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Sustainable Vehicle Routing Problem for Coordinated Solid Waste Management

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Abstract

The quick growth of urbanization and population, as well as the transformation of industrial and materials, have pushed the management of municipal solid waste into a crisis especially for developing markets based on the grand challenge of sustainable development. The compounding complexity of the multiple objectives and dynamic problem constraints required to represent coordinated solid waste management (CSWM) problem in practice is a hugely significant issue for vehicle routing problem studies. The purpose is to introduce a new coordinated framework for a practical and efficient vehicle routing problem considering the triple bottom line of sustainability. The CSWM multiple objective functions applied in this study incorporate financial, environmental and social considerations to develop a sustainable vehicle routing problem considering heterogeneous vehicle fleets operating across a multi-echelon logistics network with the optimization goals. An entirely novel development and application of the adaptive memory social engineering optimizer (AMSEO) is introduced and is shown to perform significantly better than the simulated annealing (SA) as well as the social engineering optimizer (SEO) itself. Finally, the potential overall waste disposal cost savings achievable through increased recycling (revealed by framing the logistics problem across several echelons) is of particular significance. The main findings are the practical solutions with the use of sustainability goals for the CSWM and further application and development of the AMSEO in the routing optimization.

Keywords: vehicle routing problem; municipal solid waste, coordinated solid waste management; triple bottom line concept; social engineering optimizer.

1. Introduction

This study proposes a logistics network optimization solution to the growing problem of municipal solid waste (MSW) disposal. A liberal definition of MSW is taken to include a waste stream comprising both domestic and industrial garbage, recyclable and hazardous items [1]; [2]. The past decades created a quick growth of urbanization and population as well as the transformation of industrial and materials internationally as an explosion in the generation of municipal solid waste [3]; [4]. In many jurisdictions, the management of MSW is in crisis, be they developing [5] or developed municipalities [6].

The logistics of MSW disposal is further complicated by the complex nature of the transport network [7]; [8]; increasing sensitivity to the costs of environmental impact [9]; and the practical limitations that often govern the location of processing facilities [10], the source of waste streams, recycling options, and the complexities of transportation management [11]. The environmental challenge of transportation management alone [12], the largest source of pollution and environmental concerns in the logistics system, is a significant optimization problem within itself [13]; [9].

This compounding complexity of MSW management means that many realistic constraints are often omitted when a waste collection and disposal logistics network is modelled [14]; [15]. For example, a heterogeneous fleet of waste transportation vehicles is common, but few studies accommodate the variable capacity, speed, fuel consumption, cost, emissions, and other features across the fleet that this heterogeneity entails [16]. Otherwise, the modelling approach might seek to ignore the added complexity of the intermediate transfer or waste processing facilities typically present in any MSW logistics network of reasonable scale and found to significantly impact the model performance [17]; [18].

The novelty of this paper is to introduce a new framework for practical and efficient vehicle routing optimization. It is practical because it applies a multi-objective optimization model accommodating combinatorial optimization issues such as heterogeneous fleets operating across a structured multi-echelon logistics network. It is efficient because it incorporates a novel meta-heuristic algorithm for combinatorial optimization problems. The optimization here includes three critical, though often conflicting, minimization goals: comprehensive transportation cost; total environmental emissions; and total deviation from fair load allocation. These objectives address the financial, environmental and social factors to address the triple bottom line of sustainability for MSW management. The proposed integrated framework based on the triple bottom line concept is more likely to be effective in real-world applications because it considers all tactical and operational decisions in the reverse logistics network design.

The key novel feature of the integrated framework seeks to overcome the degraded performance and excessive time taken to reach an optimal solution evident when the various exact methods (including, branch-and-bound and linear programming techniques) are applied to this type of combinatorial optimization with multiple objectives and complex constraints [19]. A mixed-integer non-linear programming (MINLP) is considered. The methodology applies an efficient version of the recently-developed, social engineering optimizer (SEO) algorithm [20]. This is the first time SEO has been applied in this way to a realistic vehicle routing problem (VRP), and this study develops a new adaptive memory extension of SEO (AMSEO).

Therefore, the main research questions in this study can be established as follows:

- ✓ How can a sustainable routing optimization based on the triple bottom line concept be modeled for the framework of CSWM?
- ✓ How can we solve this model efficiently, and what is one of the best alternatives in this regard?

This paper can be summarized as follows. Section 2 overviews the recent and important challenges arising in the vehicle routing problem (VRP) field. Section 3 develops the proposed mixed-integer non-linear programming (MINLP) method as an integrated framework to address combinatorial optimization problems with multiple objectives and complex constraints that include transportation emissions, a heterogeneous fleet and a structured logistics network. Section 4 introduces an efficient meta-heuristic solution method using SEO which this study extends through an entirely novel development of AMSEO. Section 5 presents an extensive evaluation and sensitivity analysis of the integrated framework and compares the AMSEO method directly with

SEO and simulated annealing (SA) alternatives. Finally, based on the results, the potential implications for MSW management are considered, and the conclusion is drawn in Section 6.

2. Literature review

Research on the optimization of MSW has evolved over several decades now, largely driven by the waste collection problems found in practice [21]. Typically characterized as a VRP, the strong focus has been on the optimization of waste allocation, waste flows and the routing decisions of collection trucks [22]; [23]. Central to this effort has been the development and application of mixed-integer linear programming (MILP) approaches [2]. Eiselt [24] contributed to the optimization model of a hub location-allocation problem. The goal was the optimal location of landfill sites. However, the main limitation of their model is the option of reverse logistics to cover intermediate recycling and treatment centers. Erkut et al. [17] proposed an integer programming approach to coordinate the main operational activities of the reverse logistics such as recycling, transferring, treatment and disposal. In addition, Berman et al. [25] proposed polynomial time and branch and price algorithms to efficiently solve the routing problem in a hazardous waste network. In another paper, later in 2011, Dai et al. [26] extended the MILP approach further to design a plan for capacity expansion of waste treatment and allocation centers more particular to a case study in Beijing, China. However, early developments still fell well short of providing an integrated framework because they lacked the capacity to handle a more representative subset of the operational factors in play.

The growing crisis in waste management has given added impetus to and interest in MSW management research. One key driver has been environmental and green emissions. Increasing concern with the management of hazardous waste, such as inherited ash waste from incineration [27], requires a framework where particular waste streams can be allocated to particular facilities [8]. The added complexity of the problem description has generated considerable interest and development in the particular use of operations research techniques [28]; [4]; [3]; [29].

Along with having to deal with more complexity regarding the description of this problem, many studies only considered a single optimization model as one of the main limitations of this research area. Asefi et al. [30] used a MILP approach to model the economic cost and location-routing structure, and Vidovi´c et al. [12] developed a novel MILP to maximize the profits of a two-echelon logistics network as this configuration supports the end-users, transfer stations and collection points. Harijani et al. [31] introduced a new bi-objective MILP model for MSW optimization. In addition to the profits, they considered some qualitative, non-economic criteria as the second objective to minimize the cost of them. Another bi-objective MILP model considering the geographic information system (GIS) was proposed by Asefi and Lim [8] to optimize transportation costs against time factors. Habibi et al., [32] proposed another bi-objective model to solve a case study of Tehran, Iran. They found the optimal sites of facilities and their right allocation. Tehran, Iran was also the case study location for a study by Edalatpour et al. [33] proposed another bi-objective optimization with economic and environmental impacts for a case study of Tehran, Iran with two MSW levels including recyclers and remanufacturers.

As the complexity of the problem definition has increased to reflect more realistic MSW management considerations and practical limitations, research attention has also turned to more efficient optimization techniques. Vidovi´c et al. [12] developed a meta-heuristic approach using tabu search (TS) and other well-known meta-heuristics to solve a location-routing model. Edalatpour et al. [33] applied a rudimentary genetic algorithm (GA) and Rabbani et al. [34] employed both the non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimization (MOPSO) to address a multi-objective industrial hazardous waste problem. Along with the findings of these recent papers, the review papers of Ghiani et al., [22] and Bing et al. [23] all highlight the pressing need for more efficient solution algorithms when dealing with the computational complexity, NP-hardness, of realistic MSW management problems.

Recently, Mahmoudsoltani et al., [35] proposed a location-routing model for MSW optimization with two objectives, including the total cost and risk. Their supposition was the pipelines for MSW as well as road transportation. Due to the high complexity of this model in large-scale samples, three multi-objective evolutionary algorithms (EAs) were tackled to address the model. Hu et al., [36] for the first time considered the traffic limitations as one part of the constraints for a bi-objective model. They also proposed an adaptive weight GA to find the optimal routes. Rabbani et al., [37], in another study, offered a stochastic programming approach for a multi-period, multi-echelon location-inventory MSW optimization model. Their contribution was a hybrid algorithm based on the NSGA-II and Monte Carlo simulation. As a continuation of [8], Asefi et al., [38] in another study contributed a three-echelon logistics network for the MSW optimization as they solved a case study in Tehran, Iran. For the first time in the literature, a robust bi-level optimization was studied by Pouriani et al., [39] to model the MSW optimization. In their model, the location decisions were made by the lower-level model and the allocation of different wastes was performed by the upper-level model. They also solved a case study in Babol, Iran. More recently, Delfani et al., [40] developed a scenario-based robust-possibilistic programming approach to model MSW for hazmat materials. The objectives were simultaneously optimized the total cost and the risk of logistics and population.

In order to have a conclusion, the aforementioned papers are classified based on the objective functions, constraints and solution algorithms utilized. This classification is given in Table 1. The measures are related to the type of the model, the objective functions, and the characteristics of the models and the solution algorithms. In this table, there are six common objective functions including the total cost, green emissions, customer's satisfaction, risk, fair load allocation, and the time of loading. The model's characteristics are related to the decisions of the models based on the allocation, routing, and inventory decisions. Some other suppositions are the use of uncertainty modeling, different types of waste and their methodologies for reverse options, traffic restriction, and technology selection for recycling, GIS model, multi-echelon, and time windows. Based on these criteria, the following observations are identified:

- Most of the recent studies contributed to the multi-objective decision making models.

- In addition to the total cost, environmental emissions are considered by seven studies.
- Considering the sustainability dimensions including financial, environmental and social factors only supposed in four studies like the present paper.
- There is no study except the present paper to consider the fair load allocation as a social factor.
- The current paper contributed to the allocation, routing and inventory decisions as well as the multi-echelon, technology selection and time windows.
- Most of the solution algorithms were different types of heuristics and meta-heuristics as a common approach.
- Among them, the present work is the first attempt to show the application and development of a recent meta-heuristic called SEO.

Generally speaking, the current study took up the challenge of developing an efficient optimization method for practical MSW management problems. The practicality of the proposed method seeks to step well beyond the current literature. For example, the study proposed by Habibi et al. [32] is a rare exception in the literature in so far as that study considers the fleet size of the waste transport network to be variable. However, that study failed to consider the routing decisions of the vehicles. Rabbani et al. [34] addressed the routing decisions for a heterogeneous fleet but ignored the possibility of a structured logistics network comprising intermediate transfer stations. That study also assumed fixed routing requirements, when allowing the fleet freedom to return to alternative depots offers significant scope for performance improvement and this more flexible assignment condition can lead to important financial savings [14]. Furthermore, whilst Harijani et al. [31] offered an almost unique to the literature consideration of the environmental emissions in their study, an objective function to optimize the impacts of fuel consumption, emissions, etc. was not incorporated.

Overall, many studies employed routing optimization for multi-echelon MSW management (e.g., [8]; [32]; [34]; [37]; [38]). This paper follows the same path while adding several extensions (e.g., the sustainability dimensions of MSW by considering the total cost, green emissions and fair load allocation objectives). Most importantly, the current study seeks to demonstrate a genuinely comprehensive solid waste management (CSWM) solution.

The solution proposed in this study is a novel meta-heuristic approach that builds and extends the recently developed SEO using an entirely new adaptive memory approach. The main advantage of AMSEO is not only to find a better interaction between the intensification and diversification phases, but also to improve the cost-efficiency of a general idea to reach a global optima instead of near-optimal solutions [20], and this study is the first to apply and evaluate it to CSWM.

In conclusion, this study suggests the following highlights as the novelties of this research:

- Developing a sustainable vehicle routing problem considering different fleet sizes for coordinated solid waste management;
- Implementing the concept of the triple bottom line in the framework of CSWM.

- Proposing an adaptive memory social engineering optimizer to better address the proposed model;
- Analyzing the total costs and green emissions of vehicles and the total deviation from fair load allocation to transfer stations;

Table 1. Collection of relevant studies in the area of MSW with optimization

Reference	Type of model*	Objectives						Constraints											Solution method
		Total cost	Green emissions	Customer's satisfaction	Risk	Fair load allocation	Time of Loading	Allocation	Routing	Inventory	Different types of waste	Traffic restriction	Uncertainty	Technology selection	GIS	Multi-echelon	Time windows	
[41]	BP	✓			✓			✓	✓									Exact
[15]	MILP	✓			✓				✓									Exact
[42]	Simulation				✓				✓						✓			Simulation
[43]	MILP	✓			✓			✓	✓						✓	✓		Exact
[44]	BP	✓							✓									Heuristic
[45]	IP	✓			✓			✓										Exact
[46]	MILP	✓	✓					✓	✓							✓		Exact
[25]	MILP	✓							✓								✓	Exact
[17]	MILP	✓	✓					✓								✓		Heuristic
[26]	MILP	✓							✓					✓	✓			Simulation
[47]	MINLP	✓						✓	✓				✓			✓	✓	Meta-heuristic
[12]	MILP	✓						✓	✓				✓			✓		Meta-heuristic
[31]	MILP	✓					✓	✓	✓					✓		✓	✓	Exact
[8]	MILP	✓					✓	✓	✓					✓	✓	✓	✓	Exact
[32]	MINLP	✓					✓	✓	✓							✓	✓	Meta-heuristic
[14]	MINLP	✓			✓			✓	✓				✓			✓		Meta-heuristic
[33]	MILP	✓	✓						✓	✓			✓	✓		✓	✓	Exact
[34]	MILP	✓	✓	✓				✓	✓				✓	✓		✓	✓	Meta-heuristic

[35]	MINLP	✓			✓			✓	✓					✓		✓	✓	Meta-heuristic
[48]	MINLP	✓	✓	✓				✓	✓				✓			✓		Meta-heuristic
[36]	MINLP	✓			✓			✓	✓			✓	✓			✓		Exact
[37]	MILP	✓	✓	✓				✓	✓	✓	✓					✓	✓	Meta-heuristic
[38]	MILP	✓					✓		✓		✓			✓		✓	✓	Exact
[39]	MILP	✓						✓			✓		✓			✓		Exact
[40]	MILP	✓			✓			✓	✓		✓		✓			✓		Exact
This study	MINLP	✓	✓			✓		✓	✓	✓	✓			✓		✓	✓	Meta-heuristic

*BP: Binary Programming; MILP: Mixed Integer Linear Programming; IP: Integer Programming; MINLP: Mixed Integer Non-Linear Programming

3. Proposed methodology

This section presents the proposed methodology. The CSWM framework is described in terms of the principal parameters that determine both the rich set of realistic problem constraints along with the multiple solution objectives. One key outcome is to incorporate the generated CO_2 emissions as a principal objective for the first time. Then, the proposed multi-objective MINLP model is developed and explained.

3.1. Problem framework

For a realistic CSWM framework, there are several treatment technologies ($t \in T$), recycling ($r \in R$) and disposal ($d \in D$) possible. A waste transportation heterogeneous fleet will potentially vary the class of vehicle, its capacity and associated transportation costs, and environmental emissions [34]. The choice of vehicles depends on the type of waste, and the type of waste also determines the required and allowable transportation activities.

Following Chang et al., [49], consider that an infinite number of vehicles of each type/size is available. Accordingly, the loading capacity, fuel consumption and waste type compatibility have no bounds. However, the choice of vehicle, following Habibi et al. [32] and Rabbani et al. [34], is limited to the residue transferring trucks (*U*), waste transportation semi-trailers (*S*) and waste collection vehicles (*V*).

A general overview of the CSWM framework is presented in Figure 1. Individual waste generation nodes present volumes of waste (BG_{og}) in multiple types ($o \in O$), including garbage, recyclable and hazardous waste. Waste collection vehicles ($q \in V$) begin their route from the allocated transfer station (depot) and collect appropriate waste (VO_{oq}) from the nodes of the waste generation. The collected waste is then unloaded back to the transfer station of origin. Each vehicle has two important cost factors: transportation cost (TC_{ij}^{q}) and the fixed cost of utilization (FC_q).

The transfer stations (depots) are then central to the CSWM framework. The function of each transfer station is to sort the collected waste into specified sub-types ($w \in W$), in unspecified proportions. Individual transfer stations may use different forms of waste processing technology, appropriate to different types of waste, and the balance of processing technology (P_{wk}) might vary across the logistics network.

The larger waste transportation semi-trailers ($q \in S$) also begin their route from the allocated transfer station (depot). Before departure, they load the compatible sorted waste (VW_{wq}). This load is then transported to the relevant recycling (AH_{rh}), treatment (AM_{tm}) or disposal (AL_{dl}) center. Waste processing centers then recycle and/or treat the waste, with a proportion of recycled/recovered material (LR_{wr}) and mass reduced, treated material (LT_{wt}) released out of the CSWM network. This waste processing creates multiple residue types ($f \in F$) in different amounts (E_{fi}) at the waste processing centers. The residue fleet transferring trucks ($q \in U$) then begin their routes from the origin depot, load the compatible residue (VF_{fq}) from the waste processing centers and transport it to the compatible disposal centers (LF_{fd}). All vehicles (all 3 types) then back to their original/allocated transfer station/depot.

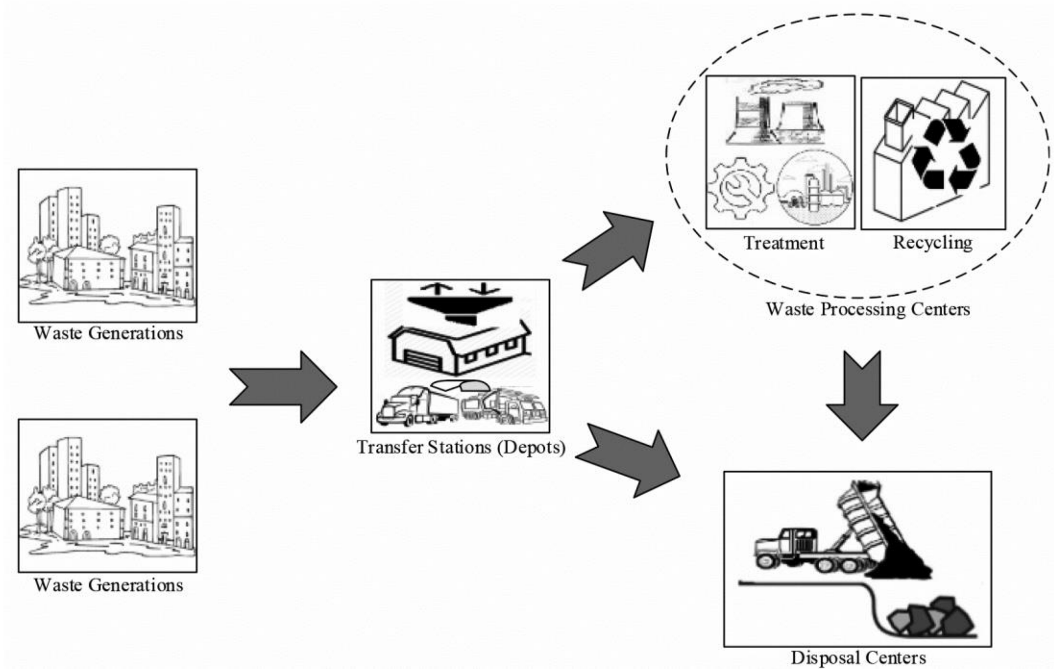


Figure 1. A general overview of the CSWM framework.

The CSWM system described in Figure 1 represents a realistic logistics network design problem and is structured across three principal echelons. Figure 2 provides a more detailed graphical rendition of the flows within this logistics network. A conventional VRP would typically consider different fleet sizes across 3 fixed segments, comprising (in various terms): the base depots, the customers to be visited, and the delivery destinations. As described in the overview in Figure 1 and represented in more detail in Figure 2, the CSWM system considered in this study allows for variable combinations of the conventional segments across multiple echelons. In this instance: Echelon I conflates the roles of depots and destinations into the same instance of a network node; Echelon II allows a single form of the node to act as both the depot and the customer; and Echelon III offers a distinctive role for each node that (for the waste processing centers, for example) can be at odds with how the same nodes are considered by other echelons. Such dynamics more realistically reflect the situations faced in practice but increase the complexity of the VRP significantly.

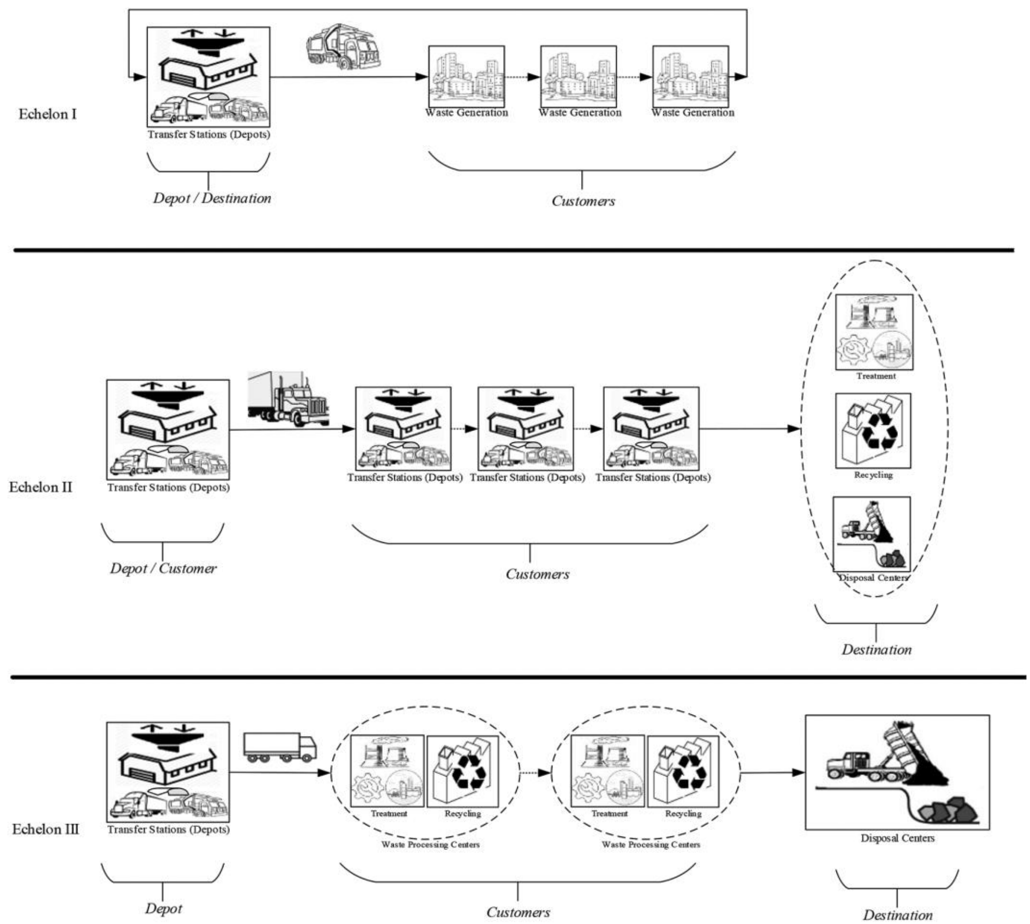


Figure 2. Three echelons utilized in the proposed logistics network.

3.2. Environmental emissions

The environmental challenge of transportation management is a significant optimization problem [9]; [13], but is of growing concern to CSWM in practice and society more broadly. Of the various environmental impacts associated with CSWM, the transportation focus is on CO_2 emissions. GE_{ij}^{q} is the amount of CO_2 emissions when a vehicle of type q travels from node i to node j. The level of CO_2 emissions $(GE_{ij}^{q} = CER_q \times FCR_q \times DIS_{ij})$ is directly related to the type of fuel and the efficiency of fuel consumption for each type of vehicle. The rate of CO_2 emission (CER_q) and fuel consumption rate (FCR_q) is therefore likely to vary for different vehicle types. For this study, following Fathollahi-Fard et al. [9] and Wang et al. [11], the CER_q is based on the type of fuel used by the vehicle. Diesel engines have found broad use in commercial vehicles and a standard CER_q for diesel fuel is 2.61 kg_{CO2}/litre. To compute the FCR_q, following Edalatpour et al. [33], a linear expression between fuel consumption and the weight of the vehicle is used. If

ROI_q and ROF_q are respectively the fuel consumption rates for an empty and a full load for vehicle type *q*, the function of FCR_q under a load of W_{qi} at the visiting node *i* is as follows:

$$FCR_q = ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi} \tag{1}$$

It should be noted that the maximum allowable capacity of vehicle *q* called as MXC_q is the average of MXO_{qo}, MXW_{qw} and MXF_{qf} as its maximum capacity based on different waste types. By considering Eq. (1), the amount of generated CO_2 for vehicle type *q* travelling between nodes *i* and *j* (DIS_{ij}) is computed by:

$$GE_{ij}^{q} = CER_q \times (ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi}) \times DIS_{ij} \tag{2}$$

3.3. Assumptions

The proposed model aims to reach an optimal assignment of waste/residues within the CSWM system framework presented by minimizing the fleet size, transportation cost, CO_2 emissions, and fair load assignment deviations in the transfer stations. To this end, the following key assumptions are made in order to formulate the problem:

- The proposed model uses a multi-objective MINLP method to minimize the fleet size, transportation cost, CO_2 emissions, and fair load assignment deviations.
- The primary decision for the model is to find the optimal number of required vehicles, allocated to specific nodes in the logistics network.
- The total cost of the system, as the first objective, is to cover the fixed cost of used vehicles and their variable cost based on the load shipped and distance travelled.
- The environmental emissions, as the second objective, is computed based on the rate of fuel consumption, shipped load and distance travelled by the transport vehicles, to estimate the total level of CO_2 emissions.
- The fair load allocation total deviation to transfer stations, as the third objective, is based on any lost capacity.
- The amount and type of waste generated is known and predefined for all generation nodes.
- The capacity of all components of the system is limited and predefined.
- At a time, each vehicle is assigned to one depot.
- There are multiple vehicle types, and each has a specific capacity, fixed usage cost, transportation cost, and variable fuel consumption rate and CO_2 emission rate for the empty and final load.
- All waste and residue collections are completed, with no permeation of partial collection.
- Each customer node is served once only by a selected vehicle, as is customary in VRP models.
- The CSWM framework is classified as a multi-depot VRP. Three echelons (I, II and III) are assumed, as illustrated in Figure 2.

- Treatment, recycling, and disposal, each require different technologies, and so each center performs only one such function.
- For each waste sorted type at a transfer station, there is only one compatible treatment, recycling, or disposal technology.
- For each residue generated type at waste processing center there is a compatible disposal technology.
- The amount of each type of waste/ and residue does not exceed the fleet capacity.
- All parameters are deterministic and known.

3.4. Formulation

Due to page limitation, the notations of developed CSWM framework are provided in Appendix A.

The first objective function, for the total cost, is presented in Eq. (3). Fixed costs are included in the first three terms and variable costs in the last three terms. The second objective, for CO_2 emissions, is presented in Eq. (4). The third objective, for the total deviation of fair load allocation, is presented in Eq. (5).

$$\begin{aligned}\text{Min } Z_1 = &\sum_{q\in V\in Q} FC_q \times (\sum_{i\in K}\sum_{j\in G} X_{ij}^q) + \sum_{q\in S\in Q} FC_q \times (\sum_{i\in K}\sum_{j\in M\cup H\cup L} X_{ij}^q) + \sum_{q\in U\in Q} FC_q \times (\sum_{i\in K}\sum_{j\in M\cup H} X_{ij}^q) \\ &+ \sum_{i\in G}\sum_{j\in K\cup G}\sum_{q\in V\in Q} TC_{ij}^q \times X_{ij}^q \times (W_{qi} + DIS_{ij}) + \sum_{i\in K}\sum_{j\in K\cup M\cup H\cup L}\sum_{q\in S\in Q} TC_{ij}^q \times X_{ij}^q \times (W_{qi} + DIS_{ij}) \\ &+ \sum_{i\in M\cup H}\sum_{j\in M\cup H\cup L}\sum_{q\in U\in Q} TC_{ij}^q \times X_{ij}^q \times (W_{qi} + DIS_{ij})\end{aligned} \tag{3}$$

$$\begin{aligned}\text{Min } Z_2 = &\sum_{i\in G}\sum_{j\in K\cup G}\sum_{q\in V\in Q} CER_q \times (ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi}) \times DIS_{ij} \times X_{ij}^q \\ &+ \sum_{i\in K}\sum_{j\in K\cup M\cup H\cup L}\sum_{q\in S\in Q} CER_q \times (ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi}) \times DIS_{ij} \times X_{ij}^q \\ &+ \sum_{i\in M\cup H}\sum_{j\in M\cup H\cup L}\sum_{q\in U\in Q} CER_q \times (ROI_q + \frac{ROF_q - ROI_q}{MXC_q} W_{qi}) \times DIS_{ij} \times X_{ij}^q\end{aligned} \tag{4}$$

$$\text{Min } Z_3 = \sum_{j\in K} \left| CPK_j / \sum_{i\in K} CPK_i - \sum_{o\in O} YK_{ok} / \sum_{o\in O}\sum_{g\in G} BG_{og} \right| \tag{5}$$

Since the proposed model is a variant of the VRP, the problem constraints can be simplified to the equation of $\sum_{i\in Depots}\sum_{j\in Customers} X_{ij}^q \le 1$, which follows most previous studies [50]; [34]; [37]. This use of the generalized form of the problem constraint equation to utilize vehicles and to allocate the customers forces all vehicles to be employed. Forcing all vehicles to be employed does raise issues about the potential to optimization the size of the fleet. This potential limitation is addressed in this study through the introduction of further constraints, as presented in Eqs. (6) to (13). These further constraints require vehicles to begin each route from a transfer station in lieu of a dedicated depot node. The constraints for vehicles utilization against each of the three echelons are formulated in Eqs. (7), (10) and (12), respectively.

$$\sum_{k\in K}\sum_{g\in G} X_{kg}^{q} \leq 1 \qquad \forall q \in V \in Q \tag{6}$$

$$\sum_{k\in K}\sum_{g\in G} X_{kg}^{q} = Z_q \qquad \forall q \in V \in Q \tag{7}$$

$$X_{ij}^{q} - Z_q \leq 0 \qquad \forall i, j \in G; q \in V \in Q \tag{8}$$

$$\sum_{i\in K}\sum_{j\in K\cup M\cup H\cup L} X_{ij}^{q} \leq MXK - 1 \qquad \forall q \in S \in Q \tag{9}$$

$$\sum_{i\in K}\sum_{j\in M\cup H\cup L} X_{ij}^{q} = Z_q \qquad \forall q \in S \in Q \tag{10}$$

$$\sum_{i\in K}\sum_{j\in M\cup H} X_{ij}^{q} \leq 1 \qquad \forall q \in U \in Q \tag{11}$$

$$\sum_{i\in K}\sum_{j\in M\cup H} X_{ij}^{q} = Z_q \qquad \forall q \in U \in Q \tag{12}$$

$$X_{ij}^{q} - Z_q \leq 0 \qquad \forall i, j \in M \cup H; q \in U \in Q \tag{13}$$

To avoid the potential for sub-tours, Eqs. (14) to (16) incorporate versions of the traditional VRP constraint for each of the three echelons, respectively. These constraints state that when a vehicle arrives at an intermediate node, it must depart that node.

$$\sum_{i\in K\cup G} X_{ij}^{q} - \sum_{i'\in G\cup K} X_{ji'}^{q} \geq 0 \qquad \forall j \in G; q \in V \in Q \tag{14}$$

$$\sum_{i\in K} X_{ij}^{q} - \sum_{i'\in K\cup M\cup H\cup L} X_{ji'}^{q} \geq 0 \qquad \forall j \in K; q \in S \in Q \tag{15}$$

$$\sum_{i\in K\cup M\cup H} X_{ij}^{q} - \sum_{i'\in H\cup M\cup L} X_{ji'}^{q} \geq 0 \qquad \forall j \in M \cup H; q \in U \in Q \tag{16}$$

As is common in standard VRP route structuring, the following constraints ensure that each customer is visited once per waste type by a compatible vehicle. This requirement is formulated for each echelon by Eqs. (17) to (19), respectively.

$$\sum_{i\in K\cup G}\sum_{q\in V\in Q} X_{ij}^{q} \times VO_{oq} = 1 \qquad \forall j \in G; o \in O \tag{17}$$

$$\sum_{j\in K\cup M\cup H\cup L}\sum_{q\in S\in Q} X_{ij}^{q} \times VW_{wq} = 1 \qquad \forall i \in K; w \in W \tag{18}$$

$$\sum_{i\in K\cup M\cup H}\sum_{q\in U\in Q} X_{ij}^{q} \times VF_{fq} = 1 \qquad \forall j \in M \cup H; f \in F \tag{19}$$

Eqs. (20) to (24) ensure that each vehicle is able to be allocated to only one transfer station. These constraints ensure that all vehicles return back to their depot of origin.

$$\sum_{j\in G} X_{kj}^{q} = ZK_{kq} = \sum_{j\in G} X_{jk}^{q} \qquad \forall k \in K; q \in V \in Q \tag{20}$$

$$\sum_{j\in K\cup M\cup H\cup L} X_{ji}^{q} - \sum_{i'\in K} X_{i'j}^{q} = ZK_{kq} = \sum_{i\in M\cup H\cup L} X_{i''j}^{q} \qquad \forall j \in K; q \in S \in Q \tag{21}$$

$$X_{ij}^{q} \le \sum_{i'\in K} X_{ji'}^{q} \qquad \forall i \in K; j \in M \cup H \cup L; q \in S \in Q \tag{22}$$

$$\sum_{j\in M\cup H} X_{ij}^{q} = ZK_{kq} = \sum_{i'\in L} X_{i'j}^{q} \qquad \forall i \in K; q \in U \in Q \tag{23}$$

$$X_{ij}^{q} \le \sum_{i'\in M\cup H} X_{i'j}^{q} \qquad \forall i \in L; j \in K; q \in U \in Q \tag{24}$$

Following Rabbani et al. [34], Eqs. (25) to (35) present the load limitations for vehicles of different capacity for all travel across all echelons.

$$W_{qi} - W_{qj} + \sum_{o\in O} VO_{oq} \times MXO_{qo} \times X_{ij}^{q} \le \sum_{o\in O} VO_{oq}(MXO_{qo} - BG_{oj}) \qquad \forall i, j \in G; q \in V \in Q \tag{25}$$

$$\sum_{o\in O} VO_{oq} \times BG_{og} \le W_{qi} \le \sum_{o\in O} VO_{oq} \times MXO_{qo} \qquad \forall i \in G; q \in V \in Q \tag{26}$$

$$\sum_{k\in K}\sum_{o\in O} X_{kg}^{q} \times BG_{og} \times VO_{oq} \le W_{qg} \qquad \forall g \in G; q \in V \in Q \tag{27}$$

$$W_{qg} \le \sum_{o\in O} VO_{oq}(MXO_{qo} + \sum_{k\in K} X_{kg}^{q} \times (BG_{og} - MXO_{qo})) \qquad \forall g \in G; q \in V \in Q \tag{28}$$

$$W_{qi} - W_{qj} + \sum_{w\in W} VW_{wq} \times MXW_{qw} \times X_{ij}^{q} \le \sum_{w\in W} VW_{wq}(MXW_{qw} - P_{wj}) \qquad \forall i, j \in K; q \in S \in Q \tag{29}$$

$$\sum_{w\in W} P_{wj} \times VW_{wq} \le W_{qi} \le \sum_{w\in W} VW_{wq} \times MXW_{qw} \qquad \forall i \in K; q \in S \in Q \tag{30}$$

$$\sum_{k\in K}\sum_{w\in W} X_{kj}^{q} \times P_{wj} \times VW_{wq} \le W_{qj} \qquad \forall j \in G; q \in S \in Q \tag{31}$$

$$W_{qi} - W_{qj} + \sum_{f\in F} VF_{fq} \times MXF_{qf} \times X_{ij}^{q} \le \sum_{f\in F} VF_{fq}(MXF_{qf} - E_{fi}) \qquad \forall i, j \in M \cup H; q \in U \in Q \tag{32}$$

$$\sum_{f\in F} E_{fi} \times VF_{fq} \le W_{qi} \le \sum_{f\in F} VF_{fq} \times MXF_{qf} \qquad \forall i \in M \cup H; q \in U \in Q \tag{33}$$

$$\sum_{k\in K}\sum_{f\in F} X_{ij}^{q} \times VF_{fq} \times E_{fi} \le W_{qj} \qquad \forall j \in M \cup H; q \in U \in Q \tag{34}$$

$$W_{qj} \le \sum_{f\in F} VF_{fq}(MXF_{qf} + \sum_{i\in K} X_{ij}^{q} \times (E_{fi} - MXF_{qf})) \qquad \forall j \in M \cup H; q \in U \in Q \tag{35}$$

Eqs. (36) to (38) are required to ensure that treatment, recycling and disposal centers respectively, only receive compatible types of waste.

$$X_{ij}^{q} \leq \sum_{w\in W}\sum_{t\in T} VW_{wq} \times LT_{wt} \times AM_{tj} \qquad \forall i \in K, j \in M; q \in S \in Q \tag{36}$$

$$X_{ij}^{q} \leq \sum_{w\in W}\sum_{r\in R} VW_{wq} \times LR_{wr} \times AH_{rj} \qquad \forall i \in K, j \in H; q \in S \in Q \tag{37}$$

$$X_{ij}^{q} \leq \sum_{w\in W}\sum_{d\in D} VW_{wq} \times LD_{wd} \times AL_{dj} \qquad \forall i \in K, j \in L; q \in S \in Q \tag{38}$$

Eq. (39) ensures that disposal centers receive only compatible residue.

$$X_{ij}^{q} \leq \sum_{f\in F}\sum_{d\in D} VF_{fq} \times LF_{fd} \times AL_{dj} \qquad \forall i \in M \cup H, j \in L; q \in U \in Q \tag{39}$$

Eq. (40) determines the amount of different waste types sorted at a transfer station ready for transport to the waste processing and disposal centers.

$$P_{wk} = AW_{wk} \sum_{o\in O} YK_{ok} \qquad \forall k \in K, w \in W \tag{40}$$

The following constraints control the demand at waste processing centers. Eqs. (41) and (42) present the residue amounts generated at treatment and recycling centers, respectively. As such, Eq. (43) determines the amounts of different residue types generated at both treatment and recycling centers ready for transport to disposal centers.

$$XM_{m} = \sum_{w\in W}\sum_{t\in T} YM_{wm} \times AM_{tm}(1 - CW_{wt}) \qquad \forall m \in M \tag{41}$$

$$XH_{h} = \sum_{w\in W}\sum_{r\in R} YL_{wh} \times AH_{rh}(1 - BW_{wr}) \qquad \forall h \in H \tag{42}$$

$$\sum_{i\in M\cup H} E_{fi} = \sum_{t\in T}\sum_{m\in M} XM_{m} \times AM_{tm} \times MUM_{f} + \sum_{r\in R}\sum_{h\in H} XH_{h} \times AH_{rh} \times MUH_{f} \qquad \forall f \in F \tag{43}$$

Eqs. (44) to (48) show the amounts of sorted, treated, recycled and disposed waste and residue at the corresponding waste processing nodes, respectively.

$$YK_{ok} = \sum_{q\in V\in Q}\sum_{g\in G} X_{gk}^{q} \times W_{qg} \times VO_{oq} \qquad \forall k \in K; o \in O \tag{44}$$

$$YM_{wm} = \sum_{q\in S\in Q}\sum_{k\in K} X_{km}^{q} \times W_{qm} \times VW_{wq} \qquad \forall w \in W; m \in M \tag{45}$$

$$YH_{wh} = \sum_{q \in S \in Q} \sum_{k \in K} X_{kh}^{q} \times W_{qh} \times VW_{wq} \qquad \forall w \in W; h \in H \tag{46}$$

$$YL_{wl} = \sum_{q \in S \in Q} \sum_{k \in K} X_{kl}^{q} \times W_{ql} \times VW_{wq} \qquad \forall w \in W; l \in L \tag{47}$$

$$YF_{fl} = \sum_{q \in U \in Q} \sum_{i \in M \cup H} X_{il}^{q} \times W_{qi} \times VF_{fq} \qquad \forall f \in F; l \in L \tag{48}$$

A common assumption for logistic network models generally is that demand should always be met, or that shortages are to be avoided. For this reason, Eq. (49) ensures that all waste created at the generation nodes is transported to the transfer stations. Similarly, Eq. (50) ensures that all sorted waste from the transfer stations is transported to waste processing and disposal centers. In turn, Eq. (51) ensures that all sorted residue from the treatment and recycling centers is transported to disposal centers.

$$\sum_{o \in O} \sum_{g \in G} BG_{og} = \sum_{o \in O} \sum_{k \in K} YK_{ok} \tag{49}$$

$$\sum_{w \in W} \sum_{k \in K} P_{wk} = \sum_{w \in W} \sum_{h \in H} YH_{wh} + \sum_{w \in W} \sum_{m \in M} YM_{wm} + \sum_{w \in W} \sum_{l \in L} YL_{wl} \tag{50}$$

$$\sum_{f \in F} \sum_{i \in M \cup H} E_{fi} = \sum_{f \in F} \sum_{l \in L} YF_{fl} \tag{51}$$

Eqs. (52) to (55) confirm that all facilities have fixed capacity limitations applied.

$$\sum_{o \in O} YK_{ok} = CPK_{k} \qquad \forall k \in K \tag{52}$$

$$\sum_{w \in W} YM_{wm} = CPM_{m} \times \sum_{t \in T} AM_{tm} \qquad \forall m \in M \tag{53}$$

$$\sum_{w \in W} YH_{wh} = CPH_{h} \times \sum_{r \in R} AH_{rh} \qquad \forall h \in H \tag{54}$$

$$\sum_{mM} XML_{ml} + \sum_{hH} XHL_{hl} = CPL_{l} \times \sum_{d \in D} AL_{dl} \qquad \forall l \in L \tag{55}$$

Finally, Eqs. (56) and (57) ensure that all variables take positive binary values, and thereby all values are feasible.

$$P_{wk}, E_{fi}, YK_{ok}, YM_{wm}, YH_{wh}, YL_{wl}, YF_{fl}, XM_{m}, XH_{h}, XML_{ml}, XHL_{hl}, W_{qi} \geq 0 \tag{56}$$

$$X_{ij}^{q}, Z_{q}, ZK_{kq} \in \{0,1\} \tag{57}$$

It should be noted that when dealing with non-linear terms in the objectives and constraints, as is the case in this model, the computational complexity and processing time is massively increased when using the exact method. To alleviate this imposition, the form of certain variables have been modified. The details of the linearization are provided in Appendix B.

4. Solution algorithm

Since VRP is generally NP-hard, the proposed problem with three objectives and many constraints is NP-hard as well. Due to the overwhelming complexity produced by the CSWM framework being proposed, a meta-heuristic algorithm is required to render the optimization process more efficient. This study adopts the novel SEO meta-heuristic algorithm recently introduced by Fathollahi-Fard et al., [20]. For the first time, a novel SEO using an adaptive memory approach (AMSEO), is proposed. The performance of the AMSEO is first compared with that of the original SEO and SA approaches. The results of the meta-heuristics are then checked against an exact method, structured using an epsilon-constraint method.

To begin, the solution representation of the algorithm is illustrated to show how the constraints of the model should be handled given the continuous search space. The SEO approach is then explained in overview and considered more specifically in the context of the multi-objective model proposed in this study. The new AMSEO extension is then developed and introduced for the first time.

4.1. Solution presentation

When a meta-heuristic algorithm is used to solve a mathematical model, it is necessary to design an encoding scheme to show how a solution can handle the constraints of the model [51]. In this study, a two-stage methodology called random-key (RK) is employed to encode the problem [52]. The significant advantage of an RK method in this context is that it avoids non-feasible solutions, which removes any need for repair and can reduce the time taken to encode significantly [53]; [54]. The first stage of RK is to generate random continuous numbers using the search engine of the algorithm. The second stage is then a heuristic procedure to transform these numbers for use as the decision variables of the model [55]; [56]; [57].

There are three primary decision variables in the proposed model: Z_q, ZK_{kq} and X_{ij}^{q}. Respectively, these primary decisions relate to which of the vehicles should be employed (refer Figure 3), how that vehicle is to be allocated to a transfer station (refer Figure 4), and how the routing decisions are to be determined (refer Figure 5). The values for all other variables are calculated based on the results of these three primary decisions.

Figure 3 illustrates the procedure for choosing which of the vehicles are to be employed. Given there is, say, five vehicles (from P_1 to P_5) available for selection, a random distribution between zero and one is applied to each candidate vehicle (Step 1). Where the random value assigned to a vehicle is less than 0.5, it is included, otherwise, it is excluded (Step 2). Accordingly, for the example shown in Figure 3, all vehicles will be employed, other than P_4.

P_1	P_2	P_3	P_4	P_5	
0.44	0.47	0.25	0.68	0.12	Step 1: Initialize the random numbers
1	1	1	0	1	Step 2: Transform to a feasible solution

Figure 3. Technique for selecting the vehicles

The procedure for then allocating selected vehicles to a specific transfer station (depot) is illustrated in Figure 4. Given there is, say, three transfer stations available, random numbers distributed by $U(0,3)$ are generated for each vehicle (Step 1). If the value is between zero and one, the vehicle is assigned to transfer station one, and so on (Step 2). Accordingly, for the example shown in Figure 4, vehicle P_1 is allocated to transfer station one, vehicles P_2 and P_5 are allocated to transfer station two, and so on.

P_1	P_2	P_3	P_5	
0.44	1.87	2.55	1.12	Step 1
1	2	3	2	Step 2

Figure 4. Technique for the allocation of selected vehicles to transfer stations.

To determine the routing for each selected vehicle from each available transfer station, the procedure illustrated in Figure 5, is applied. Whilst the instance of each customer might change depending on the echelon of the CSWM framework shown in Figure 2, for each transfer station there is a given set of customers. For example, for the case of transfer station two shown in Figure 4, where there is, say, 12 waste generation centers as customers, random numbers distributed by uniform function between zero and one are generated for each customer (Step 1). Those numbers are then ordered by value to specify a specific sequence for the routes of each vehicle (Step 2). Accordingly, for the example shown in Figure 5, vehicles P_2 and P_5 have been allocated to transfer station two and are therefore available for routing from that station. The routing is then allocated as follows:

$P_2 = \{m_2 \to m_1 \to m_8 \to m_5 \to m_{11} \to m_3\}$

$P_5 = \{m_{10} \to m_9 \to m_7 \to m_{12} \to m_4 \to m_6\}$

m_1	m_2	m_3	m_4	m_5	m_6	m_7	m_8	m_9	m_{10}	m_{11}	m_{12}	
0.24	0.08	0.48	0.89	0.34	0.91	0.76	0.32	0.67	0.51	0.42	0.82	Step 1
2	1	6	11	4	12	9	3	8	7	5	10	Step 2

Figure 5. Technique to assign customers to each rout

4.2. Social engineering optimizer and its novel extension

The social engineering optimizer (SEO) algorithm is a recently developed meta-heuristic algorithm applied successfully to solve combinatorial optimization problems such as single machine scheduling, supply chain network design, and VRP [20]. This current study is newly to apply SEO to CSWM.

Due to page limitation, the illustration of SEO and its multi-objective version is transformed into Appendix C. Although there are a few modifications and hybridization of SEO recently [54]; [58], the proposed idea is unique and for the first time applied to the MSW optimization and our CSWM framework. The SEO generally has four steps. First, after initializing an attacker and defender randomly, the attacker would like to train and retrain the defender based on some key information with regards to the main traits of the defender personally. With four different techniques to spot an attack, the attacker determines an attack and each time, tries to find a new way to extract all information from the attacker. Finally, the attacker will be stronger than before from each iteration and a new defender will be considered randomly.

Without a doubt, the intensification and diversifications phases are the main properties of all meta-heuristics [55]; [56]. The main feature of recent meta-heuristics is to have an intelligence plan to do these phases and to find a better balance among them [57]; [58]. Typically, as a local search meta-heuristic like SA, the diversification phase is more important to have an improvement. From the main idea of SEO, the training and retraining activities are the key to the intensification phase. One merit of the developed AMSEO is to have an intelligent exploration phase behaviour.

The step of training and retraining in SEO is to choose the traits of defender randomly with a percentage α. Having more details about the SEO, the Electronic Supplementary Materials F3 is available attached. In our proposed AMSEO, an updated memory for the training and retraining phase is contributed [59]. If the new defender can dominate the old one, the selected traits have more chance with the use of a roulette wheel selection for the next iteration.

To compute the probability of each trait in the defender, assume that we have four traits in the defender and attacker and the rate of α is 0.25. Hence, one trait would be selected. Now, assume that we are in 15^{th} iteration. During four iterations, the new defender cannot dominate the old one. The success rate of the traits {3, 4, 2, 2}. With the use of a roulette wheel selection procedure, the probability of selection of each trait is {0.27, 0.36, 0.18, 0.18}, respectively. Accordingly, the success probability of the second trait is more than others. Generally, this idea is the proposed AMSEO.

5. Experimental results

In this section, some constrained test problems of varying complexities are generated, and the parameters for each meta-heuristic approach are tuned accordingly. The results against constrained problems are validated using an epsilon-constraint exact method, and the relative performance of each meta-heuristic approach is compared. The high relative efficiency of the AMSEO is then tested using sensitivity analysis. Notably, all coding treatments of the meta-heuristics and the exact method were executed in Windows® 8, using an Intel® Core™ i5, 2.40 GHz and 4 Gb RAM.

5.1. Data generation

A series of 20 test problems (P1 to P20) are generated to represent small (P1 to P6), medium (P7 to P12), and large (P13 to P20) problem search spaces. The search time for each test problem is set for all meta-heuristics to ensure a fair comparison. Table 2 presents the characteristics of each test problem and its set computational time. For all test problems, the generation of parameters is then based on the random functions provided in Table 3.

Table 2. Details of the generated test problems

Level	Identifier	Problem size (G, K, M, H, L, V, S, U, O, W, F, T, R, D)	Search time (seconds)
Small	P1	(2, 3, 2, 2, 2, 3, 3, 3, 2, 2, 2, 2, 2, 2)	10
	P2	(3, 6, 2, 2, 2, 5, 5, 5, 3, 3, 2, 2, 2, 2)	15
	P3	(4, 6, 3, 3, 3, 5, 5, 5, 4, 4, 3, 3, 3, 3)	15
	P4	(4, 6, 4, 4, 4, 7, 7, 7, 5, 5, 3, 3, 3, 3)	20
	P5	(6, 6, 5, 5, 5, 9, 9, 9, 7, 7, 4, 3, 3, 3)	30
	P6	(8, 6, 7, 7, 7, 9, 9, 9, 8, 8, 4, 3, 3, 3)	30
Medium	P7	(12, 8, 10, 10, 10, 10, 10, 10, 10, 10, 5, 4, 4, 4)	40
	P8	(14, 8, 12, 12, 12, 10, 10, 10, 12, 12, 5, 4, 4, 4)	40
	P9	(18, 10, 16, 14, 12, 12, 10, 11, 14, 12, 6, 5, 5, 5)	50
	P10	(20, 10, 17, 16, 14, 13, 11, 12, 16, 14, 6, 5, 5, 5)	60
	P11	(23, 12, 18, 18, 16, 14, 14, 12, 20, 16, 6, 5, 5, 5)	70
	P12	(28, 14, 20, 20, 18, 14, 14, 12, 22, 20, 7, 6, 6, 6)	90
Large	P13	(34, 14, 24, 24, 20, 14, 14, 14, 26, 24, 8, 6, 6, 6)	120
	P14	(38, 15, 28, 26, 24, 15, 14, 14, 30, 28, 8, 6, 6, 6)	140
	P15	(44, 15, 32, 30, 28, 15, 15, 14, 34, 32, 8, 6, 6, 6)	180
	P16	(48, 16, 34, 32, 28, 15, 15, 15, 34, 34, 8, 6, 6, 6)	180
	P17	(54, 18, 38, 36, 30, 16, 16, 16, 38, 36, 9, 7, 7, 7)	220
	P18	(56, 18, 40, 36, 32, 16, 16, 16, 40, 38, 9, 7, 7, 7)	220
	P19	(64, 21, 48, 44, 38, 18, 18, 16, 52, 46, 9, 8, 8, 8)	240
	P20	(72, 24, 54, 48, 48, 18, 18, 18, 58, 56, 10, 9, 9, 9)	280

Table 3. Parameters for the developed model.

Parameter	Surface value
(x_i, y_i)	$1000 \times (U(0,1), U(0,1))$
(x_j, y_j)	$1000 \times (U(0,1), U(0,1))$
DIS_{ij}	$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
FC_q	Rand$\{1, 2, \ldots, 5\} \times 10^6$ Rial

$VO_{oq}, VW_{wq}, VF_{fq}, AM_{tm}, AH_{rh}, AL_{dl}$	Rand{0, 1}
TC_{ij}^{q}	Rand{1, 2, …, 5}×10^3 Rial
CER_q	2.61 (i.e., the CO_2 emission rate for diesel oil) 2.17 (i.e., the CO_2 emission rate for natural gas) 2.57 (i.e., the CO_2 emission rate for gasoline)
$MXO_{qo}, MXW_{qw}, MXF_{qf}$	Rand{1, 5, …, 20}×10^2 m^3
BG_{og}	Rand{1, 2, …, 8}× Kg
ROI_q	*U(0.1, 0.3)*
ROF_q	*U(0.2, 0.5)*
$LT_{wt}, LR_{wr}, LD_{wd}, LF_{fd}$	Rand{0, 1}
$CPK_k, CPM_m, CPL_l, CPH_h$	Rand{1, 2,…, 4}× 10^4 m^3
$AW_{wk}, BW_{wr}, CW_{wt}, MUM_f, MUH_f$	*U(0.1, 1)*

5.2. Assessment metrics and Calibration

The proposed CSWM framework has three conflicting objectives. To evaluate this framework as it has more than one objective, some multi-objective assessment metrics are usually needed to employ the quality of the non-dominated solutions generated by the meta-heuristics [9]; [55]; [56]; [57]. This study utilizes the number of Pareto solutions (NPS), the spread of non-dominance solutions (SNS), mean ideal distance (MID), and hyper volume (HV). Most recent studies have employed these metrics to evaluate their optimization methodology (see, for example, [34]; [9]; [55]; [51]). The definition and desirability of the employed metrics are provided in Appendix D.

The calibration and tuning of meta-heuristics play a key role in performance, and it is needed to tune the input parameters of meta-heuristics before solving the simulated test studies. This paper utilizes the Response Surface Method (RSM) to do the calibration set [60]. The RSM has been shown in a number of recent logistics network design studies to calibrate the parameters of meta-heuristics efficiently [9]; [55]; [51]; [58].

Due to page limitation, the details and implementation of RSM are explained in Appendix E. Finally, Table 4 presents the approximate values of the tuned parameters, the *R*-squared (R^2) of assessment metrics, and the total desirability (*D*). For both of them, a higher is favorable for the algorithm.

Table 4. Calibrated algorithms, their respective R-squared (R^2) and desirability (D)

Optimizer	Tuned parameters	R^2 (%)				D
		NPS	MID	SNS	HV	
SA	Sb-It=32; T0=700; $R_{\propto}$=0.9396	54	72	60	58	0.6634
SEO	N_{att}=38; α=0.15; β=0.15	58	86	62	66	0.7238
AMSEO	N_{att}=45; α=0.25; β=0.1	52	78	72	78	0.7581

5.3. Validation

To verify the reliability of each meta-heuristic, it is necessary to compare the results with the output of the exact method as a benchmark [58]. Here, the epsilon-constraint (EC) method implemented by coding in GAMS 24.7.3 software is used to solve the small level and test models. To validate the non-dominated solutions of a meta-heuristic, the positive ideal solution (PIS) and negative ideal solution (NIS) should be reached [9]; [10]. The use of the PIS and NIS allows efficient solutions among all non-dominated solutions generated by meta-heuristics to be updated. Generally, the EC method is formulated to optimize one objective and to limit the other objectives as allowable bounds [52]; [54]. This algorithm was first developed by Haimes et al. [61] to solve multi-objective optimization problems. From the EC method, the Pareto optimal frontier is generated by modifying the bounds of the objective function [58]. The formulation of the EC method for this study is presented by:

$$\begin{aligned}
&\text{Min } Z_1 \\
&\text{s.t.} \\
&\quad \text{Eqs. (6) – (57)} \\
&\quad Z_2 \le \varepsilon_1 \\
&\quad Z_3 \le \varepsilon_2 \\
&\quad Z_2^{min} \le \varepsilon_1 \le Z_2^{max} \\
&\quad Z_3^{min} \le \varepsilon_2 \le Z_3^{max}
\end{aligned} \tag{58}$$

To run the EC method for a test problem (e.g., P1) as given in Eq. (58), the main objective function (Z_1) should be minimized. To reach the PIS and NIS, other objectives (i.e., Z_2^{min} and Z_3^{max}) can be defined as the core objective to be optimized. To estimate the bounds of the EC (i.e., ε_1 and ε_2), the PIS and NIS averages, and their upper quarter are calculated.

For ease of evaluation, the sorted solutions of the three meta-heuristics and the EC are tabulated, as shown for P1 in Table 5. To have a comparison between the solutions of EC and our meta-heuristics, we have considered the modified NPS (MNPS) metric [9]. After that we have considered the percentage of ($\frac{MNPS}{NPS}$) to measure the validation of the non-dominated solutions. It shows that how much percentage of the non-dominated solutions are acceptable in each algorithm. For a number of small test studies, this metric is calculated by Table 6.

The results of this validation exercise, as illustrated in Table 5, show that all three meta-heuristic algorithms generate high-quality non-dominated solutions and our AMSEO is performing the best. The results provided in Table 6, confirm this issue as the average number of Pareto non-dominated solutions relative to the EC method is shown to be 0.75, and significantly higher than for the results for SA (0.54) and SEO (0.63).

Table 5 Non-dominated solutions generated by the EC method and each meta-heuristic

EC			SA			SEO			AMSEO		
Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3
1.1167E+09	4235	1003	**1.1199E+10**	**4164**	**1031**	**1.1188E+09**	**3750**	**967**	**1.1175E+09**	**4199**	**1046**
1.1168E+09	4152	1020	**1.1208E+10**	**3625**	**1036**	**1.1192E+09**	**4015**	**971**	**1.1181E+09**	**3753**	**1047**
1.1173E+09	4070	1038	**1.1259E+10**	**3821**	**1042**	**1.1196E+09**	**3898**	**978**	**1.1189E+09**	**4178**	**1058**
1.1196E+09	3988	1055	**1.1291E+10**	**3636**	**1047**	**1.1219E+09**	**4352**	**982**	**1.1197E+09**	**3744**	**1058**
1.1208E+09	3906	1072	**1.1296E+10**	**3647**	**1054**	1.1228E+09	4042	988	1.1203E+09	4266	1084
1.1235E+09	3823	1090	1.1305E+10	4258	1064	1.1234E+09	4445	996	1.1219E+09	3826	1088
1.1483E+09	3741	1107	1.1308E+10	4156	1068	**1.1242E+09**	**3832**	**996**	**1.1231E+09**	**3709**	**1104**
1.1839E+09	**3659**	**1124**	1.1322E+10	3853	1070	**1.1249E+09**	**3901**	**1013**	**1.1238E+09**	**3750**	**1110**
-	-	-	1.1331E+10	4360	1078	**1.1252E+09**	**3802**	**1021**	**1.1249E+09**	**4028**	**1126**
-	-	-	-	-	-	**1.1259E+09**	**3794**	**1023**	**1.1255E+09**	**3919**	**1132**
-	-	-	-	-	-	1.1272E+09	4410	1078	-	-	-
-	-	-	-	-	-	1.1301E+09	4166	1094	-	-	-

Table 6. Validation results for each meta-heuristic

Test problem	SA		SEO		AMSEO	
	MNPS	MNPS/NPS	MNPS	MNPS/NPS	MNPS	MNPS/NPS
P1	5	0.55	8	0.66	8	0.8
P2	6	0.75	8	0.66	9	0.69
P3	4	0.44	6	0.54	10	0.83
P4	5	0.5	9	0.75	10	0.71
P5	5	0.45	8	0.57	9	0.75
P6	6	0.6	6	0.6	10	0.76
Average		0.54		0.63		**0.75**

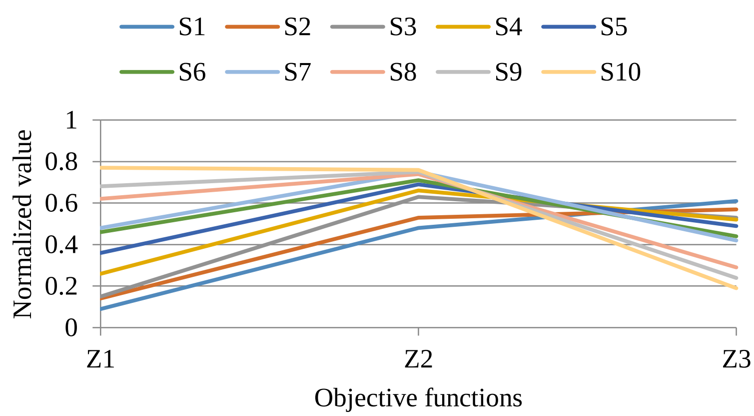
5.4. Comparison

Based on the evaluation metrics provided in Electronic Supplementary Materials F4, the performance of each meta-heuristic is recorded in Table 7. This comparison shows that AMSEO outperforms both SA and SEO by having the highest count of best cases in each evaluation metric overall by a factor of 51 (AMSEO) to 24 (SEO) to 11 (SA).

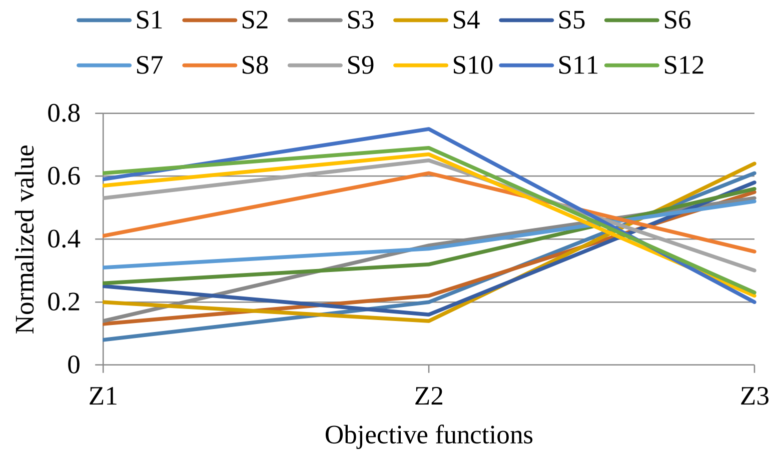
The convergence and diversity of the solution set across all three objectives is a useful indication of the meta-heuristic utility. The parallel coordinates plot is recommended to provide an effective, immediate visual comparison. However, since the range and units of the three objective functions are clearly different, the normalized values of non-dominated solutions are calculated based on the amount of PIS and NIS solutions generated by the EC method. For example, Figure 6 presents the parallel coordinates plots for each meta-heuristic specific to the test problem P4. In this case, SA generated 10 solutions (Figure 6a), SEO generated 12 solutions (Figure 6b), and AMSEO generated 14 solutions (Figure 6c). A visual comparison of these three plots reveals clearly that AMSEO identifies more solution diversity than the two other meta-heuristic algorithms.

Table 7 Results of the evaluation metrics for each meta-heuristic.

Test problem	NPS			MID			SNS			HV		
	SA	SEO	AMSEO	SA	SEO	AMSEO	SA	SEO	AMSEO	SA	SEO	AMSEO
P1	9	**12**	10	2.7	1.45	**1.6567**	39053	33613	**42156**	**2.86E+09**	1.98E+09	2.17E+09
P2	8	12	**13**	1.41	3.18	**1.3832**	71532	72664	**84093**	2.91E+09	2.85E+09	**3.81E+09**
P3	9	11	**12**	**1.88**	3.41	2.5528	103674	**105584**	104846	3.84E+09	4.81E+09	**5.36E+09**
P4	10	12	**14**	1.7	1.62	**1.2058**	116854	113207	**118923**	5.18E+09	3.97E+09	**6.48E+09**
P5	11	**14**	12	3.53	2.19	**1.1014**	199064	206584	**209671**	4.82E+09	5.18E+09	**8.13E+09**
P6	10	10	**13**	2.63	2.26	**1.1175**	**298976**	225643	268749	6.49E+09	5.92E+09	**8.92E+09**
P7	11	13	**15**	1.41	2.62	**1.1044**	289074	319065	**326843**	**8.18E+09**	7.39E+09	7.49E+09
P8	10	**14**	13	4.23	2.66	**1.3081**	375463	382970	**385034**	**9.22E+09**	8.14E+09	9.11E+09
P9	**14**	13	13	**1.97**	3.71	2.8128	519065	563271	**573297**	8.50E+09	9.60E+09	**1.29E+10**
P10	10	15	**16**	1.59	**1.19**	2.1869	40937	45748	**46743**	2.18E+10	1.82E+10	**2.85E+10**
P11	12	**14**	**14**	1.96	**1.17**	1.5879	76134	**79267**	70864	1.03E+10	**1.43E+10**	1.39E+10
P12	12	**16**	15	3.26	**2.11**	2.51	100689	**106429**	101948	4.81E+10	2.81E+10	**2.64E+11**
P13	**15**	14	14	**1.43**	2.25	2.1424	112637	119835	**121553**	3.02E+10	8.51E+10	**8.20E+10**
P14	14	**16**	**16**	4.91	3.18	**1.8053**	209685	213758	**216795**	6.94E+10	8.30E+10	**1.03E+11**
P15	11	**14**	**14**	4.81	**3.31**	3.6272	245361	**255738**	251678	6.29E+10	8.21E+10	**9.14E+10**
P16	14	**16**	**16**	**3.26**	4.24	3.3502	322074	**328045**	326571	8.02E+10	**9.85E+10**	8.19E+10
P17	**16**	15	14	3.65	5.74	**3.5413**	392185	**410934**	398675	1.49E+11	1.09E+11	**2.87E+11**
P18	12	13	**16**	5.66	6.01	**4.4601**	523416	584304	**591057**	1.52E+11	1.82E+11	**2.54E+11**
P19	13	**16**	15	5.31	4.19	**4.0216**	306571	317654	**322059**	1.83E+11	5.82E+11	**6.83E+11**
P20	12	**15**	**15**	6.17	5.91	**4.1894**	398675	406294	**412478**	2.85E+11	**6.19E+11**	5.85E+11
Best	3	11	**12**	4	4	**12**	1	6	**13**	3	3	**14**



(a)



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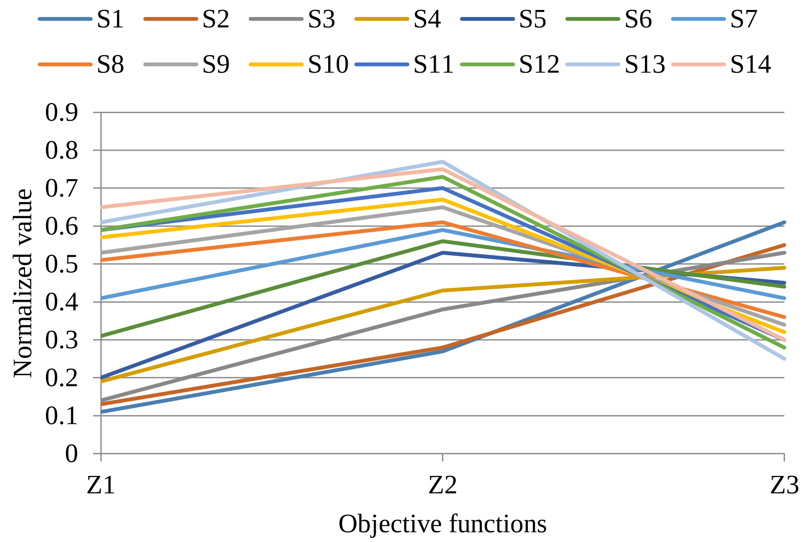


(c)

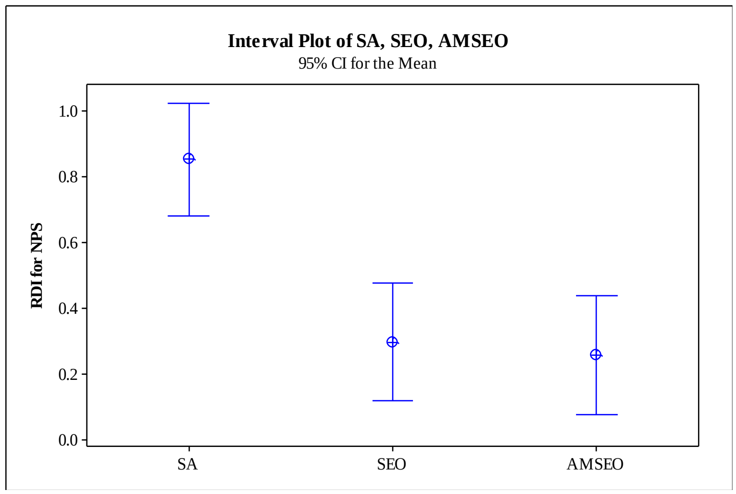
Figure 6 Parallel coordinates plots of meta-heuristics (a) SA, (b) SEO, and (c) AMSEO specific to test problem P4

To do some statistical tests, the results reported in Table 7 are scaled by the relative deviation index (RDI) as follows:

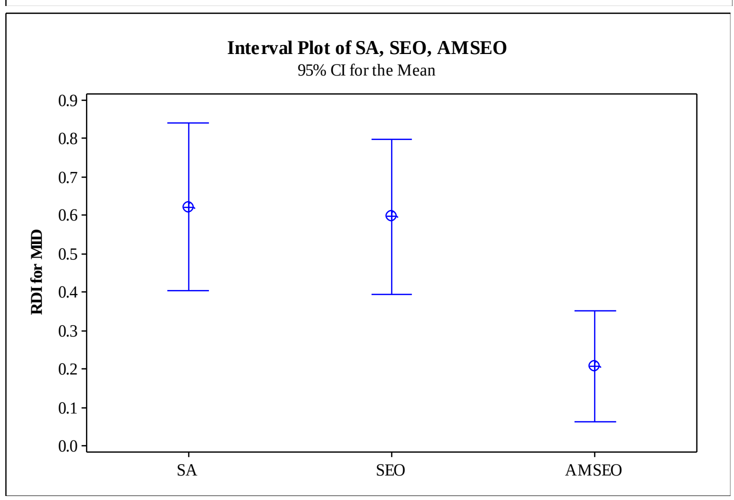
$$RDI = \frac{\left| ID_{sol} - AL_{sol} \right|}{MAX_{sol} - MIN_{sol}} \tag{59}$$

This metric is previously defined in several similar studies such as [9, 20, 53-54]. A lower value of this metric is favorable of the algorithms.

To study the efficiency of the meta-heuristics in comparison with each other, interval plots are provided in Figure 7. The RDI metric is considered to depict these plots. As given in Figure 7a, the performance of SEO and AMSEO are similar for the NPS. However, as given in Figure 7b, the AMSEO performance is highly better than two other algorithms for the MID metric. As given in Figure 7c, the SEO and AMSEO performances are also similar in terms of the SNS, with AMSEO marginally superior. As given in Figure 7d, finally, the AMSEO performance is once again highly superior for the HV metric. All these metrics confirm the efficiency of the AMSEO in this field.



(a)



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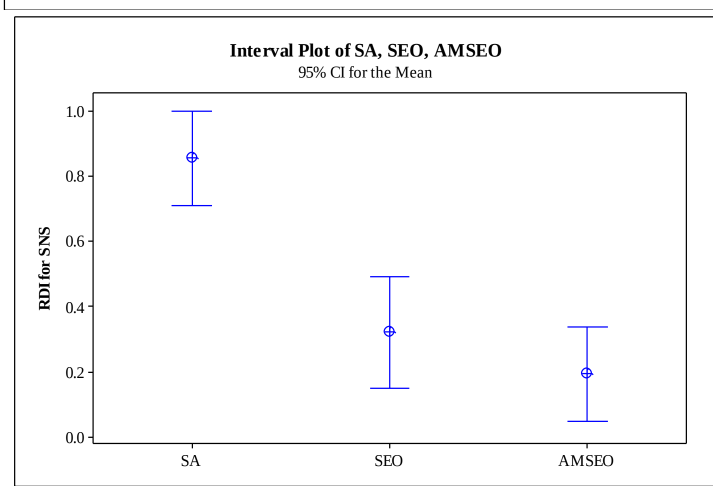
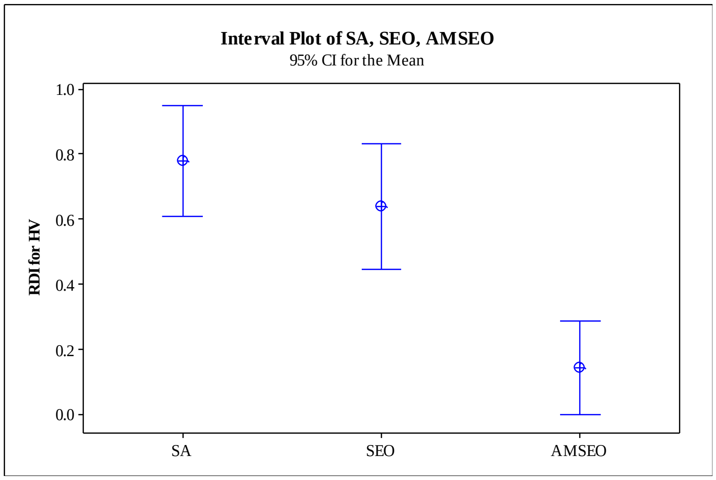


(c)



(d)

Figure 7 Interval plots of the RDI metric for (a) NPS, (b) MID, (c) SNS, and (d) HV

5.5. Sensitivity analysis

To assess the potential variability of the proposed model given variations in the key parameters, a sensitivity analysis is performed. The key parameters considered are the fixed utilization cost of vehicles (FC_q), the transportation cost (TC_{ij}^q), the amount of waste at waste generation nodes (BG_{og}), and the total number of vehicles (Q). For a range of values in each parameter, the average value of each objective function across all non-dominated solutions is taken as the indicator of sensitivity. Each parameter is varied individually across four scenarios (C1-C4) and the results presented numerically in Tables 8-11, and graphically in Figures 8-11. The objective functions considered against each parameter comprise the total cost (Z_1), the green emissions (Z_2), and the total deviation from fair load allocation (Z_3).

Using the resulting figures listed in Table 8, the sensitivity of the fixed utilization cost of vehicles (FC_q) is illustrated in Figure 8. A review of Figure 8 indicates that each objective function responds differently to variations in the value of (FC_q). Broadly, the total cost (Z_1) increases as the fixed utilization cost increases, whereas green emissions (Z_2) and the total deviation from fair load allocation (Z_3) have more complex relationships. The value of (Z_2) first falls and then increases as the fixed utilization cost increases. Conversely, the value of (Z_3) first increases, and then falls as the fixed utilization cost increases. In other words and overall, as the fixed utilization cost increases, the financial and environmental impacts tend to increase but the social impact is reduced.

Table 8. A sensitivity analysis of the fixed utilization cost of vehicles.

Num. of cases	FC_q	Z_1	Z_2	Z_3
C1	Rand {1,2}	3.28E+11	171895	5562
C2	Rand {2,3}	3.50E+11	168439	5648
C3	Rand {3,4,5}	4.59E+11	175094	5650
C4	Rand {4,5,6}	4.81E+11	176829	5439

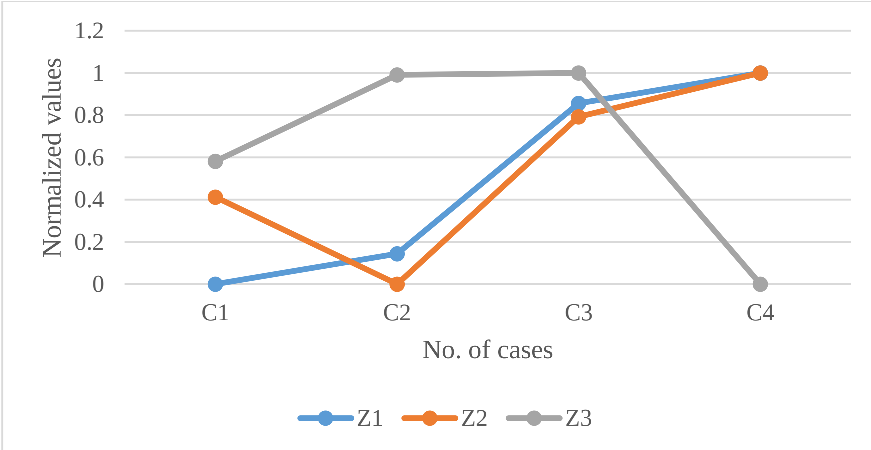


Figure 8. Behavior of the objective functions relative to changes in the fixed utilization cost.

Using the resulting figures listed in Table 9, the sensitivity of the transportation cost (TC_{ij}^{q}) is illustrated in Figure 9. A review of Figure 9 indicates that the objective function responses are more consistent to variations in the value of (TC_{ij}^{q}) than they were for variations in the value of (FC_q). The total cost (Z_1) and green emissions (Z_2) both increase steadily as the transport cost increases. The total deviation from fair load allocation (Z_3) is however quite volatile and there is no clear trend between it and an increase in transport costs. In other words and overall, as the transportation cost increases, the financial and environmental costs also increase, but the social impact is highly variable.

Table 9. A sensitivity analysis of the transportation cost.

Num. of cases	TC_{ij}^{q}	Z_1	Z_2	Z_3
C1	2	3.99276E+11	174651	5638
C2	4	5.48676E+11	175539	5639
C3	6	6.98076E+11	175893	5635
C4	8	8.47476E+11	176292	5637

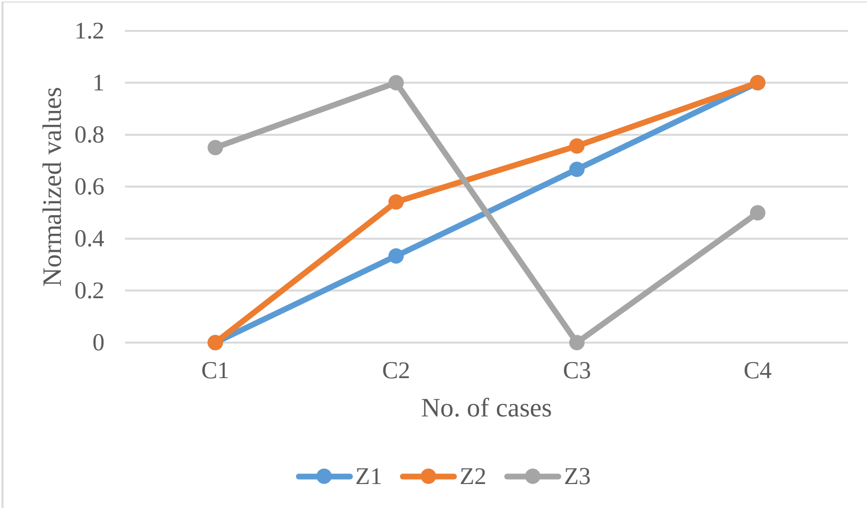


Figure 9. Behavior of the objective functions relative to changes in the transportation cost.

Using the resulting figures listed in Table 10, the sensitivity to the amount of waste at waste generation nodes (BG_{og}) is illustrated in Figure 10. A review of Figure 10 indicates that the objective function responses are broadly consistent with variations in the value of (BG_{og}). The total cost (Z_1) and green emissions (Z_2) both increase steadily as the amount of waste at waste generation nodes increases. The total deviation from fair load allocation (Z_3) reduces steadily as amount of waste at waste generation nodes increases. In other words and overall, as the transportation cost increases, the financial and environmental costs are steadily increased, and the social impact is steadily reduced.

Table 10. A sensitivity analysis of the amount of waste at waste generation nodes.

Num. of cases	BG_{og}	Z_1	Z_2	Z_3
C1	2	5.3678E+11	162298	5839
C2	4	5.4638E+11	163839	5759
C3	6	6.7418E+11	165892	5725
C4	8	8.6219E+11	172019	5620

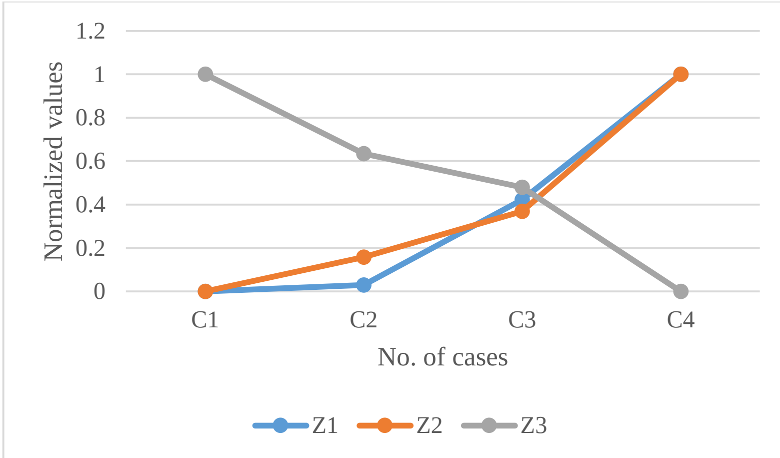


Figure 10. Behavior of the objective functions relative to changes in the amount of waste.

Finally, using the resulting figures listed in Table 11, the sensitivity of the total number of vehicles (Q) is illustrated in Figure 11. The variation in (Q) might comprise a variation in the relative numbers of each vehicle class and/or the total number of vehicles across all vehicle classes (V, S, and U). In this case, the relative proportion of each class is kept steady (equal proportion in each class), and only the total number of vehicles is increased. A review of Figure 11 indicates that the objective function responses are entirely consistent with variations in the value of (Q). The total cost (Z_1), green emissions (Z_2), and total deviation from fair load allocation (Z_3) all increase steadily as the total number of vehicles are increased. In other words and overall, as the total number of vehicles is increased, the financial, environmental, and social impacts are all steadily increased.

Table 11. A sensitivity analysis of the total number of fleet vehicles.

No. of cases	V	S	U	Z_1	Z_2	Z_3
C1	13	13	13	5.0328E+11	162504	5746
C2	15	15	15	5.2815E+11	165539	5788
C3	16	16	16	5.8239E+11	168845	5844
C4	18	18	18	6.7425E+11	173894	5865

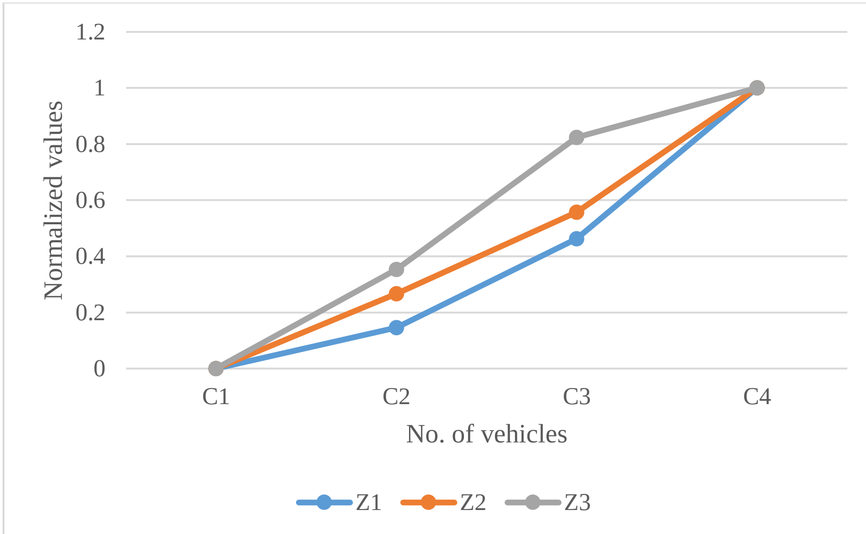


Figure 11. Behavior of the objective functions relative to changes in the total number of vehicles.

6. Conclusion, managerial solutions and further research

In this paper, the viability of a CSWM optimization with multiple objectives and real-life constraints using a novel multi-objective MINLP were demonstrated. An adaptive memory of SEO (AMSEO) was offered to solve the proposed model especially well given the particular three objectives. In this regard, the AMSEO performs significantly better than simulated annealing (SA) or SEO itself when all methods are tuned and compared regarding the NPS, SNS, MID, and HV. The epsilon-constraint method was employed to validate the model results in a small size, and some sensitivity analyses were considered to assess the sustainability dimensions of the model based on the changes in the parameters. Finally, some managerial solutions were considered by these results and findings.

Academically, the decision-making models of operational MSW management aim to optimize the fleet size of each vehicle class independently, using a simplified objective function. However, in many contexts; most importantly, in developing countries where the MSW management is of particular concern, such a simplified approach is failing to deliver satisfactory financial, environmental and social outcomes. The purpose of the present paper is to introduce a new framework for practical and efficient routing optimization. The proposed framework needs a multi-objective optimization model accommodating heterogeneous fleets operating for a multi-echelon logistics network. To solve the proposed model efficiency, a strong algorithm for combinatorial optimization problems which are manageable computationally.

The CSWM optimization viability with multiple objectives and real-life constraints, is demonstrated by this study results. The CSWM problem is addressed by a novel MINLP model and a new solution is also generated by the adaptive memory extension of SEO (AMSEO). The problem characteristics are well solved by the performance of AMSEO. Although the definition of the proposed problem is still simple in comparison with all dynamic and potential aspects of CSWM problem is a real domain, the developed framework is more complex than the vast majority of previous MSW problems. The significant contribution is to cover the sustainability dimensions of CSWM as the objectives of the total cost, green emissions and fair load allocation, simultaneously, for the first time. As a complex problem, in this regard, the efficiency of the AMSEO lends great attention to the broader application and development of this algorithm for other equivalent problem domains compounding complexity.

The aforementioned contributions technically provide new managerial implications based on the results. First of all, the future tractability of CSWM optimization confirms principal highlights in practice. With regards to the grand challenge of the sustainable development in the MSW management, most especially in developing countries, considering multiple financial, environmental and social goals hybridized with dynamic constraints, is characterized by practical solutions to the framework of CSWM efficiently. Last but not least, further research on the AMSEO development to MSW optimization is warranted.

Another important managerial insight refers to the shifting from MSW to CSWM management, entailing a manageable solution for the reverse and closed-loop logistic network design problems. In this regard, the options of the reverse and closed-loop logistic network create the added-value for CSWM considering multiple echelons for all activities of the processing, recycling and disposal of raw waste and transportation. Most notably, the potential overall waste disposal cost savings achievable through increased recycling (revealed by framing the logistics problem across several echelons) is of particular significance. Our algorithms also provide a full range of conditions and a high diversity based on three conflicting objectives to give this option to managers to select the best ideal solution (Figures 6).

Other managerial solutions are generated by some sensitivity analyses of sustainability dimensions with regards to key parameters as given in Figures 8-11. For example, the total deviation volatility from fair load allocation (Z_3) to variations in the cost of transportation revealed in Figure 9, warrants further research on the routing optimization of CSWM. Similarly, the contrasting behavior of the total deviation from fair load allocation (Z_3) to both the total cost (Z_1) and green emissions (Z_2) in most situations is also noteworthy. Conversely, the consistent objective function responses to variations in the total number of vehicles when the relative proportion of each class is kept steady (shown in Figure 11) invites more detailed investigation.

In conclusion, this study is a good point to define a sustainable framework for the CSWM, but still faces some limitations. There is no standard real-life case for our framework and it needs more research on the optimization of MSW in practice. To achieve sustainable development goals more broadly, it is needed to consider more social factors such as consumer risks and job opportunities. This study also applied a deterministic model. Hence, the consideration of fuzzy, stochastic or robust optimization methods is a good future remark. Without a doubt, several other heuristics and meta-heuristics cane be offered to examine the efficiency of AMSEO for this model or other optimization models for routing and scheduling problems.

Appendix A. Notations

The CSWM framework proposed, in line with standard VRP definitions, is considered by a graph $F=(N, A)$, where N is the n nodes set and A is the arc set as $A=(i, j)$: $0\leq i, j\leq n$; $i\neq j$. In this regard, the notations of the developed formulation are defined below:

Indices:

g	Index of waste generation nodes, $g \in \{1, 2, \ldots, G\}$
k	Index of transfer station nodes, $k \in \{1, 2, ..., K\}$
m	Index of treatment center nodes, $m \in \{1, 2, ..., M\}$
h	Index of recycling center nodes, $h \in \{1, 2, ..., H\}$
l	Index of disposal center nodes, $l \in \{1, 2, ..., L\}$
q	Index of the vehicle fleet, $q \in \{1, 2, \ldots, Q\}$; $Q = V \cup S \cup U$; the technology of vehicles
v	Index of collection vehicles fleet, $v \in \{1, 2, \ldots, V\}$
s	Index of semi-trailer transportation vehicles fleet, $s \in \{1, 2, \ldots, S\}$
u	Index of semi-trailer residue transferring vehicles fleet, $u \in \{1, 2, ..., U\}$
o	Index of waste types accumulated at generation nodes, $o \in \{1, 2, ..., O\}$
w	Index of waste types sorted at transfer station nodes, $w \in \{1, 2, ..., W\}$
f	Index of residue types generated at treatment and recycling centers, $f \in \{1, 2, ..., F\}$
t	Index of treatment technologies, $t \in \{1, 2, ..., T\}$
r	Index of recycling technologies, $r \in \{1, 2, ..., R\}$
d	Index of disposal technologies, $d \in \{1, 2, ..., D\}$

Parameters:

FC_q	Fixed cost of using vehicle q
BG_{og}	Amount of waste type o accumulated at waste generation node g
TC_{ij}^{q}	Transportation cost per unit between nodes i and j by using vehicle q; this includes all nodes in our transportation network (i.e., g, k, m, h, l, o, w)
VO_{oq}	1, if waste type o is completed with collection vehicle $q \in V \in Q$; 0, otherwise
VW_{wq}	1, if waste type w is completed with transferring vehicle $q \in S \in Q$; 0, otherwise
VF_{fq}	1, if residue type f is completed with residue transferring vehicle $q \in U \in Q$; 0, otherwise
AM_{tm}	1, if the treatment technology t exists at treatment center m; 0, otherwise
AH_{rh}	1, if the recycling technology r exists at recycling center h; 0, otherwise
AL_{dl}	1, if the disposal technology d exists at disposal center l; 0, otherwise
DIS_{ij}	Traveling distance between nodes i and j
CER_q	CO_2 emissions rate for vehicle q
FCR_q	Rate of fuel consumption for vehicle q
GE_{ij}^{q}	Amount of CO_2 emissions generated by vehicle q for traveling distance between nodes i and j $(GE_{ij}^{q} = CER_q \times FCR_q \times DIS_{ij})$
LT_{wt}	1, if waste type w is compatible with treatment technology t; 0, otherwise
LR_{wr}	1, if waste type w is compatible with recycling technology r; 0, otherwise
LD_{wd}	1, if waste type w is compatible with recycling technology d; 0, otherwise
LF_{fd}	1, if residue type f is compatible with recycling technology d; 0, otherwise

MXO_{qo}	Maximum allowable load of vehicle *q* which is compatible with waste type *o*
MXW_{qw}	Maximum allowable load of vehicle *q* which is compatible with waste type *w*
ROI_q	Empty load of fuel consumption rate for vehicle *q*
ROF_q	Final load of fuel consumption rate for vehicle *q*
MXF_{qf}	Maximum allowable load of vehicle *q* which is compatible with residue type *f*
MXC_q	Maximum allowable load of vehicle *q* based on the average of MXO_{qo} MXW_{qw} and MXF_{qf}
MXK	Maximum number of transfer stations
AW_{wk}	Ratio of sorting waste type *w* at transfer station *k*
BW_{wr}	Proportion of total recycling of waste type *w* by recycling technology *r*
CW_{wt}	Ratio of mass reduction of waste type *w* after treatment by treatment technology *t*
MUM_f	Proportion of generated residues of a treatment center which is type *f*
MUH_f	Proportion of generated residues of a recycling center which is type *f*
CPK_k	Capacity of transfer station *k*
CPM_m	Capacity of treatment center *m*
CPH_h	Capacity of recycling center *h*
CPL_l	Capacity of disposal center *l*

Decision variables:

X_{ij}^{q}	1, if node *i* visited just after node *j* by vehicle *q*; 0, otherwise
P_{wk}	Amount of waste type *w* sorted at transfer station *k*
E_{fi}	Amount of residue type *f* generated at treatment/recycling center i ∈ M ∪ H
Z_q	1, if vehicle *q* is used; 0, otherwise
ZK_{kq}	1, if vehicle *q* is used and allocated to transfer station *k*; 0, otherwise
YK_{ok}	Amount of waste type *o* processed at transfer station *k*; 0, otherwise
YM_{wm}	Amount of waste type *w* processed at treatment center *m*
YH_{wh}	Amount of waste type *w* recycled at recycling center *h*
YL_{wl}	Amount of waste type *w* disposed at disposal center *l*
YF_{fl}	Amount of residue type *f* disposed at disposal center *l*
XM_m	Total amount of residue produced at treatment center *m*
XH_h	Total amount of residue produced at recycling center *h*
XML_{ml}	Amount of residue of treatment center *m* to send to disposal center *l*
XHL_{hl}	Amount of residues of recycling center *h* to send to disposal center *l*

W_{qi} Load of vehicle q after visiting node i

Appendix B. Linearization

To begin the linearization, from the objective functions and Eq. (44), the notation $X_{ij}^{q} \times W_{qi}$ is converted to XW_{ij}^{q} by adding the following constraints to the proposed model. In this way, from Eqs. (45) to (48) in the model given in Section 3, the non-linear terms of two variables are converted into only one.

$$XW_{ij}^{q} \le M' \times X_{ij}^{q} \qquad \forall i \in G,\ j \in G \cup K;\ q \in V \in Q \qquad \text{(B-1)}$$

$$XW_{ij}^{q} \le W_{qi} \qquad \forall i \in G,\ j \in G \cup K;\ q \in V \in Q \qquad \text{(B-2)}$$

$$XW_{ij}^{q} \le W_{qi} - (1 - X_{ij}^{q}) \times M' \qquad \forall i \in G,\ j \in G \cup K;\ q \in V \in Q \qquad \text{(B-3)}$$

$$XW_{ij}^{q} \ge 0; M' \ge \infty \qquad \forall i \in G,\ j \in G \cup K;\ q \in V \in Q \qquad \text{(B-4)}$$

Similarly, from Eq. (31), the non-linear term of $X_{kj}^{q} \times P_{wj}$ is converted to XP_{kjw}^{q} by adding the following constraints.

$$XP_{kjw}^{q} \le M' \times X_{kj}^{q} \qquad \forall j \in G; q \in S \in Q; w \in W \qquad \text{(B-5)}$$

$$XP_{kjw}^{q} \le P_{wj} \qquad \forall j \in G; q \in S \in Q; w \in W \qquad \text{(B-6)}$$

$$XP_{kjw}^{q} \le P_{wj} - (1 - X_{kj}^{q}) \times M' \qquad \forall j \in G; q \in S \in Q; w \in W \qquad \text{(B-7)}$$

$$XP_{kjw}^{q} \ge 0; M' \ge \infty \qquad \forall j \in G; q \in S \in Q; w \in W \qquad \text{(B-8)}$$

The non-linear term of $X_{ij}^{q} \times E_{fi}$ in Eq. (34) is converted to XE_{ijf}^{q} by adding the following constraints.

$$XE_{ijf}^{q} \le M' \times X_{ij}^{q} \qquad \forall i \in K,\ j \in M \cup H; q \in U \in Q;\ f \in F \qquad \text{(B-9)}$$

$$XE_{ijf}^{q} \le E_{fi} \qquad \forall i \in K,\ j \in M \cup H; q \in U \in Q;\ f \in F \qquad \text{(B-10)}$$

$$XE_{ijf}^{q} \le E_{fi} - (1 - X_{ij}^{q}) \times M' \qquad \forall i \in K,\ j \in M \cup H; q \in U \in Q;\ f \in F \qquad \text{(B-11)}$$

$$XE_{ijf}^{q} \ge 0; M' \ge \infty \qquad \forall i \in K,\ j \in M \cup H; q \in U \in Q;\ f \in F \qquad \text{(B-12)}$$

Finally, the non-linear term in the third objective function is redefined by changing the variables in line with the following constraints.

$$SIA_i = \sum_{o \in O} YK_{ok} / \sum_{o \in O} \sum_{g \in G} BG_{og} : \text{Actual load at transfer station } i \qquad \forall i \in K \qquad \text{(B-13)}$$

$SIE_i = CPK_j / \sum_{i \in K} CPK_i$: Expected load at transfer station i $\forall i \in K$ (B-14)

$SID_i = SIA_i - SIE_i$: Deviation of fair load allocation at transfer station i $\forall i \in K$ (B-15)

Appendix C. Multi-objective SEO

SEO algorithm starts with two random solutions. The better performing solution of the two is then nominated as the attacker, and the other solution is considered as a defender. Following Fathollahi-Fard et al., [20], and as shown in Figure C.1, the SEO randomly applies four techniques as the main search engine of the algorithm. As each technique is applied, and the defender values are modified in response to the attack, the fitness for the purpose of the changed defender position is compared with previous values. The better position is adopted. Should the fitness of the defender now become stronger than the attacker, their roles are exchanged? The process is repeated until the attacks end, at which point the current defender is deleted, and a new random solution is generated to replace it.

The proposed CSWM framework represents a multi-objective optimization problem with minimizing the fleet size and transportation cost as the financial costs, CO_2 emissions and fuel consumption of vehicles as the second objective concerning the environmental pollution, and the fair load assignment deviations in transfer stations as the third objective contributing to the social impacts. A Pareto-based optimization algorithm is required to find the interaction between these objective functions [62], and a multi-objective version of SEO is presented below.

Generally, the solution of any multi-objective model is a set of candidate solutions in the form of a Pareto optimal frontier [63-64]. The best set of candidate solutions are those non-dominated solutions when compared to other candidates [65]. One solution will dominate another during the comparison if it has better fitness in at least one of the objective functions [66-67]. In this manner, a non-dominated solution set is generated. Figure C.2 provides a pseudo-code description of this process.

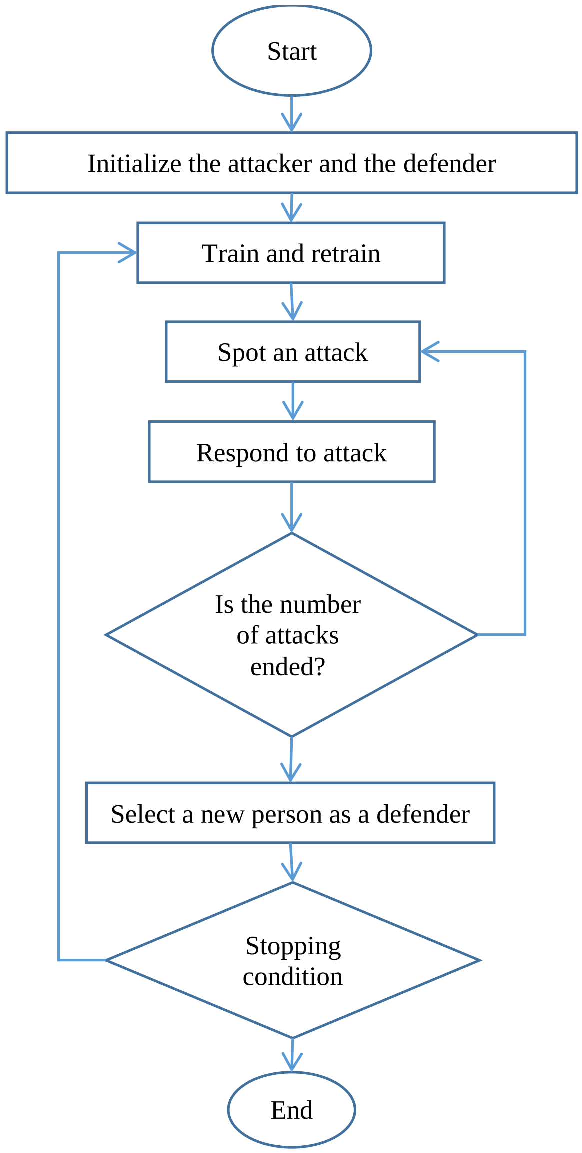


Figure C.1. Flowchart of the proposed SEO algorithm.

T_1=clock;
Initialize attacker and defender.
Consider the non-dominated Pareto solutions.
It=1;
while *solving_time* < *Max_time*
    Do training and retraining;
    if the new position of new defender can dominate the defender
    Check and update the non-dominated solution sets.
    end
    Num_attack=1;
    while *Num_attack* < *Max_attack*
        Spot an attack;

```
            Check the boundary;
            Respond to attack;
            Update the Pareto optimal frontier.
            if the new position of defender dominated than the attacker
              Exchange the defender and attacker position;
            endif
            Num_attack= Num_attack+1;
        endwhile
        Create a new solution as a defender;
        Update the non-dominated solutions.
        It=It+1;
        T2=clock;
        Solving_time=T2- T1;
endwhile
Return the best non-dominated
```

Figure C.2. Pseudo code for a multi-objective version of SEO.

Appendix D. Multi-objective evaluation metrics

This study utilizes four popular evaluation metrics: the number of Pareto solutions (NPS), the spread of non-dominance solutions (SNS), mean ideal distance (MID), and hyper volume (HV). The definition and desirability of the employed metrics are provided in Table D.1.

Table D.1. Evaluation metrics of Pareto-optimal set.

Assessment metric	Definition	Desirability	A reference application
Number of Pareto Solutions (NPS)	The number of best non-dominated solutions	Larger is more favorable	[9]
Spread of Non-dominance Solutions (SNS)	Measuring the diversity of solutions	Larger is more favorable	[55]
Mean Ideal Distance (MID)	Measuring the distance between Pareto solutions	Smaller is more favorable	[56]
Hyper Volume (HV)	Measuring the portion size of the objective function	Larger is more favorable	[57]

Appendix E. Tuning of parameters using RSM

As mentioned before, tuning of parameters is one of the main challenges for the implementation of the algorithms on industrial logistics and supply chains [68-71]. In the RSM, specific factors relate to each of the meta-heuristic input parameters. Based on the range of each factor, the response value is computed as a measure for the overall desirability of that optimizer. Each factor (x_i) is measured at two levels, coded as -1 to 1, relative to the low (x_l) and high (x_h) levels given by the selected range. Hence, the independent variables (z_i) relating to each factor considered is generated by:

$$z_i = \frac{x_i - (x_h + x_l)/2}{(x_h - x_l)/2}, i = \{1, 2, ..., K\} \quad \text{(E-1)}$$

where K is the number of variables. To calculate the response of the set of independent variables, a polynomial response surface function (y) is presented by:

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j z_j + \sum_{j=1}^{k} \sum_{i<j}^{k} \beta_{ij} z_i z_j + \sum_{j=1}^{k} \beta_{jj} z_{jj}^2 + \varepsilon \tag{E-2}$$

where β_0, β_j, β_{ij} and β_{jj} are the constant of the linear coefficient, the interaction coefficient (β_{ij}), and the quadratic coefficient (β_{jj}), respectively.

To start the RSM, the employed optimizers are given in Table E.1, along with their factors based on their range. As such, the total number of experiments is measured by n_f=2^k as a fraction of normal treatments, n_{ax} = 2k is the number of axial points, and n_{cp} is the number of central points.

Table E.1. Calibration of the meta-heuristics

Meta-heuristic	Factors and their surface value			Total number of treatments=(n_f, n_{ax}, n_{cp})
SA	SubIt (20, 50)	T0 (500, 1000)	$R_\propto$ (0.99, 0.999)	20=(2^3, 6, 6)
SEO and AMSEO	N_{att} (10, 70)	α (0.1, 0.4)	β (0.05, 0.25)	20=(2^3, 6, 6)

A utility function proposed by Derringer and Suich [72] is applied to assess the metrics of each Pareto-optimal set, and optimize the multiple responses of the RSM, as computed by:

$$d_i(y_i) = \left(\frac{h_i - y_i}{h_i - l_i}\right)^s, \qquad l_i < y_i < h_i \tag{E-3}$$

where the multiple response y_i has been transformed into the measurement of the utility function (d_i). l_i and h_i are the lower and upper bounds of response variables, respectively. The emphasis on the utility function amount is calculated by s. Less emphasis of the assessment metrics equates with less importance. Accordingly, the amount of s is 1, 1, 2, and 3, to reflect the relative importance of the evaluation metrics NPS, SNS, MID and HV, respectively. The desirability of the algorithm in terms of the number of utility functions for all applied assessment metrics is computed by:

$$D = \sqrt[m]{d_1(y_1) \times d_2(y_2) \times \ldots \times d_m(y_m)} \tag{E-4}$$

where m is the number of evaluation metrics. As such, D is the total desirability of the algorithm. It is evident that the higher value of D the more favorable is the algorithm.

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