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A Multi-objective PSO Approach for Sustainable Production Routing: Balancing Cost, Emissions, and Social Impact

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ABSTRACT

The Production Routing Problem (PRP) has been extensively studied in logistics optimization. However, research that explicitly integrates environmental and social sustainability dimensions remains limited. This research proposes a sustainable production routing problem (SU-PRP) as a multi-objective optimization model, minimizing the total operating cost, CO_2 emissions cost, and social cost simultaneously. The complex model is addressed using Multi-Objective Particle Swarm Optimisation (MOPSO), which has been modified to handle discrete decision variables in a supply chain environment. The algorithm's performance is benchmarked against NSGA-II using three quality indicators: Spacing Metric (SM), Inverted Generational Distance (IGD), and Hypervolume (HV). Numerical testing was performed using a moderate-sized problem instance comprising two plants, five customers, two products, and a two-period planning horizon, with 663 binary variables and 546 constraints. In the results, it can be observed that MOPSO has reached a larger HV, indicating better coverage of the objective space. Nevertheless, NSGA-II outperforms MOPSO in terms of solution uniformity and convergence, as evidenced by smaller SM and IGD values. The results suggest that MOPSO is more effective in operational planning scenarios where fast computation and solution diversity are crucial, such as real-time production and routing adjustments. In contrast, NSGA-II is more suitable than MOPSO for strategic planning tasks, as it yields more accurate and evenly distributed Pareto solutions.

1. Introduction

Several coordination strategies have been developed to synchronize supply chain (SC) processes and activities, aiming to enhance overall SC performance. Coordination is considered a prerequisite for integrating SC operations to achieve common goals [1].

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Production and distribution are the most critical operational decisions in any SC. Therefore, the integration of production and distribution is an important research area in supply chain management. Simultaneous planning of production, inventory, and distribution routes to minimize total costs is known as the Production Routing Problem (PRP). This problem falls within the scope of the Integrated Production-Distribution Problem [2]. PRP is well-analyzed in the literature because it can be a solution that minimizes costs and enhances the reliability of delivery. It is applicable across a broad range of sectors, from food logistics to hazardous goods handling, and up to cold chain distribution, where operational coordination is essential. Although the PRP has been widely studied in theoretical contexts, industrial applications are increasingly emerging in diverse areas. Some studies have addressed specific sectoral challenges such as meat product logistics [3], [4], catering services [5], and oxygen or blood platelet supply chains [6], [7]. Chemical factories, battery manufacturing, and petrochemical distribution are other examples of applications as studied in [8], [9], and [10]. These studies demonstrate that PRP models are becoming increasingly practical for logistics planners, particularly when tailored to specific sector demands.

Nevertheless, the majority of PRP models have been developed from a cost-oriented perspective, focusing on minimising production, inventory, and transportation costs. Nonetheless, the increased awareness of the environment and the pressures towards sustainability have led researchers to extend the PRP in terms of environmental and social aspects. This broader viewpoint has led to the development of the Sustainable Production Routing Problem (SU-PRP), which considers economic, environmental, and social sustainability criteria. The transition between classical and sustainable PRP emphasises the need for a modelling approach that closely represents real-life trade-offs and regulatory restrictions. However, the current PRP models for sustainability have some limitations. Environmental impact assessments often consider only transportation emissions whilst ignoring contributions from production processes, storage conditions, and product handling. Likewise, the social dimension and the risks of occupational safety and road accidents are frequently underestimated or are qualified by qualitative indicators [11]. Such gaps diminish the operational relevance of sustainability models, particularly in industries where social and environmental risks significantly influence planning decisions.

Research related to the Production Routing Problem (PRP) has undergone significant development, with various multi-objective (MO) approaches being employed to balance economic, environmental, and social objectives. Kumar, et al. [12] developed a self-learning particle swarm optimization (PSO) algorithm within the MOMILP framework to manage the trade-off between cost and emissions. Casas-Ramírez, et al. [13] employed a BOMILP approach combined with a bi-objective GRASP algorithm, focusing on cost efficiency and social workload. Meanwhile, Karimi, et al. [14] employed NSGA-II and the multi-objective imperialist competitive algorithm in the MINLP model, which focused on cost optimisation without considering environmental and social aspects. Li, et al. [15] proposed a two-phase iterative approach based on epsilon constraint and fuzzy logic in MOMILP to optimize economic aspects. Peng, et al. [16] extended the MOMILP framework by incorporating environmental and social dimensions, considering emissions from production, storage, and product handling throughout the supply chain. Chan, et al. [4] applied a global local near-neighbour-based PSO for perishable product logistics, considering customer satisfaction as a social proxy. Zeddam, et al. [17] and Peivastehgar, et al. [18] also considered economic and environmental aspects in MOMILP, but did not explicitly include social risks. Garside, et al. [19] refined the approach by integrating all sustainability dimensions into MOMILP using a combination of weighted sum and NSGA-

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II. Although several studies have begun to combine social and environmental dimensions, there are still limitations in the comprehensive integration of emissions from all activities (production, storage, and handling), as well as a lack of efforts to monetise social impacts, such as work accidents and traffic, quantitatively. In addition, in-depth comparative studies of various metaheuristic algorithms in the context of sustainable PRP are still very limited [12], [13], and [16].

Three important gaps can be identified from the literature. First, while environmental criteria are being incorporated more often, in the majority of studies, only transport-related emissions are analysed, omitting significant sources, such as storage and product handling. Second, few efforts have been made to monetise safety risks into quantifiable costs, and the social aspect is currently underdeveloped. Third, considering the dominance of NSGA-II in the solution approaches for MO-PRP, the potential of MOPSO in MO-PRP, especially in models based on discrete variables, which are common in the logistics literature, has not been fully explored. In this study, a multi-objective SU-PRP model is developed to minimise operational cost, CO_2 emission cost, and social impact cost. The model includes a detailed description of emissions released from production, storage, and handling activities, as well as monetised risks of occupational and road accidents. A discrete-adapted MOPSO algorithm is employed to solve the model, offering diverse Pareto optimal solutions. The performance of the algorithm is compared with NSGA-II on three standard metrics: Spacing Metric (SM), Inverted Generational Distance (IGD), and Hypervolume (HV).

Motivated by these industrial considerations, the SU-PRP model is designed to address practical sustainability concerns in sectors where delays, emissions, and safety risks are significant. This includes cold chain logistics, medical waste management, and hazardous materials transportation, all of which require environmental compliance and social responsibility in operational planning. The study contributes to the literature on sustainable supply chain strategies by proposing a multi-objective optimisation model that explicitly considers cost, emission, and safety objectives. A discrete-adapted MOPSO algorithm is proposed to solve the SU-PRP. It is compared with the NSGA-II by three well-known performance metrics.

2. Methods

2.1 Problem Description

This study considers a variant of the Production Routing Problem (PRP) that incorporates sustainability-related concerns encompassing economic, environmental, and social dimensions. The problem is defined on a complete graph G = {N, A}, where N denotes the set of nodes consisting of plants P and customers R, and A = $\{(i, j): i, j \in N, i \neq j\}$ represents the set of arcs connecting them. Each plant $p \in$ P can produce multiple products $k \in$ K, subject to production capacity limits and inventory constraints. The production process incurs setup and variable costs, and generates CO_2 emissions, both from setup (sepk) and per-unit production (pepk). In addition, production activities involve a risk of workplace injuries, which is influenced by the number of workers required per unit and the probability of accidents (op_{pk}).

Customer nodes $r \in$ R are characterized by time-dependent demands d_r^{kt}warehouse capacities and minimum inventory requirements. Delivered products are stored and handled at these locations, generating handling costs and emissions (he_{rk}), and exposing workers to potential injuries (oh_{rk}). A heterogeneous fleet of vehicles V, where each plant operates its own subset V(p), is used to distribute products. Each vehicle $v \in$ V has a specific capacity, fuel characteristics, and physical parameters influencing its energy

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consumption. Transportation activities not only incur fixed and fuel costs but also generate CO_2 emissions and traffic accident risks. Emissions from vehicle operation are quantified based on fuel usage and energy parameters, and then monetised using the CO_2 emission cost (CE). Social costs associated with road accidents are calculated based on the accident probability per route (ot_{ij}^{v}) and the vehicle load (L_{ij}^{vt}).

The decision variables involve binary choices regarding production setup, vehicle routing, and delivery schedules, as well as continuous variables for production quantities, inventory levels, and vehicle load distribution. A summary of the key sets, parameters, and decision variables is presented in Table 1. A more detailed description of all model parameters, including technical, economic, environmental, and social aspects, can be found in the research by Garside, et al. [11].

Table 1. Summary of Key Parameters and Decision Variables

Type	Notation	Description
Technical Parameter	w_k	weight of product *k* (kg/unit)
Technical Parameter	PC_{pk}	Production capacity of plant p for product k (unit)
Technical Parameter	VC_v	Capacity of vehicle v (kg)
Technical Parameter	v_{ij}^{v}	Speed of vehicle v between i and j (km/h)
Technical Parameter	sc_{pk}	setup cost of product *k* at plant *p* ($)
Economic Parameter	pc_{pk}	Production cost per unit of product k at plant p ($/unit)
Economic Parameter	ic_{pk}	Inventory cost per unit of product k at plant p ($/unit)
Economic Parameter	f_v	Fixed cost of vehicle v ($)
Economic Parameter	E_c	Energy consumption per liter of diesel (kJ/litre)
Economic Parameter	c_f	Fuel price ($/L)
Environmental Parameter	pe_{pk}	CO_2 emissions per unit of product k produced at plant p (kg CO_2/unit)
Environmental Parameter	ie_{ik}	CO_2 emissions per unit held at node i (kg CO_2/unit)
Environmental Parameter	c_e	Carbon emissions cost ($/kg CO_2)
Social Parameter	op_{pk}	Probability of work injury during production of product k at plant p
Social Parameter	ot_{ij}^{v}	Probability of road accident from i to j by vehicle v
Decision Variable	p_{pk}^{t}	Quantity of product k produced at plant p in period t (unit)
Decision Variable	I_{ik}^{t}	Inventory level of product k at node i at the end of period t (unit)
Decision Variable	y_{ij}^{vt}	Binary variable: 1 if arc (i,j) is travelled by vehicle v in period t
Decision Variable	L_{ij}^{vt}	Load carried by vehicle v on arc (i,j) in period t (kg)
Decision Variable	x_{pk}^{t}	Binary variable: 1 if product k is produced at plant p in period t
Decision Variable	d_{pr}^{kvt}	Quantity of product k delivered from plant p to customer r by vehicle v in period t (unit)
Decision Variable	c_{rv}^{t}	Binary variable: 1 if customer r is visited by vehicle v in period t
Decision Variable	x_{pk}^{t}	Binary variable: 1 if production setup for product k is done at plant p in period t

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2.2 Model Formulation

Based on the previously defined sets, parameters, and decision variables, this section presents the mathematical formulation of the Sustainable Production Routing Problem (SU-PRP) as a multi-objective mixed-integer linear programming (MOMILP) model. The formulation aims to simultaneously optimise three conflicting objectives, each representing a distinct sustainability dimension: economic cost minimisation, environmental impact reduction, and social risk mitigation. These objectives are constrained by a set of operational, routing, and feasibility constraints consistent with the PRP framework.

The first objective function (OF_{Eco}) seeks to minimise the total economic cost incurred throughout the planning horizon. This includes setup and variable production costs, inventory holding costs at both plant and customer locations, handling costs at customer sites, fixed operational costs of vehicles, and fuel consumption costs based on the energy usage of each vehicle. The detailed mathematical formulation of the economic objective function is as in Equation (1).

$$\begin{aligned} OF_{Eco} = & \sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(sc_{pk}x_{pk}^{t} + pc_{pk}p_{pk}^{t}) + \sum_{p\in P}\sum_{k\in K}\sum_{t\in T} ic_{pk}I_{pk}^{t} + \sum_{r\in R}\sum_{k\in K}\sum_{t\in T} ic_{rk}I_{rk}^{t} \\ & + \sum_{p\in P}\sum_{r\in R}\sum_{k\in K}\sum_{v\in V}\sum_{t\in T} hc_{rk}\, d_{pr}^{kvt} + \sum_{i\in P}\sum_{j\in R}\sum_{v\in V}\sum_{t\in T} f_v\, y_{ij}^{vt} \\ & + \frac{c_f}{Ec}\sum_{(i,j)\epsilon A}\sum_{v\epsilon V}\sum_{t\epsilon T} \alpha_{ij}^{v} cw^{v} d_{ij} y_{ij}^{vt} + \alpha_{ij}^{v} d_{ij} L_{ij}^{vt} + \beta_v (v_{ij}^{v})^2 d_{ij} y_{ij}^{vt} \end{aligned} \tag{1}$$

Each term in the objective function corresponds to a specific cost component that reflects actual operational expenses in the real world. These include setup and variable production costs (scpk, pcpk), inventory-related costs (icpk, icrk), handling costs (hcrk), vehicle operating costs (fv), and energy-related fuel costs derived from detailed vehicle energy consumption models. Similar to prior research integrating cost and emission aspects in inventory and transport decisions [20], our economic objective function embeds both direct production costs and logistics-related expenses, including energy-based fuel consumption.

The second objective function (OF_{Env}) aims to minimise the total environmental cost associated with CO_2 emissions throughout the supply chain. Emission sources considered in this model include emissions from production setup, unit production, storage at both plants and customer warehouses, product handling activities, and fuel-based transportation. Each emission quantity is converted into monetary cost using a carbon price coefficient. The function is expressed in Equation (2).

$$\begin{aligned} OF_{Env} = c_e \Bigg(& \sum_{p\in P}\sum_{k\in K}\sum_{t\in T}(se_{pk}x_{pk}^{t} + pe_{pk}p_{pk}^{t}) \\ & + \sum_{i\in N}\sum_{k\in K}\sum_{t\in T} ie_{ik}I_{ik}^{t} + \sum_{p\in P}\sum_{r\in R}\sum_{k\in K}\sum_{v\in V}\sum_{t\in T} he_{rk}\, d_{pr}^{kvt} \\ & + \gamma \sum_{(i,j)\epsilon A}\sum_{v\epsilon V}\sum_{t\epsilon T} \alpha_{ij}^{v} cw^{v} d_{ij} y_{ij}^{vt} + \alpha_{ij}^{v} d_{ij} L_{ij}^{vt} + \beta_v (v_{ij}^{v})^2 d_{ij} y_{ij}^{vt} \Bigg) \end{aligned} \tag{2}$$

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The third objective function (OF_{Soc}) addresses the social dimension of sustainability by minimising the cost of safety-related incidents (Equation (3)). It incorporates probability estimates of workplace injuries during production and handling, as well as road accidents during transportation. Each risk is monetised using respective accident cost coefficients, producing an overall cost representation of social impact.

$$
\begin{aligned}
OF_{Soc} = {} & c_{wi} \sum_{p \in P} \sum_{k \in K} \sum_{t \in T} \left(op_{pk} mp_{pk} p_{pk}^{t} \right) + c_{wi} \sum_{p \in P} \sum_{r \in R} \sum_{k \in K} \sum_{v \in V} \sum_{t \in T} \left(oh_{rk} mh_{rk} d_{pr}^{kvt} \right) \\
& + c_{ra} \sum_{(i,j) \epsilon A} \sum_{v \in V} \sum_{t \epsilon T} \left(ot_{ij}^{v} d_{ij} L_{ij}^{vt} \right)
\end{aligned} \tag{3}
$$

All three objective functions are subject to a comprehensive set of constraints that ensure the logical consistency and operational feasibility of the SU-PRP model. These include capacity limitations, flow conservation rules, inventory balance relationships, and vehicle routing requirements. For instance, the production capacity constraint guarantees that the total quantity of each product manufactured at a plant in each period does not exceed its maximum production capacity (Equation (4)).

$$
p_{pk}^{t} \le x_{pk}^{t} PC_{pk}, \forall p \in P, k \in K, t \in T \tag{4}
$$

The inventory balance constraint maintains continuity across periods by updating the stock level based on production and delivery quantities. These constraints are modelled in Equation (5) and (6).

$$
I_{pk}^{t} = I_{pk}^{t-1} + p_{pk}^{t} - \sum_{r \in R} \sum_{v \in V(p)} d_{pr}^{kvt}, \forall p \in P, k \in K, t \in T \tag{5}
$$

$$
I_{rk}^{t} = I_{rk}^{t-1} + \sum_{p \in P} \sum_{v \in V} d_{pr}^{kvt} - D_{rk}^{t}, \forall r \in R, k \in K, t \in T \tag{6}
$$

Additional constraints ensure the proper functioning of routing such as Vehicle Capacity Constraints and Sub-tour elimination constraint can be see in Equation (7)-(9);

$$
\sum_{p \in P(v)} \sum_{r \in R} \sum_{k \in K} w_k d_{pr}^{kvt} \le VC_v, \forall v \in V, t \in T \tag{7}
$$

$$
\sum_{j \in N \setminus \{r\}, i=r} L_{ji}^{vt} - \sum_{i=r, j \in N \setminus \{r\}} L_{ij}^{vt} = \sum_{p \in P(v)} \sum_{k \in K} w_k d_{pr}^{kvt}, \forall\, r \in R, v \in V, t \in T \tag{8}
$$

$$
L_{ij}^{vt} \le VC_v\, y_{ij}^{vt}, \forall (i,j) \in N, i \neq j, v \in V, t \in T \tag{9}
$$

A complete and detailed formulation of all constraints can be found in research by Garside, et al. [11], which also outlines the exact solution methodology for solving the SU-PRP.

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2.3 Multi-objective Particle Swarm Optimization Algorithm

Since its introduction by Kennedy and Eberhart in 1995, Particle Swarm Optimization (PSO) has become one of the most widely adopted metaheuristic algorithms for solving complex real-world optimization problems. Its popularity stems from its simple implementation, strong global search ability, and relatively low number of control parameters compared to other nature-inspired methods [21]. PSO mimics the social behavior of bird flocks or fish schools in searching for optimal food sources.

Multi-objective PSO (MOPSO) extends this technique to address problems involving multiple conflicting objectives. According to Zhang, et al. [22], MOPSO has demonstrated robust performance in exploring a wide solution space, providing efficient approximation of Pareto fronts due to its balance between global convergence and solution diversity. Moreover, PSO has been successfully employed in several studies, such as in solving solving capacitated location allocation problems for solar power generation [23], optimizing vehicle routing [24], [25], showing its adaptability in addressing practical industrial optimization tasks.

In this study, we apply MOPSO to solve the Sustainable Production Routing Problem (SU-PRP), which involves three conflicting objectives: minimizing economic cost, environmental emissions, and social risk. A widely used approach for handling multiple objectives in MOPSO is the scalarization method, which converts a multi-objective problem into a single-objective one using weighted sums. As described by [26], scalarization integrates all objective components into a single fitness value, allowing standard PSO operations to be applied directly. This approach has also been commonly adopted in the early development of MOPSO, as noted by [27] and further elaborated by [28]. Following this principle, the fitness function in this study is formulated as Equation (10).

$$Fitness\ (Xi)\ = w_1 OF_{Eco} + w_2 OF_{Env} + w_3 OF_{Soc} \tag{10}$$

To ensure a fair and balanced evaluation across all sustainability objectives, we assign equal weights of $w1 = w2 = w3 = 0.333$. This neutral weight configuration avoids prioritizing any single dimension. It aligns with prior studies where no explicit stakeholder preferences are available. Equal weighting has been practically applied in optimisation contexts, such as by [29] for cross-layer path selection, where scalarization with equal weights yielded fair solutions among conflicting network performance metrics. Gunantara, [30] further emphasised equal weighting as a baseline scalarization scheme in multi-objective metaheuristic optimisation, including comparative experiments involving the PSO and GA algorithms.

The MOPSO algorithm starts by initializing a population of particles, where each particle i has a position vector $Xi = [xi1, xi2, \dots, xiD]$ and a velocity vector $Vi = [vi1, vi2, \dots, viD]$ in a D-dimensional search space. Each particle updates its movement based on the personal best $Pbest_i$ and global best $Gbest$ positions using the following velocity and position update rules as in Equation (11) and (12).

$$v_{id}(t+1) = \omega * v_{id}(t) + c_1 \times rand_1 \times \left(pbest_{id}(t) - x_{id}(t)\right) + c_2 \times rand_2 \times \left(Gbest_d(t) - x_{id}(t)\right) \tag{11}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{12}$$

where ω is the inertia weight, c_1 and c_2 are the cognitive and social acceleration coefficients, and r_1 and r_2 are uniformly distributed random values in [0,1]. The inertia weight is adjusted dynamically using Equation (13).

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$$\omega(it) = \left(\omega_{max} - (\omega_{max} - \omega_{min})\frac{it}{it_{max}}\right) \tag{13}$$

The values of ω_{max} and ω_{min} are the maximum and minimum values of the inertia weight, t is the current iteration, and t_{max} is the maximum number of iterations. The pseudo-code of the MOPSO algoritm is shown on Figure 1.

```
Initialization
Define the swarm size N and the number of dimensions D
for each particle i ∈ [1, ..., N]
Randomly generate X_i and V_i, and evaluate the fitness of X_i using (4)
Set Pbest_i = X_i and f (Pbest_i) = f (X_i)
end for
Set Gbest = Pbest_1 and f (Gbest) = f (Pbest_1)
for each particle i ∈ [1, ..., N]
    if f (Pbest_i) < f (Gbest) then
        f (Gbest) = f (Pbest_i)
    end if
end for
while t < maximum number of iterations
for each particle i ∈ [1, ..., N]
Evaluate its velocity v_id (t + 1) using (5)
Update the position x_id (t + 1) of the particle using (6)
 if f (x_i (t + 1)) < f (Pbest_i) then
 Pbest_i = x_i (t + 1)
     f (Pbest_i) = f (x_i (t + 1)
 end if
 if f (Pbest_i) < f (Gbest) then
  Gbest = Pbest_i
  f (Gbest) = f (Pbest_i)
 end if
Update inertia weight using equation (7)
end for
t = t + 1
end while
return Gbest
```

Figure 1. Pseudo Code of Proposed Algorithm

2.4 Data Set

This study employs a generated instance of the Sustainable Production Routing Problem (SU-PRP), consisting of two plants and five customers. The configuration comprises four diesel-powered vehicles with heterogeneous characteristics (V1–V4), operating across a network with inter-location distances ranging from 49 km to 393 km.

The dataset was generated using structured formulas based on established literature, primarily adapted from [16], and further enhanced with context-specific adjustments to suit the SU-PRP framework. Key parameter groups are summarized below:

- Demand data is generated for two products over two periods per customer, with values ranging from 3 to 27 units per product per period. Each customer has product-specific inventory constraints and handling labour requirements, ranging from 0.01 to 0.04 workers/unit.

- Production and inventory parameters at each plant specify the initial stock, minimum inventory levels (set to zero and 10 units, respectively), and labour needs per product. For instance, producing one unit of Product 1 at Plant 1 requires 0.3 workers, while producing one unit of Product 2 requires 0.15 workers.
- Vehicle parameters include dimensions, capacity (ranging from 8,000 to 10,000 kg), curb weight, fixed cost per trip (ranging from $600 to $850), aerodynamic characteristics, and operational speed ranges (45–65 km/h, depending on the vehicle type). Additional dynamic attributes such as acceleration, drag coefficients, rolling resistance, and travel time uncertainty are also incorporated.
- Environmental and social impact parameters are monetised using empirical conversion factors and external references. These include:
    - CO_2 emission cost = $0.022 per kg CO_2[31].
    - Fuel cost = $1.206 per litre, with diesel's emission factor of 2.692 kg CO_2/liter.
    - Work injury cost = $1080 per worker.
    - Road accident cost = $0.00014 per kg-km.

The complete dataset, including Excel files and parameter descriptions, is publicly accessible at: https://tinyurl.com/yvcftfnm.

3. Results and Discussion

3.1 Computational Results

In this study, the Multi-Objective Particle Swarm Optimisation (MOPSO) algorithm was employed to solve the Sustainable Production Routing Problem (SPRP). The parameters were set as follows: population size N = 100, inertia weight ω varying from 1.0 to 0.3, and acceleration coefficients $c_1 = c_2 = 1.4692$. The algorithm was executed for a maximum of 100 iterations on a 13th Generation Intel(R) Core(TM) i7-13700H processor with a 2.40 GHz clock speed and 16 GB of RAM

To ensure a fair comparison, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was also employed using the gamultiobj function in MATLAB. NSGA-II produced 46 non-dominated solutions. Accordingly, MOPSO was independently executed 46 times to generate a comparable set of solutions. After eliminating duplicates, 14 unique Pareto-optimal solutions were identified from the MOPSO results.

The considered problem instance is two plants, five customers, two products, and a two-period planning horizon. The formulated SU-PRP model consists of 663 variables, 288 of which are binary, and 546 constraints. This configuration is considered a moderately complex multi-objective problem, allowing for a more meaningful comparison of algorithm performance via the Pareto solutions.

Following the practice of [32], who emphasized the importance of repeated independent runs to mitigate randomness in metaheuristics, the average value and standard deviation were calculated to reflect the accuracy and stability of the optimization outcomes, respectively. These statistical indicators help provide a more robust and reliable assessment of algorithmic performance. Table 2 presents the statistical summary of the objective function values for both MOPSO and NSGA-II.

Table 2. Statistical summary of objective function values for MOPSO and NSGA-II

Algorithm	Total operational cost ($)		Total CO_2 emissions cost ($)		Total social impact cost ($)	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
PSO	7,774.27	389.27	49.53	2.02	5,665.05	288.25
NSGA-II	7,742.99	472.57	44.84	3.93	5,695.85	352.79

The results indicate that while NSGA-II achieved slightly better average performance in terms of operational and emissions costs, MOPSO demonstrated greater robustness across all objectives, as reflected by its lower standard deviations. This stability suggests that MOPSO consistently generates high-quality solutions under repeated runs.

3.2 Analysis of Pareto Optimal Solutions

The Pareto optimal solutions obtained by MOPSO are given in Table 3. This trade-off of the three sustainability objectives is a sign of the trade-off nature. The trade-off relations are also evident: Solution 1 yields the smallest operational cost and the most significant social cost, whereas Solution 14 yields the least social cost and the least operational performance. These trade-offs indicate the conflict between the different dimensions of sustainability. For instance, to reduce the social cost, safer vehicles or operations should be deployed, which may result in higher emissions or operational costs.

Table 3. Pareto Optimal Solutions Obtained from MOPSO

Solution	Total operational cost ($)	Total CO_2 emissions cost ($)	Total social impact cost ($)
1	8655.139	52.979	5038.629
2	8245.138	54.110	5234.040
3	8195.325	50.883	5469.931
4	8136.679	48.615	5412.187
5	7877.372	49.433	5499.021
6	7667.295	48.384	5764.795
7	7620.847	50.264	5783.851
8	7571.809	50.040	5819.183
9	7561.842	47.995	5876.365
10	7599.170	48.165	5719.469
11	7548.482	48.934	5835.991
12	7388.539	47.205	5951.232
13	7387.064	49.198	5952.295
14	7385.011	47.189	5953.774

3.3 Visualisation of Pareto Front

Figure 2 presents a three-dimensional visualization of the Pareto front, where each point represents a non-dominated solution generated by the MOPSO algorithm. A colour gradient is used to indicate the magnitude of total social impact cost, enabling visual differentiation of solution quality across the objective space. The Pareto front displays a convex and non-uniform shape, suggesting the presence of trade-offs among the three sustainability objectives. The non-uniform distribution of solutions indicates that some regions in the objective space are less explored or more challenging to reach, reflecting the complexity of balancing conflicting objectives within the feasible solution space.

Three extreme points are highlighted to represent distinct decision-maker preferences: one solution offers the lowest operational cost (Min OpCost), another yields the lowest emissions cost (Min Emission), and a third minimizes social impact cost (Min Social). These solutions serve as reference anchors for stakeholders prioritizing a single sustainability dimension.

In addition, a dominance zone is outlined in the mid-range region of the front, connecting solutions 5 through 9. This zone represents a set of solutions that achieve moderate trade-offs across all objectives, making them especially relevant for decision-makers seeking balanced strategies that do not excessively sacrifice one objective for another.

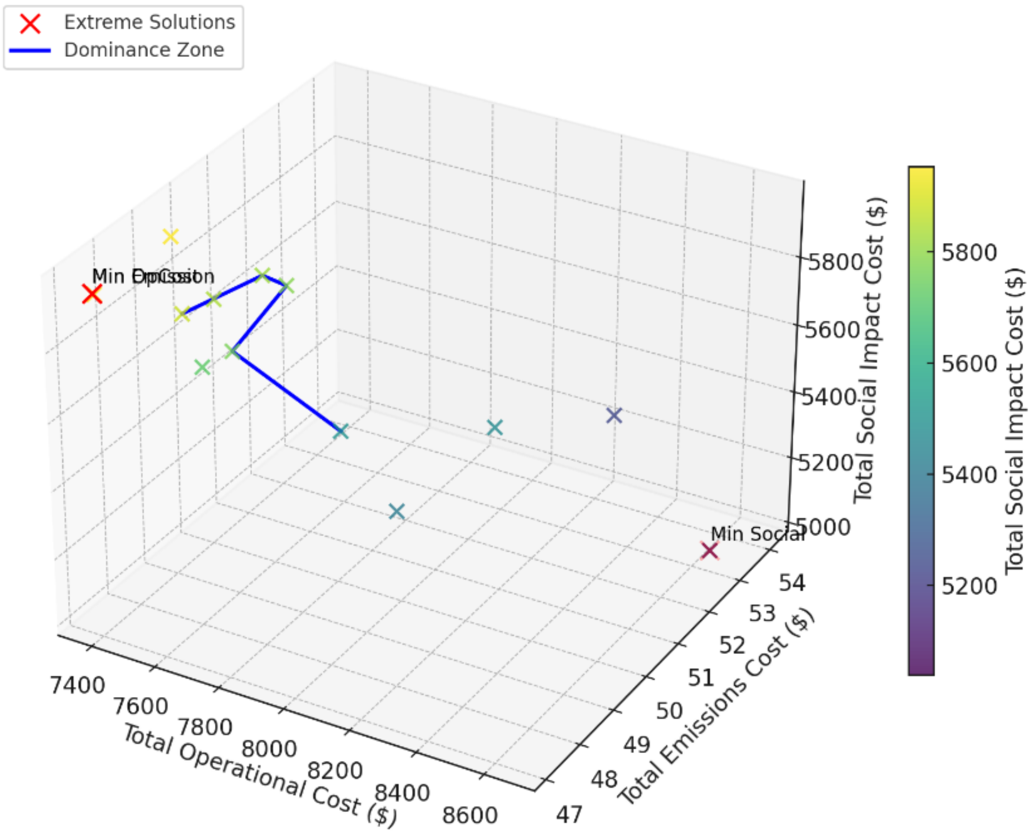

Figure 2. Pareto Front with Extreme Solutions and Dominance Zone

3.4 Performance Analysis Using Quality Metrics

For further quality assessment of the generated Pareto fronts, three performance metrics — Spacing Metric (SM), Inverted Generational Distance (IGD), and Hypervolume (HV) — were utilised. These metrics not only evaluate solution diversity and convergence but also complement the earlier statistical summary, allowing a more holistic comparison between MOPSO and NSGA-II.

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Spacing Metric (SM), also referred to as Range Variance (RV), measures the uniformity of the distribution of non-dominated solutions along the Pareto front. A low SM value indicates an even spread, while a high value suggests poor diversity. The computation steps follow the methodology proposed by [12]. Furthermore, Inverted Generational Distance (IGD), introduced by [33], quantifies the distance between each point in a true Pareto front and its closest member in the approximated front. Lower IGD values indicate better convergence and diversity. This metric has been widely used in evolutionary multi-objective optimization studies [34].

Hypervolume (HV) measures the volume in objective space dominated by the approximated Pareto front concerning a fixed reference point. A higher HV value implies better convergence and coverage of the objective space [22]. In this study, HV was approximated using a geometric approach based on the convex hull volume, calculated with the ConvexHull function from the SciPy library in Python [35]. Although this method does not compute the exact hypervolume, it provides a reliable estimation and has been widely adopted [36].

Table 4. Performance comparison between MOPSO and NSGA-II

Algorithm	**Computation time (seconds)**	**Number of Pareto Solutions**	**SM**	**IGD**	**HV**
MOPSO	5,844.25	14	118.54	611.74	230,459.10
NSGA-II	8,575.32	46	37.44	588.84	183.42

A performance comparison between MOPSO and NSGA-II is presented in Table 4. It shows that NSGA-II exhibits a lower SM value (37.44), indicating a more evenly distributed Pareto front compared to MOPSO (118.54). Similarly, IGD is lower for NSGA-II, indicating its better proximity to the actual Pareto front. However, MOPSO achieved a significantly higher hypervolume (HV = 230,459.10), meaning that the non-dominated solutions generated by MOPSO cover a broader region of the objective space. Additionally, MOPSO required less computation time (approximately 31.8% less), making it more efficient for applications that require rapid decision support. The findings are also consistent with the statistical summary in Table 3, where MOPSO demonstrates lower standard deviations across all objectives, indicating more consistent and stable performance. Despite its lower number of non-dominated solutions, MOPSO offers a reliable approximation with broad objective coverage, making it suitable for decision-makers who prioritize robustness and solution stability.

3.5 Practical and Theoretical Implications

The trade-offs represented in the Pareto front reflect practical consequences. For instance, reducing social impact costs might involve deploying more vehicles, adopting slower delivery schedules, or rotating driver shifts to mitigate fatigue, which can lead to higher operational costs. On the other hand, efforts to reduce emission-related costs might lead to route selections that are less congested but longer and steeper, which helps lower pollution levels while potentially raising fuel usage and extending delivery times. It is the inherent trade-offs in these decisions that signal supply chain managers should match optimization solutions to their specific sustainability priorities and compliance requirements.

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The findings are also aligned with the broader context of sustainability. Strategies to reduce emissions are cost-effective for preserving the environment (e.g., SDG 13: Climate Action). At the same time, those that mitigate hazards associated with work are targeted at improving worker safety and health (e.g., SDG 3: Good Health and Well-being). Cost-effective solutions contribute to the economic sustainability and stability of industrial processes (e.g., SDG 9 - Industry, Innovation and Infrastructure). This is the foundation that enables multi-objective optimization models to contribute to the sustainability of supply chain planning, both in economic, environmental, and social goals [37].

From a theoretical perspective, this study contributes to the literature by demonstrating that a metaheuristic technique, such as the MOPSO algorithm, can be effectively applied to a complex SU-PRP model enriched with monetized social costs for the first time. The inclusion of sustainability objectives in the optimization formulation, along with a rigorous performance measurement, establishes a methodological basis for further studies in sustainable logistics planning.

Nevertheless, this study has several limitations. The dataset is based on modified benchmark instances, not real industrial data. All input parameters were assumed to be deterministic. In contrast, real-world operations involve uncertainties such as fluctuating demand, travel delays, and accident risks. Furthermore, decision-maker preferences were not integrated into the algorithmic process. Future work could address these aspects by incorporating stochastic modeling or sensor-driven data acquisition to support real-time and adaptive optimization. Additionally, performance aspects such as convergence speed and parameter sensitivity—although not covered in this study—are acknowledged as important factors for future research to ensure a comprehensive evaluation of optimisation algorithms in dynamic supply chain environments.

The evaluation of the SU-PRP for the proposed MOPSO algorithm's performance demonstrates its ability to generate high-quality and diverse Pareto solutions. The trade-offs between economic, environmental, and social objectives are revealed, illustrating the complex decision-making process required for sustainable supply chain operation. These findings underscore the importance of developing optimisation strategies that align with realistic operational and long-term sustainability objectives. Furthermore, recent studies have shown that transparent information sharing is a critical enabler of supply chain efficiency and productivity. Sugito and Kusrini [38] found that adequate and accurate information flow would directly lead to improvements in manufacturing lead time and responsiveness if production and distribution coordination is applied.

4. Conclusion

This study presents a multi-objective optimisation model that considers economic, environmental, and social perspectives to resolve the Sustainable Production Routing Problem (SPRP). The MOPSO algorithm has been demonstrated to be effective in exploring various trade-offs between competing objectives and handling well-defined discrete decision variables. It was shown that MOPSO provides shorter computation time than NSGA-II and better coverage of the Pareto front; however, NSGA-II converges slightly better in terms of the propensity solutions. Despite these promising results, the study has some limitations. First, we have only performed computational experiments with generated datasets, which cannot replicate the complexity and dynamics of a real-world supply chain. A second limitation of the model is that it assumes deterministic parameters; however, the modelis inputs, such as demand, travel time, and the probability of accidents, are uncertain. Third, the scalability to larger problems has not been well demonstrated; hence, the application to large-scale problems can be limited. To bridge these gaps, future research may focus on the following directions. First, there is potential to pragmatically apply the developed optimisation framework to a sample of real-world case studies, within selected industry sectors (such as cold chain logistics or dangerous goods distribution) in order to assess the applicability and practicality of the model. Second, the model needs to be extended to consider the dynamic and stochastic demand case in order to enhance model robustness and make the model more applicable to decision-making control. Third, the real-time data from IoT-connected sensors could increase the model's sensitivity to operational disturbances. Furthermore, hybrid MOPSO with local search/decomposition-based hybridisations, combined with adaptive parameter tuning strategies and the use of high-quality solutions as personal bests, can further enhance the convergence rate and solution quality in large-scale problems.

Declarations

Author contribution: Annisa Kesy Garside: Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Mohd Nabil Bin Muhtazaruddin**: Supervision, Methodology, Validation, Writing – review & editing. **Robiah Ahmad**: Supervision, Methodology, Validation, Writing – review & editing. **Amelia Khoidir**: Writing – review & editing.
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