot and several customers [4]. Over the years, significant research progress has been made in this field. To limit our scope, the following survey will concentrate on the literature closely pertinent to this study. Thorough reviews of the FLP can be found in several publications [5–9]. Textbook treatments include [10–12].

2.1. The Multi-Objective FLP

Some studies [3,13] provided comprehensive reviews on multi-objective facility location modeling. These two papers found that most multi-objective models tend to include an economic objective (e.g., cost, profit, or revenue) and other objectives, such as environmental impacts, coverage, or distance, equity, and service quality. Furthermore, Eskandarpour et al. [2] reviewed the sustainable FLP that contains at least two or three dimensions of sustainable development: Economic aspects, environmental performance, and social responsibility.

Integration of environmental performance into the FLP is a natural idea to cope with the growing concern for environmental risks. In the literature, environmental performance has been measured by many possible criteria that generally arise from the economic sectors concerned, such as GHG emissions, waste produced, energy consumed, and materials recovered [14–19].

Carbon footprint, which is the total equivalent amount of GHG emitted by a company or a supply chain, is the most popular metric for measuring environmental impacts among the aforementioned criteria. For example, Mogale et al. [15] presented a bi-objective decision support model for food grain supply chain with the objectives of minimizing the cost and carbon dioxide (CO₂) emissions. The approach of fixed transportation emissions per vehicle was used to calculate the total transportation emissions. Baud-Lavigne et al. [20] proposed a joint family product and supply chain optimization model that considers carbon footprint and economic costs simultaneously. Carbon footprints from production, transportation, and components were all considered in their optimization model. In a study conducted by Ghodratnama et al. [16], a MOO model was developed
to solve a capacitated single-allocation hub location problem. The objectives are to minimize the total transportation and installation costs, the weighted sum of service times in the hubs, as well as the total GHG emitted by vehicles and plants. Canales-Bustos et al. [21] introduced a multi-objective model for the design of an effective decarbonized supply chain in mining. They considered the transportation and installation costs as the economic objective, the emissions from transportation and operations as the environmental objective, and the efficiency of processing plants as the technological objective. In addition, Das and Roy [22] presented a multi-objective transportation-p-facility location problem that integrates the FLP and the transportation problem. In this study, three objectives, including the total transportation costs, transportation time, and carbon emission costs, were considered.

2.2. Solution Methods for the Multi-Objective FLP

The MOO problem is very common in the real world and such problem is featured by an optimum set of alternative solutions, known as Pareto-set, rather than by a single optimum [23,24]. There have been a wide variety of solution methods capable of finding the Pareto-set of a MOO problem. The literature related to MOO techniques in the facility location field can be broadly grouped into two categories: (1) Research applying the classical/preference-based methods and (2) that applying the metaheuristics. In classical methods, a MOO problem would be converted into a single objective formulation using the weighted sum or the $\varepsilon$-constraint approach, for example. This can be found in several studies [20,25–27]. The main advantage of classical methods is to model and solve the multi-objective problem with single-objective approaches. However, various values of weightings must be given in order to approximate the Pareto front.

Compared to the classical methods, the metaheuristic algorithms can offer the flexibility to select good compromise solutions that balance various objectives, so that the decision-maker has a choice of tradeoff solutions without the need of a prior decision regarding the relative importance of various objectives. In the literature, the metaheuristics have been widely used to solve the multi-objective FLP. For example, Altiparmak et al. [28] developed a solution procedure based on genetic algorithm for a single product, multi-stage network problem that minimizes the total costs, minimizes equity of the capacity utilization ratio, and maximizes customer service simultaneously. Chibeles-Martins et al. [29] presented a metaheuristic algorithm based on the simulated annealing methodology for a bi-objective mixed linear programming model with economic and environmental objectives. In a study by Shen [30], a hybrid genetic algorithm based on variable-length chromosome coding was proposed to solve the deterministic equivalence of their multi-objective chance-constrained model for uncertain sustainable supply chain network. Three methods, including the $\varepsilon$-constraint, NSGA-II, and multi-objective particle swarm algorithms, were used by Ghezavati and Hosseinifar [31] to minimize the total amount of value at risk and the total costs of the network in a bi-objective hub location problem.

This extensive literature review indicates that there exist a large number of models and solution methods for the multi-objective FLP, but very few studies have investigated the impact of customer allocation on the facility location. To our knowledge, there exists only one paper contributed by Harris et al. [32] to date. In this study, a multi-objective location model considering economic costs and CO$_2$ emissions simultaneously and the SEAMO2 algorithm embedded with Lagrangian relaxation were proposed for the design of green logistics networks. Two customer allocation rules in respect of two objectives were used to examine the flexibility of customer allocations and the robustness of location solutions. In contrast, our study presents the following advances: (1) Presenting a new practical multi-objective location model for sustainable logistics, (2) proposing two genetic algorithms embedded with the CPLEX optimizer to solve the problem, and (3) applying more allocation rules (both related and irrelated to the objectives) to perform the assignment of customers for assessing their impacts.
3. Mathematical Model

Location decisions on logistics facilities are inherently strategic and long term in nature. There are likely to be many possibly conflicting objectives that need to be considered. With increasing concerns over environmental sustainability, reducing carbon emissions from logistics operations is becoming a part of business owners’ social responsibility. On the other hand, business owners would like to minimize their economic costs. Thus, there is a tradeoff between carbon emissions and economic costs. The proposed model, as we shall see, can assist in qualifying this sort of tradeoff.

As we know, the covering, p-median, p-center, and fixed-charge location model are at the heart of many models that have been widely used to locate logistics facilities [11,12]. For addressing the real-world complexities, they have been variously extended [2,13]. In the literature, there exist a considerable number of approaches that can be incorporated into them for estimating the carbon emissions from freight transport [33]. However, those approaches are often too complex to be used in practice. In this study, the capacitated fixed-charge location model is employed and extended to a MOO by considering environmental issues, based on a very practical approach for calculating carbon emissions. The proposed multi-objective location model is a mixed-integer linear programming model and can be formulated as follows.

Objective function (1) is the classical economic objective that aims to minimize the total costs. It consists of the variable shipping costs of serving the demand of customers and the fixed costs of running the open facilities. Objective function (2) acts to minimize the total carbon emissions from vehicles. The term in square bracket estimates the amount of carbon emissions per unit distance from a truck with a load of $h_j$. Constraints (3) state that each customer can be assigned to exactly one open facility. Constraints (4) ensure that the capacity limit of each facility cannot be violated. Constraints (5) and (6) define decision variables as binary.

4. Solution Algorithms

In this study, the NSGA-II and SEAMO2 algorithms are employed to determine which facilities should be opened at Level 1. Within the framework of either algorithm, three different allocation rules are separately applied to perform the assignment of customers to open facilities at the tactical level.
4.1. General Structures of Two Algorithms

The NSGA-II developed by Deb et al. [23] is widely recognized as a leading multi-objective evolutionary algorithm. It is elitist and uses non-dominated principles to ensure the solutions are widely and evenly distributed. These enable the NSGA-II to possess all the qualities that are needed to be considered when solving a MOO problem. Figure 1 presents the framework of the NSGA-II.

In contrast, the SEAMO2 developed by Mumford [34] relies on much simpler techniques. It disposes of all selection mechanisms based on fitness values and utilizes a straightforward uniform selection procedure instead, i.e., the algorithm sequentially selects each individual in the population to serve as the first parent once and pairs it with the second parent selected randomly from the population. Thus, no dominance ranking is required. The improvements in population and the progress of genetic search depend entirely upon the replacement strategy. The offspring replaces a current member of the population following three simple rules: if any of best-so-far objectives are improved or if the offspring dominates either of its parents or if the offspring is neither dominated by nor dominates either parent.

Figure 1. The framework of the NSGA-II.

4.2. Assignment of Customers to Facilities

As can be seen in Figures 1 and 2, the allocation of customers to open facilities is an essential part of making location decisions. Within the framework of each algorithm, three different allocation rules are separately used to perform the customer-to-facility assignment so as to evaluate their impacts. Rule 1 assigns each customer to its nearest open facility with sufficient capacity to serve it using the greedy heuristic, which bears no explicit relation to two objectives. Rules 2 and 3 are associated with the economic and environmental objectives, respectively. The assignment of customers following Rule 2 or 3 will be implemented by the CPLEX optimizer.

For Rule 2 (regarding economic objective), once facility location decision is made at the strategic level, the opening costs of facilities will be confirmed and become a fixed value. Thus, minimizing the sum of shipping and opening costs in objective function (1) can be reduced to minimize only the shipping costs, as shown in Expression (7).

\[
\sum_{j} c_{kj} x_{kj} \quad \forall k \in I_{open}
\]

where \( k \in I_{open} \) (\( I_{open} \) is the set of open facilities). Expression (7) aims to minimize the transportation costs of assigning all customers to open facilities while subject to the following constraints.

\[
\sum_{j} x_{kj} \leq \sum_{i} y_{ij} \quad \forall k \in I_{open}
\]

\[
\sum_{j} y_{ij} \leq h \quad \forall i \in J
\]

\[
x_{kj} \in \{0,1\} \quad \forall k \in I_{open}, j \in J
\]

Obviously, the model formulated by Expressions (7)–(10) is a generalized assignment problem that can be readily solved by the CPLEX optimizer. Rule 3 (regarding environmental objective) can be handled in the same way. For the sake of brevity, it is not repeated.

Figure 2. The framework of the SEAMO2.
4.2. Assignment of Customers to Facilities

As can be seen in Figures 1 and 2, the allocation of customers to open facilities is an essential part of making location decisions. Within the framework of each algorithm, three different allocation rules are separately used to perform the customer-to-facility assignment so as to evaluate their impacts. Rule 1 assigns each customer to its nearest open facility with sufficient capacity to serve it using the greedy heuristic, which bears no explicit relation to two objectives. Rules 2 and 3 are associated with the economic and environmental objectives, respectively. The assignment of customers following Rule 2 or 3 will be implemented by the CPLEX optimizer.

For Rule 2 (regarding economic objective), once facility location decision is made at the strategic level, the opening costs of facilities will be confirmed and become a fixed value. Thus, minimizing the sum of shipping and opening costs in objective function (1) can be reduced to minimize only the shipping costs, as shown in Expression (7).

\[
\min \sum_{k} \sum_{j \in J} c_{kj} h_{j} d_{kj} Y_{kj} \tag{7}
\]

where \( k \in I_{\text{open}} \) (\( I_{\text{open}} \) is the set of open facilities). Expression (7) aims to minimize the transportation costs of assigning all customers to open facilities while subject to the following constraints.

\[
\sum_{k \in I_{\text{open}}} Y_{kj} = 1, \forall j \in J \tag{8}
\]

\[
\sum_{j \in J} h_{j} Y_{kj} \leq Q_{k}, \forall k \in I_{\text{open}} \tag{9}
\]

\[
Y_{kj} \in \{0, 1\}, \forall k \in I_{\text{open}}, j \in J \tag{10}
\]

Obviously, the model formulated by Expressions (7)–(10) is a generalized assignment problem that can be readily solved by the CPLEX optimizer. Rule 3 (regarding environmental objective) can be handled in the same way. For the sake of brevity, it is not repeated.

5. Computational Experiments

5.1. Experiment Setups

In the literature, a considerable number of benchmark instances are available for the single objective facility location problems. Unfortunately, those data instances only contain demand, capacity, distance, and cost elements, and there is no information regarding vehicle emissions that is needed to apply our MOO model. For this reason, a total of 57 benchmark instances from Delmaire et al. [35] (available at http://www-eio.upc.es/~elena/ssclp/index.html) were employed and modified to carry out our experiments. All these instances were supplemented with the carbon emission rate of a fully loaded truck \( \epsilon_{\text{cf}} = 1.096 \) and that of an empty truck \( \epsilon_{\text{ce}} = 0.772 \).

The proposed algorithms were coded in MATLAB R2018b. For each test on an instance, ten replicated runs were performed with each allocation rule and each algorithm. For either algorithm, an initial population twice the size of potential facilities was generated at random. The crossover probability and the mutation probability were 0.9 and 0.1, respectively. The maximum number of generations was set to 200 since the solutions for the instances become stabilized.

5.2. Experimental Results

To avoid data overload, only the results of one tested instance (named p27) with 50 customers and 20 potential facilities are presented as an illustration. Tables 1 and 2 report the test results of three allocation rules with the NSGA-II and the SEAMO2, respectively. It is not difficult to find:
• Both the NSGA-II and the SEAMO2 are effective in approximating the Pareto fronts of the proposed multi-objective sustainable location problem. Although the NSGA-II outperforms the SEAMO2 in solution quality, it is outperformed by the SEAMO2 in computation time, as shown in Figures 3 and 4. The simple genetic operators of the SEAMO2 makes it much faster than the NSGA-II with small reductions in solution quality.

• The economic and environmental objectives are conflicting, i.e., lower-cost solutions often produce higher carbon emissions and lower-emission solutions often produce higher economic costs. Some good compromise solutions located in the middle of Pareto fronts are generally reasonable tradeoffs between economic costs and carbon emissions. In the sustainable logistics context, the best choice for decision-makers is not the solutions with minimum costs, a more likely the solutions trading off the economic costs and carbon emissions.

Table 1. Test results of three allocation rules with the NSGA-II.

| Rule 1 | Rule 2 | Rule 3 |
|-------|-------|-------|
| Costs \(10^4\) | Emissions \(10^2\) | Costs \(10^4\) | Emissions \(10^2\) | Costs \(10^4\) | Emissions \(10^2\) |
| 2.3049 | 4.9622 | 2.1201 | 6.0414 | 2.1201 | 6.0414 |
| 5.4475 | 1.8640 | 5.4475 | 1.8640 | 5.4475 | 1.8640 |
| 4.2961 | 2.0342 | 2.1904 | 5.2682 | 2.1936 | 5.2184 |
| 2.6097 | 3.4989 | 2.6097 | 3.4989 | 2.2482 | 4.2521 |
| 3.9397 | 2.0249 | 3.0035 | 2.7666 | 2.6097 | 3.4989 |
| 2.3855 | 3.9801 | 2.4272 | 4.2585 | 3.0035 | 2.7666 |
| 2.6217 | 2.3232 | 4.0457 | 2.1357 | 3.1775 | 2.6913 |
| 2.3731 | 4.6381 | 3.9397 | 2.2049 | 4.7011 | 1.9590 |
| 5.1391 | 1.8926 | 5.1391 | 1.8926 | 4.0457 | 2.1357 |
| 4.7785 | 1.9304 | 4.7785 | 1.9304 | 5.1391 | 1.8926 |
| 3.5287 | 2.4831 | 4.4701 | 1.9590 | 4.7756 | 1.9304 |
| 4.4701 | 1.9590 | 2.6217 | 3.2332 | 2.4820 | 3.1777 |
| 2.4852 | 3.8128 | 2.2343 | 4.6804 | 2.6217 | 3.2332 |
| 3.7515 | 2.2645 | 4.4338 | 2.0311 | 2.2343 | 4.6804 |
| 2.6030 | 3.6363 | 3.7515 | 2.2645 | 2.3843 | 3.9631 |
| 2.9487 | 2.9526 | 2.4820 | 3.7177 | 4.4338 | 2.0311 |
| 2.3800 | 4.3006 | 2.9647 | 2.9611 | 3.2914 | 2.5802 |
| 2.7536 | 3.2277 | 2.7536 | 3.2277 | 2.7536 | 3.2277 |
| 2.7747 | 3.0278 | 3.3458 | 2.6212 | 2.2340 | 5.0153 |
| 4.0457 | 2.1357 | 2.2340 | 5.0153 | 2.5261 | 3.6672 |
| 3.0035 | 2.7666 | 2.7747 | 3.0278 | 2.7747 | 3.0278 |
| 3.3465 | 2.4945 | 3.5775 | 2.3397 | 3.4655 | 2.4945 |
| 2.5426 | 3.7781 | 3.1935 | 2.6998 | 3.5775 | 2.3397 |
| 3.5775 | 2.3397 | 4.2339 | 2.0761 | 2.5261 | 2.0761 |
| 3.7152 | 2.3366 | 2.8505 | 2.9719 | 3.7515 | 2.2645 |
| 4.4338 | 2.0311 | 3.3458 | 2.4945 | 3.8797 | 2.2049 |
| 2.9049 | 3.0130 | 2.3843 | 3.8631 | 3.7152 | 2.366 |
| 3.1177 | 2.7537 | 3.4842 | 2.4914 | 2.9049 | 3.0130 |
| 2.3208 | 4.8248 | 3.5205 | 2.4192 | 3.4842 | 2.4914 |
| 3.2345 | 2.6118 | 3.7152 | 2.3366 | 3.5205 | 2.4192 |
| − | − | 2.3454 | 4.0815 | 2.9487 | 2.9526 |
| Avg. time (s) | 14.1 | 180.2 | 170.5 |

Table 2. Test results of three allocation rules with the SEAMO2.

| Rule 1 | Rule 2 | Rule 3 |
|-------|-------|-------|
| Costs \(10^4\) | Emissions \(10^2\) | Costs \(10^4\) | Emissions \(10^2\) | Costs \(10^4\) | Emissions \(10^2\) |
| 3.7515 | 2.2645 | 3.6319 | 2.3808 | 3.1775 | 2.6913 |
| 3.3465 | 2.4945 | 2.8505 | 2.9719 | 3.0035 | 2.7666 |
| 2.3800 | 4.3006 | 3.2345 | 2.6118 | 2.2482 | 4.2521 |
| 2.8505 | 2.9719 | 5.1391 | 1.8926 | 2.1936 | 5.2184 |
| 5.1391 | 1.8926 | 2.6449 | 3.4702 | 3.4009 | 2.5355 |
| 4.4701 | 1.9590 | 3.5205 | 2.4192 | 2.3843 | 3.9631 |
| 3.0245 | 2.8967 | 3.2319 | 2.7324 | 2.1201 | 6.0414 |
| 2.7747 | 3.0278 | 2.2077 | 5.2040 | 2.7957 | 3.1579 |
| 2.5480 | 3.7356 | 2.6587 | 3.3628 | 3.0579 | 2.8576 |
Table 2. Cont.

| Rule 1 | Rule 2 | Rule 3 |
|--------|--------|--------|
| Costs (10^4) | Emissions (10^2) | Costs (10^4) | Emissions (10^2) | Costs (10^4) | Emissions (10^2) |
| 2.9049 | 3.0130 | 2.1201 | 6.0414 | 2.6097 | 3.4989 |
| 2.4068 | 4.0117 | 3.3465 | 2.4945 | 2.6587 | 3.3628 |
| 2.9096 | 3.0468 | 3.0035 | 2.7666 | 2.5097 | 3.9111 |
| 3.0579 | 2.8076 | 3.1935 | 2.6998 | 2.2340 | 5.0153 |
| 2.7360 | 3.3816 | 2.9487 | 2.9526 | 4.2961 | 2.0342 |
| 3.0626 | 2.8414 | 3.5261 | 3.6872 | 2.3932 | 4.2423 |
| 2.3855 | 3.9801 | 2.9049 | 3.0130 | 2.5261 | 3.6872 |
| 3.2914 | 2.5802 | 2.6217 | 3.2332 | 2.3343 | 4.3473 |
| 2.6313 | 3.4921 | 2.3454 | 4.9166 | 3.1177 | 2.7557 |
| 3.1935 | 2.6998 | 2.7536 | 3.2277 | 3.1935 | 2.6998 |
| 3.0035 | 2.7666 | 4.2961 | 2.0342 | 3.8717 | 2.2110 |
| 2.6217 | 3.2332 | 2.4590 | 3.9863 | 2.6217 | 3.2332 |
| 3.2345 | 2.6118 | 2.8633 | 3.1337 | 2.7536 | 3.2277 |
| 2.7757 | 3.3515 | 3.1919 | 2.7754 | 2.6030 | 3.6363 |
| 2.4059 | 4.1094 | 2.5480 | 3.7356 | 2.9487 | 2.9526 |
| 2.4852 | 3.8128 | 2.7747 | 3.0278 | 2.4820 | 3.7177 |
| 2.9487 | 2.9526 | 2.6097 | 3.4989 | 2.2703 | 4.7859 |
| 2.6030 | 3.6363 | 2.4820 | 3.7177 | 2.3801 | 4.2853 |
| 3.9397 | 2.2049 | 3.1775 | 2.6913 | 2.3454 | 4.0816 |
| 2.6517 | 3.6214 | 2.7957 | 3.1579 | 2.9049 | 3.0130 |
| 3.1177 | 2.7537 | 3.5276 | 2.4630 | 2.2343 | 4.6804 |
| 2.6824 | 3.5093 | 2.9647 | 2.9611 | 2.9069 | 3.0468 |
| 3.1775 | 2.6913 | 3.0057 | 2.8731 | 3.3465 | 2.4945 |
| 2.7957 | 3.1579 | 3.2914 | 2.5802 | 3.1384 | 2.7855 |
| 2.5426 | 3.7781 | 2.8527 | 3.0784 | 5.3949 | 1.9935 |
| 2.7536 | 3.2277 | 2.1960 | 5.3039 | 2.7757 | 3.3515 |
| 2.3208 | 4.8248 | 3.7515 | 2.2645 | 2.4852 | 3.8128 |
| 2.9647 | 2.9611 | 2.3843 | 3.9631 | 2.6313 | 3.4921 |
| 2.8527 | 3.0784 | 3.4009 | 2.5355 | 2.7747 | 3.0278 |
| 2.6097 | 3.4989 | 3.1177 | 2.7557 | 3.5775 | 2.3397 |
| 3.0057 | 2.8731 | 3.5775 | 2.3397 | 2.8505 | 2.9719 |
| Avg. time (s) | 10.3 | 135.3 | 132.5 |

More importantly, the following observations should be emphasized.

- Over 60% solutions obtained with Rule 1 are the same as those obtained with Rules 2 and 3 (18 of 30 for the NSGA-II and 27 of 40 for the SEAMO2), as highlighted in boldface in Tables 1 and 2. Further, the generational distances (GDs) between every two Pareto fronts are very close, as seen in Table 3. The GD was proposed by Van Veldhuizen and Lamont [36] as a measure of distance between two Pareto fronts and can be calculated as follows.

\[
GD = \sqrt{\frac{1}{n} \sum_{i=1}^{n} d_i^2}
\]

where \(d_i\) denotes the Euclidean distance between the \(i\)th point on one Pareto front and its nearest point on another Pareto front, and \(n\) is the number of points on the Pareto front.

- The computation time required by Rule 1 is significantly less than that required by Rule 2 or 3. The average runtimes with Rules 2 and 3 are very close, but over 10 times longer than those with Rule 1, using either the NSGA-II or the SEAMO2, as depicted in Figure 4.
Table 3. The GDs between Pareto-sets obtained with three allocation rules using NSGA-II and SEAMO2.

|       | Rule 1 | Rule 2 | Rule 3 | Rule 1 | Rule 2 | Rule 3 |
|-------|--------|--------|--------|--------|--------|--------|
| Rule 1| 0      | 143.6  | 118.3  | 0      | 151.1  | 215.4  |
| Rule 2| 244.3  | 0      | 61.0   | 350.0  | 0      | 186.8  |
| Rule 3| 240.7  | 41.2   | 0      | 353.1  | 161.4  | 0      |

Figure 3. The comparison of Pareto fronts obtained with three allocation rules.
6. Conclusions and Perspectives

The MOO has been widely used in the field of facility location to cope with real-world complexities. However, very few studies have been conducted to investigate the impact of the assignment of customers on the location of facilities in the MOO context. In this paper, a new practical multi-objective location model considering economic costs and vehicle emissions simultaneously is introduced, and two multi-objective metaheuristics are used to solve the model. Further, three different allocation rules derived from the optimization of customer allocation based on distance, cost, and emissions are applied to perform the customer assignment so as to evaluate their impacts. The results of extensive computational experiments demonstrate the flexibility of customer allocations, the robustness of location solutions, as well as the efficiency of Rule 1. That is to say, the allocation rule based on the distance will be a top priority for the assignment of customers in multi-objective sustainable location problem, in view of its implementation simplicity, accuracy, and computational performance.

There are some limitations to this study. On the one hand, the proposed model is too simple to address the real-world complexities. For example, in the real world, business owners may focus more on equity, service level, as well as other environmental risks, customer demands may be uncertain rather than deterministic. On the other hand, our findings are achieved through three allocation rules and two genetic algorithms. Extending the findings to other allocation rules and solution algorithms may be a serious challenge. For future research, one prospective task would be to incorporate more aforementioned factors into the model to extend its realistic application scope. Another prospective task would be to make more evaluations for various allocation rules based on various algorithms to investigate their impacts so as to simplify the location-allocation analysis in the multi-objective location problems.

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