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Research Article

Optimization of In-Plant Logistics Through a New Hybrid Algorithm for the Capacitated Vehicle Routing Problem with Heterogeneous Fleet

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ABSTRACT

The vehicle routing problem (VRP) is a crucial group of transportation problems, and the traditional capacitated VRP (CVRP) directly handles external logistics with a homogeneous vehicle fleet. This study examines CVRP from the perspective of in-plant logistics, focusing on a heterogeneous fleet within an automotive factory. The homogeneous and heterogeneous vehicle fleets were compared to address the factory's actual in-plant logistics issues. First, simulated annealing (SA), tabu search (TS) algorithms, and mathematical modeling were used. A hybrid approach was proposed, and all the proposed meta-heuristic algorithms were evaluated for homogeneous and heterogeneous vehicle fleets. According to the results, the reduction rates of fleet area and distribution costs using CVRP with heterogeneous fleets are 17% and 36%, respectively. In addition, to examine the effect of the hybrid algorithm parameters on the results, the traveling distance was calculated for different scenarios, and multiple regression analyses were performed. According to the multiple regression analysis, the hybrid algorithm's most affected parameter was the cooling coefficient.

1. Introduction

Production logistics refers to in-plant logistics activities undertaken by manufacturing shops during the production process [1]. Compared with incoming and outbound logistics, in-plant logistics is a less researched area [2]. Ensuring the integration of production logistics with the production process is crucial for achieving efficiency and productivity [3]. A poorly designed material handling system results in excessive in-production material stock, insufficient material supply, and inefficient use of transport resources. Costs can be minimized by standardizing and making the in-plant material handling system traceable.

VRP problems are complex and involve different application areas and cannot be solved by classical methods. There are variations in VRP, such as split delivery VRP, CVRP, multi-depot VRP, VRP with time windows (VRPTW), and periodic VRP. This problem's primary purpose is to minimize the number of vehicles used and the total route length and time while reducing the cost function [4].

This study develops an easily manageable, standardized in-plant transportation system that can reduce costs and increase the value-added time of automotive factories. This research examines the existing in-plant transportation systems of factories in the automotive industry and identifies areas for improvement.

In this study, SA and TS algorithms, along with mathematical modeling, were used to determine semi-finished goods distribution routing with the aim of minimizing the traveling distance with a homogeneous vehicle fleet. Subsequently, a

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hybrid algorithm that combines the TS and SA algorithms was proposed to solve CVRP. Furthermore, all meta-heuristic algorithms were tested on both homogeneous and heterogeneous vehicle fleets. The test results indicate that a heterogeneous vehicle fleet can reduce the number of vehicles and the route distance. The results were also compared with the current situation, demonstrating that the proposed approach enables efficient use of distribution vehicles and reduces non-value-added activities and transportation costs. To analyze the effect of the hybrid tabu search (HTS) algorithm's parameter on the results, the traveling distance was calculated for different parameters, and multiple regression analyses were conducted. According to the multiple regression analyses, the hybrid algorithm's most affected parameter was the cooling coefficient.

Numerous studies have been conducted on VRP. Some relevant studies are summarized below:

Leung et al. [5] and Harmanani et al. [6] proposed the SA algorithm to solve CVRP. Juan et al. [7] proposed a straightforward procedure for solving heterogeneous fleet VRP. Bozyer et al. [8] proposed a heuristic algorithm based on the First Group's principle to solve CVRP. They also proposed a hybrid algorithm that combines SA and Savings Algorithms. Sen et al. [9] proposed two methodologies to address the VRP arising from the demands of a supermarket chain, utilizing a clustering algorithm in the first approach and a genetic algorithm (GA) in the second, with their performance compared through ANOVA analysis. Shaabani and Kamalabadi [10] proposed a hybrid SA algorithm based on GA to solve an ınventory routing problem. The proposed algorithm outperformed the SA and GA alone. Birim [11] used SA to solve the VRP problem via cross-docking. Yu et al. [12] applied SA to solve the hybrid VRP. Wang et al. [13] proposed a hybrid model that combined the SA and TS algorithms, and it demonstrated good results on large-scale problems. Dassisti et al. [14] optimized the routes for material distribution from the depot to production lines using ant colony optimization and mixed ınteger linear programing (MILP). Ferreira and Queiroz [15] proposed two SA-based approaches to solve the CVRP. Wei et al. [16] used SA to solve the two-dimensional CVRP problem and demonstrated superior performance to existing algorithms. Helal et al. [17] proposed two approaches for CVRP systems with evidential demand, both using SA to test problems in the literature. Yazgan and Büyükyılmaz [18] addressed the simultaneous pickup and delivery VRP for a company serving 76 customers, proposing a MILP model and a novel heuristic algorithm to minimize travel distance and vehicle usage, with the algorithm's performance evaluated on various datasets using regression analysis. Simsir and Ekmekci [19] used an artificial bee colony algorithm to solve the VRP problem with simultaneous delivery and pickup. Normasari et al. [20] conducted a study on green CVRP, developed a mathematical model , and proposed SA as a solution; they obtained better solutions in a reasonable time. Zidi et al. [21] proposed a hybrid model that includes SA and TS algorithms for the static ambulance routing problem. Rezaei et al. [22] investigated green VRP with time window constraints while considering a heterogeneous fleet of vehicles and filling stations. Golsefidi and Jokar [23] described the MILP for the production routing problem and proposed SA and GA to solve it. Sakiani et al. [24] developed a mathematical model of the inventory routing problem and solved it using a specialized SA algorithm with a crossover-based search method. Jaballah et al. [25] presented the time-dependent shortest path and VRP, utilizing SA to solve this issue with a fleet of identical vehicles servicing dispersed customer locations across a vast network with travel times subject to time variations. Messaoud [26] investigated a stochastic electric CVRP using a hybrid GA and Monte Carlo simulation procedure. Li and Fu [27] used an improved Symbiotic Organisms Search algorithm combined with variable neighborhood search to solve CVRP, and they demonstrated high solution stability compared to other algorithms. Cavaliere et al. [28] proposed an effective heuristic algorithm for large-scale CVRP instances. Vincent et al. [29] proposed a solution for heterogeneous fleet VRP systems with multiple forward/reverse cross-docks. The proposed solution manages vehicles with dissimilar capacities and delivery and return processes. The authors addressed the challenges of fleet management and routing by employing the SA algorithm with the variable neighborhood descent algorithm as a local search heuristic integrated into the SA framework. . Kumari et al. [30] proposed a novel hybrid algorithm, GA-RR, combining genetic algorithms with the ruin-and-recreate method to solve the CVRP, demonstrating superior performance on 34 benchmark instances and achieving an effective exploration-exploitation balance. Muriyatmoko et al. [31] compared heuristic and metaheuristic algorithms for the CVRP in faculty transportation, highlighting the superior performance of metaheuristics like guided local search and SA for complex scenarios. Fitzpatricket al. [32] introduced a hybrid heuristic for large-scale CVRP, integrating machine learning-based constructive methods with integer linear programming techniques to dynamically partition problems, ensuring fleet-size constraints and achieving solution quality within 3% of the best-known benchmarks. Chi et al. [33] addressed the CVRP with three-dimensional loading constraints (3L-CVRP), proposing improved relocation constraints and a mixed-integer linear programming model, solved using a branch-and-price algorithm, to enhance volume utilization and reduce costs through necessary relocations.

Among the reviewed studies, the scarcity of research on VRP for in-plant logistics is remarkable. To our knowledge, no case study in the current literature has solved the CVRP problem for in-plant logistics systems using the meta-heuristic methods employed in this study while considering both heterogeneous and homogeneous vehicle fleets.

The main contributions of this study are summarized as follows:

(i) This study proposes a hybrid algorithm to solve CVRP that departs from existing approaches. (ii) This study is the first to consider a heterogeneous vehicle fleet for in-plant logistics systems. (iii) A case study was conducted to evaluate the effectiveness of the proposed algorithms in terms of solving identified problems. (iv) Solutions to the vehicle routing problem can be successfully applied in an in-plant logistic system, leading to substantial improvements. (v) Multiple regression analysis was employed to further investigate the impact of the hybrid algorithm's parameters on the case study outcome.

The manuscript is structured into several sections. Section 2 presents the VRP and meta-heuristic algorithm used to solve the problem. Subsequently, Section 3 presents a case study that demonstrates the effectiveness of the proposed algorithm. Finally, Section 4 concludes the paper and provides recommendations for future research.

2. Material and Methods

2.1. Mathematical formulation of CVRP

The VRP was first studied by Dantzig et al. in 1954, marking a significant milestone in the field of operational research [34]. Subsequently, Clarke and Wright [4] expanded on Dantzig and Ramser's method by introducing the classical saving method, which became widely adopted in logistics optimization. A variety of models and algorithms have been proposed to address the diverse complexities of VRPs. VRP solution methods are frequently employed to optimize companies' distribution and collection routes [35].

The characteristics of CVRP, which is the main subject of this study, are as follows [36]:

- The problem involved creating route sets for each vehicle while adhering to cost-efficiency and capacity constraints.
- All vehicles had equal capacities, which were predetermined.
- Customer demands were predefined and known prior to routing.
- Vehicles started and ended their routes at the warehouse.
- Each customer was served exactly once.

The objective function and constraints of the problem were mathematically modeled as follows [37]:

N= Nodes $\{N_1, N_2,\ldots, Nn\}$, N_0= Warehouse

n: Total number of nodes

L_{ij}= Length of the arc from customer i to customer j, (for CVRP $L_{ij} = L_{ji}$)

$V=\{v_1, v_2, \dots, v_m\}$ vehicle fleet

m: Total number of vehicles

$C=\{C_1, C_2, \dots, Cm\}$ vehicle capacities (for CVRP $C_1= C_2= \dots = Cm$)

d_i= Demand of customer i

$$x_{ij}^k=\begin{cases}1, \text{ if vehicle k visits j after i;}\\ 0, \text{ otherwise.}\end{cases}$$

$$y_i^k=\begin{cases}1, \text{ if vehicle k serves node i;}\\ 0, \text{ otherwise.}\end{cases}$$

Objective function:

$$Min\ \sum_{v\in V}\sum_{i,j\in N} L_{ij}x_{ij}^v \quad (1)$$

Constraints:

$$\sum_{v\in V}\sum_{i\in N} x_{ij}^v=1 \qquad \forall i\in N \quad (2)$$

$$\sum_{j\in N} x_{ij}^v+\sum_{j\in N} x_{ji}^v=1 \qquad \forall i\in N,\ v\in V \quad (3)$$

$$\sum_{v=1}^{V}\sum_{j=1}^{n} x_{0j}^v=\mathrm{V} \quad (4)$$

$$\sum_{j\in N} x_{0j}^v=1 \qquad \forall v\in V \quad (5)$$

$$\sum_{j\in N} x_{j,n+1}^v=1 \qquad \forall v\in V \quad (6)$$

$$x_{ij}^v=1\ \Rightarrow y_i d_i=y_j \qquad \forall i,j\in N,\ \forall v\in V \quad (7)$$

$$y_0=C,\ 0\leq y_i \qquad \forall i\in N \quad (8)$$

$$\sum_{v=1}^{m}\sum_{i=1}^{n} d_i \sum_{j=0,\, i\neq j}^{n} x_{ij}^v \leq C \qquad v\in\{1,\dots,m\} \quad (9)$$

$$\sum_{j\in N} x_{0j}\leq m \qquad v\in\{1,\dots,m\} \quad (10)$$

$$\sum_{j\in N} x_{j0}\leq m \qquad \forall j\in N \quad (11)$$

$$x_{ij}^v\in\{0,1\} \qquad \forall i,j\in N, \forall v\in V \quad (12)$$

Equation (1) defines the objective function aimed at minimizing the total distance traveled by the vehicles. Equation (2) ensures that each customer is served by exactly one vehicle, while Equation (3) prevents unnecessary return trips. Equation (4) guarantees that all vehicles depart from the warehouse, and Equation (5) restricts each vehicle to depart only once. Equation (6) mandates that each vehicle visits customers exactly once. Equation (7) calculates the remaining capacity of a vehicle traveling from node *i* to node *j*. Equation (8) defines the initial capacity of each vehicle as Q. Hence, Equation (9) restricts the total demands of customers on a route from exceeding capacity Q. Equations (10) and (11) limit the number of vehicles used to a maximum of m. Finally, Equation (12) ensures that variable x takes binary values (0 or 1).

2.2. Simulated annealing algorithm

The SA algorithm is a stochastic optimization method that mimics the physical annealing process, where a solid transitions to a low-energy state through gradual cooling.

The term annealing refers to the process of transitioning a solid from a high-energy state to a stable low-energy state within a heat bath. This process generally comprises two processes [38].

- The initial temperature of the heat bath is elevated to facilitate the melting of solids.
- Solids attain higher stability at low-energy states, which correspond to lower temperatures. In other words, the arrangement of solid particles becomes more uniform and ordered at lower temperatures. Therefore, the temperature of the heat bath is gradually decreased, allowing the particles to stabilize into a self-regulating and ordered structure.

The SA algorithm aims to find an x solution that optimizes a defined function f (x) in a subset (S) of all possible solution points. The SA starts searching for a randomly selected initial solution. A suitable mechanism then determines a solution adjacent to this solution, and the change in f (x) is calculated. If the difference is in the desired direction, the neighboring solution is the current solution. If no change is observed in the desired direction, the SA accepts this solution with the probability value obtained by the “Metropolis Criteria.” Adopting a solution that creates an inverse change in the objective function with a specific probability value allows the SA to eliminate local best points. When the T value exceeds the above-mentioned probability value, the objective function accepts most of the increases. The acceptance rate decreases as the T value decreases. Therefore, to avoid getting stuck at local SA points, the initial temperature should be high and gradually reduced [39].

Table 1 outlines the pseudocode implementation of the SA algorithm. The main parameters of the SA algorithm are T0: initial temperature, T: current temperature, α: cooling coefficient, P: the acceptance criteria for non-improving solutions, and MaxIt: maximum number of iterations at temperature.

In the beginning, T is set to T0. The value of T can be reduced using the T = T* α formula. When T is below one, the algorithm terminates. If the new solution is better than the best solution, it is updated; otherwise, the new solution may be accepted according to the value P [11].

The following neighborhood structures were illustrated in Figure 1 and explained below.

Swap Method: Two points in a solution are randomly selected. Then, they swap the numbers in these two points [40].

Insertion Method: Two points in a solution are randomly selected. The cell with the minor position is inserted into the position just before the other cell [11].

Reversion Method: Two random points are selected, and the parts standing between them are replaced with each other using the mirror method [23].

Table 1. The SA pseudocode

Algorithm 1: Simulated annealing algorithm	
Step 1:	Select a model
Step 2:	Parameters T0, α, MaxIt
Step 3:	Set Randomize: For Seed = 1 to 10
Step 4:	Generate an random initial solution (X)
Step 5:	Calculate cost of initial solution (X)
Step 6:	Update best solution: Best Solution: X
Step 7:	The current temperature was set to the initial : temperature: T = T0;
Step 8:	Where (T > 1)
Step 9:	for it = 0 to MaxIt2
Step 10:	Create neighbor solutions using swap, reversion and insertion
Step 11:	Generate a random number between 0 and 1: m = rand(0 1)
Step 12:	case m ≤ 0.25 do swap
Step 13:	case m ≥ 0.75 do ınsertion
Step 14:	case % 0.25-0.75 do reversion
Step 15:	Calculate cost of New Solution (xnew)
Step 16:	if cost of xnew ≤ Cost of x
Step 17:	Accept new solution: x = xnew;
Step 18:	else delta = xnew.Cost-x.Cost; p = exp (-delta/T)
Step 19:	Generate a random number between 0 and 1
Step 20:	if random number ≤ P
Step 21:	Accept new solution: x = xnew;
Step 22:	if (Cost of X) ≤ (Cost of Best Solution) and vehicle capacities are not exceed
Step 23:	Update best solution: Best Solution = x;
Step 24:	Reduced temperature : T = α*T
Step 25:	Record the final solution and the corresponding objective value for each seed (from 1 to 10)
Step 26:	End

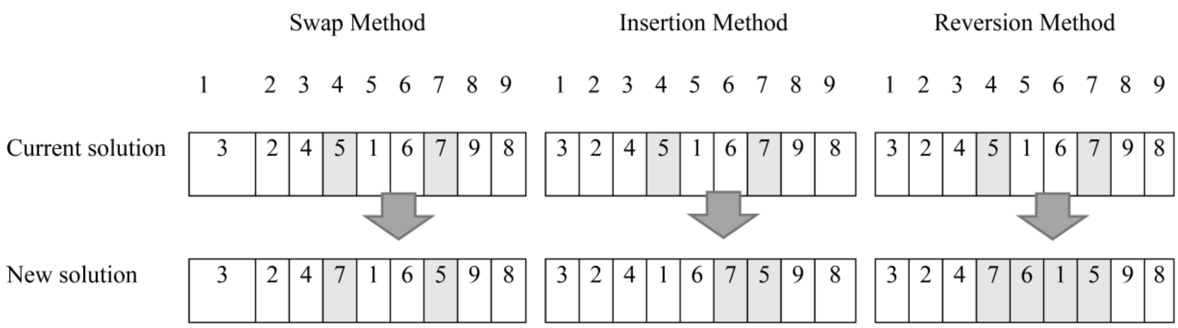

Figure 1. Create a neighborhood structure

2.3. Tabu search algorithm

The TS algorithm is an iterative search algorithm developed by Glover [41]. Meta-heuristic algorithms can perform circular motion while searching the solution space and, in some cases, can be installed at local minimum and maximum points. To avoid cycling, some moves were kept in the Tabu List. This reduces repetitions around exact solutions and helps make discoveries in the search space [42].

The general steps of the proposed TS algorithm are summarized as follows [43]:

Step 1: Determine the initial solution. Memorize the current and best solution.

Step 2: Find neighboring solutions that can be crossed using the specified replacement function.

- Choose a neighboring solution that, if it is not tabu or satisfies the aspiration criterion, even if it is tabu.
- The transition from the current solution to the new one is determined as a tabu.
- If the new solution is better than the best solution, it is considered the best solution.

Step 3: Repeat Step 2 until the stop criterion is met.

The proposed TS algorithm begins with a starting solution and iteratively attempts to identify better solutions. In each iteration, a neighbor of the current solution is selected and evaluated by non-tabu movement. If the objective function value is improved, the neighboring solution is considered the current solution. If a selected move is tabu but meets the aspiration criterion, it can be applied to create the new current solution. Some movements are recorded in the taboo list to prevent backtracks and re-prohibited for a particular time. The algorithm stops working according to a specified stop condition. All steps were repeated for seeds 1–10. The pseudocode for the proposed TS is given in Table 2.

2.4. Proposed hybrid tabu search algorithm (HTS)

A hybrid method integrating the TS and SA algorithms was developed to address the CVRP. The details of the proposed hybrid algorithm are outlined in the subsequent subsections.

2.4.1. Solution representation

Figure 2 illustrates a sample solution representation for the proposed TS algorithm. The solution is represented as a vector, where each element L ∈ {1, 2, 3, ..., n} corresponds to an assembly line, and cell 0 indicates the material distribution depot. Each route begins and terminates at the material stock area. According to this vector, the material distribution routes were determined as r (1): [0 2 1 4 5 0], r (2): [0 3 14 13 12 11 17 15 16 0], r (3): [0 10 9 0], r (4): [0 18 19 7 0], r (5): [0 6 8 0]. Similarly, each route's demand was calculated as r(i.).

2.4.2. Initial solution generation

The method used to create the initial solution affects the performance of meta-heuristic algorithms. Algorithm 1 is used to create the initial solution to improve the proposed algorithm's performance.

2.4.3. Action list generation

The number of possible movements was determined based on the number of assembly lines in the model. A double combination of all assembly lines is created and saved in the action list. For example, the number of movements of the 19 assembly lines can be calculated as 19×(19-1) = 342. The movements are recorded in the action list as [1 2], [2 1] ... [18 19].

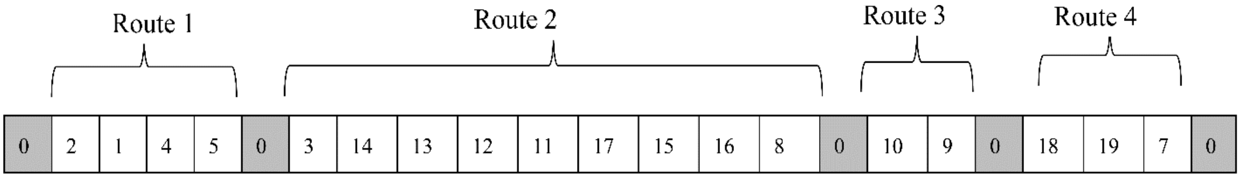

Figure 2. Solution vector

Table 2. Tabu search algorithm pseudocode

Algorithm 2: Tabu Search Algorithm	
Step 1:	Select a model
Step 2:	Set parameters MaxIt, TLs
Step 3:	Create action list
Step 4:	Set randomization: For Seed = 1 to 10
Step 5:	Generate an random initial solution (X)
Step 6:	Calculate cost of X
Step 7:	Update best solution: Best Solution:X
Step 8:	Create empty tabu list
Step 9:	For it = 0 to MaxIt
Step 10:	For i = 1 to nAction
Step 11:	if i. Action is not kept in tabu list
Step 12:	Do i. Action and create new solution (xnew)
Step 13:	Calculate cost of New Solution (xnew)
Step 14:	if cost of xnew ≤ Cost of x
Step 15:	Accept new solution: x = xnew;
Step 16:	end
Step 17:	Update best solution: Best Solution = x;
Step 18:	For i = 1:nAction
Step 19:	if i is the same best solution action index, add i. Action in tabu list
Step 20:	Else Reduce the tabu counter
Step 21:	End
Step 22:	if (Cost of X) ≤ (Cost of Best Solution) and vehicle capacities do not exceed
Step 23:	Update best solution: Best Solution = x;
Step 24:	Record the final solution and final objective value for each seed (from 1 to 10)
Step 25:	End

2.4.4. The HTS procedure

The proposed HTS algorithm is governed by six key parameters, detailed as follows:

MaxIt1: Specifies the maximum number of iterations performed at each temperature level.
MaxIt2: Maximum number of iterations.
TLs: Coefficient used to navigate tabu list size (Tabu list Size = round (TLs*nAction)).
T0: Initial temperature.
Alpha1: Cooling coefficient of initial solution algorithm (cooling formula T = alpha1*T).
Alpha2: Cooling coefficient (cooling formula T = alpha2*T).

The pseudocode of the proposed HTS algorithm is presented in Table 3.

Table 3. Tabu search algorithm pseudocode

Algorithm 3: Hybrid Tabu Search Algorithm	
Step 1:	Select a model
Step 2:	Set parameters T0, alpha, alpha2, MaxIt1, MaxIt2, TLs
Step 3:	Create action list
Step 4:	Set Randomize: For Seed = 1 to 10
Step 5:	Generate an initial solution (x) by using Algorithm 1 (SA Algorithm)
Step 6:	Calculate cost of x
Step 7:	Update best solution: Best Solution: x
Step 8:	Create empty tabu list
Step 9:	For it = 0 to MaxIt2
Step 10:	For i = 1 to nAction
Step 11:	If i. Action is not kept in tabu list
Step 12:	Do i. Action and create new solution (xnew)
Step 13:	Calculate cost of new solution (xnew)
Step 14:	Calculate the deterioration rate:100 * (cost of new solution-cost of the best solution) / cost of best solution
Step 15:	If the cost of xnew ≤ Cost of x
Step 16:	Accept new solution: x = xnew;
Step 17:	elseif Deterioration rate ≤ random number between 0 and 50
Step 18:	Delta = xnew. Cost-x. Cost; P = exp(-delta/T);
Step 19:	Generate a random number between 0 and 1
Step 20:	If random number ≤ P
Step 21:	Accept new solution: x = xnew;
Step 22:	end
Step 23:	Update best solution: Best Solution = x;
Step 24:	For i = 1: nAction
Step 25:	if i is the same best solution action index, add i. Action in tabu list
Step 26:	Else Reduce the tabu counter
Step 27:	End
Step 28:	If (Cost of X) ≤ (Cost of Best Solution) And vehicle capacities are not exceed
Step 29:	Update best solution: Best Solution = x;
Step 30:	Reduced temperature: T = alpha2*T
Step 31:	Write final solution and final objective value for each seed (from 1 to 10)
Step 32:	End

For all possible movements in the member list but not in the taboo list, new solutions from the existing solution were created using the reversion method. The cost and deterioration rate of the new solutions were calculated. If the new solution's cost was lower than that of the current solution, the new solution was accepted. According to the SA algorithm's probability of acceptance (P) characteristic, bad solutions were accepted with operations between 17 and 21 steps. Suppose that the cost of the new solution exceeds that of the current solution. A random number between 0 and 50 was generated (Step 17).

If the deterioration rate was less than the random number, acceptance probability (P), a feature of the SA algorithm, was calculated (Step 18).

A new random number between 0 and 1 was created in Step 19.

If the probability of acceptance was less than the random number (Step 19), the new solution was considered the existing solution (Step 20). Thus, bad solutions in a particular range were selected dynamically, and the algorithm was prevented from being installed in local optimum solutions.

The tabu list was updated with the operations between Steps 23 and 26. The best solution was updated in Step 29. After these processes, the current temperature was reduced according to the determined cooling coefficient. All these operations were repeated to the maximum number of iterations determined in the parameter section.

2.4.5. Move operator and neighborhood structure

The move operator in the HTS algorithm is the reversion method. In this method, two random points are selected, and the parts that stand between them are replaced with each other using the mirror method [23]. For example, the reversion method for [3 2 4 5 1 6 7 8 10 9] when motion is selected from the action list (4, 7) is shown in Figure 3.

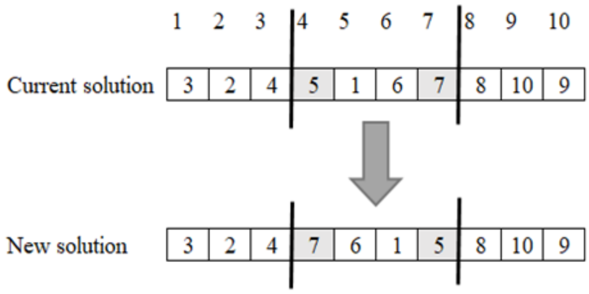

Figure 3. Example reversion method

2.4.6. Tabu list and tabu list size

The tabu list determines which selections should be included in the tabu group within any iteration and determines the number of selected and updated. The size of the tabu list can significantly affect the outcome. The experimental results demonstrate that as the size of the problem increases, the size of the tabu list should increase proportionally to the problem size. In this study, the tabu list was determined by the size of the action list. The formula is the size of the tabu list= round (TLs * size of action list). The TLs coefficient is used to navigate the tabu list size.

2.4.7. Aspiration criteria

The classical aspiration criterion was used in the proposed HTS algorithm. The classical aspiration criterion indicates that if a tabu solution’s cost is better than the best-known solution’s cost, it is accepted even if it exists in the tabu list [44].

3. Implementation

3.1. Problem definition

In this section, the proposed solution approach is implemented for the semi-finished product distribution operations of an automotive factory in Türkiye. To prove the applicability of the meta-heuristic approach and the proposed HTS algorithm, the actual data of the factory were used with some modifications, such as considering homogeneous and heterogeneous fleets. Automotive wire harness production was carried out in 19 assembly lines in the factory. Although the wire harness varies according to the type of vehicle, it consisted of at least 750 m of cable and 2000 different components. Figure 4 shows the use of the harnesses in the vehicle. An

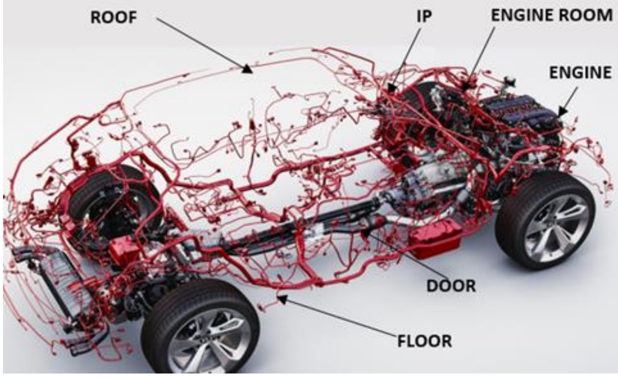

Figure 4. Display of wire harness on a vehicle

average of 85000 semi-finished products were produced daily using 45 wire-cutting machines. The assembly lines (L1 - L19) and the semi-finished goods stock area (D0) are shown in Figure 5. Six homogeneous vehicles were used to distribute semi-finished goods, and 10 operators per shift were assigned to this task. The distribution route of each vehicle starts and ends in the stock area (D0). For instance, route 1 was [D0 L9 L10 D0], and route 6 was [D0 L3 L15 L16 L1 D0].

The objective of this study was to enhance the in-plant material handling systems of automotive factories using the proposed meta-heuristic algorithms. Specifically, this study focused on the distribution of semi-finished goods from the stock area to assembly lines.

Currently, no scientific method has been developed to determine the distribution routes and follow-up of the process. Upon examination of the current situation, the following problems were identified:

- Material distribution routes were not defined.
- No route/task distribution among operators.
- The operators had to cover a greater walking distance.
- Operator performance could not be monitored

3.2. Data set and variables

The data presented below were obtained from observations made within the scope of the application:

- Distribution time

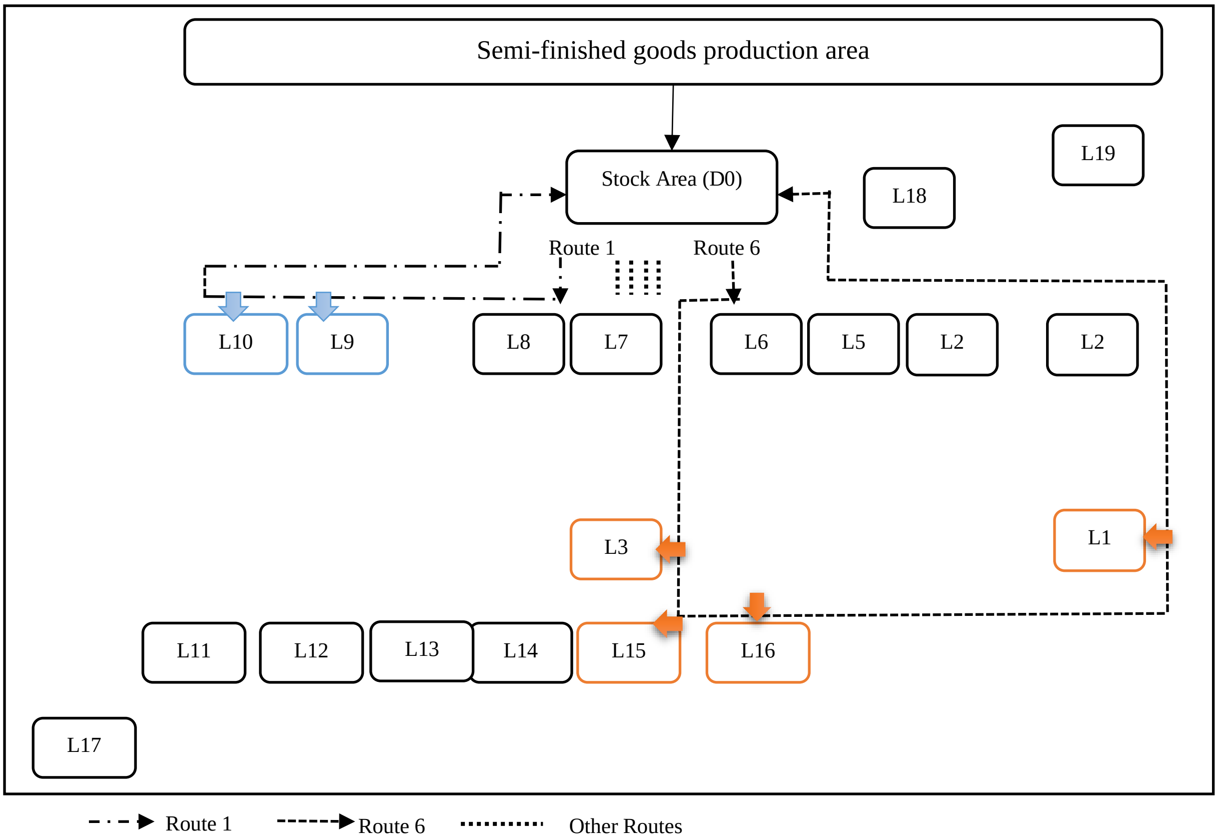

Figure 5. Example layout and routes

In accordance with the time studies, the distribution time of one centimeter of the material was calculated to be 2.3 s/cm.

- Walking time

In accordance with the time studies, walking time was determined to be 2 s/m.

- Capacity of distribution vehicles

The material transport vehicle was equipped with 20 sling arms, each with a length of 20 cm, allowing for a total material capacity of 400 cm. The material distribution vehicle is shown in Figure 6.

- Demand for assembly lines

The demand for the assembly lines was calculated based on the wire specifications, such as the size and length (in cm). The hourly average demand quantities for the assembly lines are given in Table 4.

Table 4. Demand for assembly lines

Assembly line	Request cm for 60 min	Assembly line	Request cm for 60 min
L1	25	L11	28
L2	37	L12	24
L3	24	L13	84
L4	261	L14	74
L5	75	L15	67
L6	213	L16	79
L7	66	L17	18
L8	178	L18	281
L9	244	L19	53
L10	108		


Figure 6. Material distribution vehicle

- Distance between assembly lines

The distances between the stock area and assembly lines are given in Table 5.

The following assumptions were considered in the study:

- In-line transport was not considered.
- The walking speed was calculated based on the observations.
- The material transport vehicle was not malfunctioning.
- All vehicles in the system are homogeneous in the current state.

Table 5. The distance between the assembly lines

	0	L1	L2	L3	L4	L5	…	…	L18	L19
0	0	94	44	40	31	17	…	…	34	66
L1	94	0	47	53	64	74	…	…	58	66
L2	44	47	0	83	17	27	…	…	10	22
L3	40	53	83	0	67	57	…	…	73	105
L4	31	64	17	67	0	10	…	…	8	39
L5	17	74	27	57	10	0	…	…	16	47
…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…
L18	34	58	10	73	8	16	…	…	0	31
L19	66	66	22	105	39	47	…	…	31	0

3.3. Computational experiments and analyses

The mathematical model of CVRP (MM of CVRP), TS, and SA algorithms were proposed to determine the routing that minimizes the number of vehicles required and the traveling time. In addition, a hybrid approach that combines the TS and SA algorithms was proposed to solve this problem. In this section, we present the results obtained using the proposed solution methods.

The CVRP mathematical model was solved using LINGO 18.0, and meta-heuristic algorithms were implemented through coding in MATLAB.

First, the above-mentioned solution methods were used to determine the material distribution routing of the six homogeneous vehicles used in the current state. The obtained results are shown in Tables 6-9.

In Table 6, the routes generated by the mathematical model solution and the distances of these routes were given. The total route length obtained from the mathematical model solution was 691 m.

The routes generated by the proposed TS algorithm are summarized in Table 7. According to the solution, the total route length was 764 m. Table 8 lists the routes generated by the SA algorithm. According to the solution, the total route length was 653 m.

The routes generated by the proposed HTS algorithm are summarized in Table 9. According to the solution, the total distance of the routes was 623 m.

Table 6. The mathematical model (MM of CVRP) solution results

Vehicle no.	Route	Vehicle capacity (cm)	Route length (m)	Demand (cm)	Vehicle occupancy rate %	Route cycle time (min)
1	[0 3 15 16 1 0]	400	188.5	195	49%	14
2	[0 5 4 0]	400	57.5	336	84%	15
3	[0 6 8 0]	400	36	391	98%	16
4	[0 7 14 13 12 11 17 0]	400	197	294	74%	18
5	[0 9 10 0]	400	80	352	88%	16
6	[0 18 2 19 0]	400	132	371	93%	19
Total		2400	691	1939	81%	97

Table 7. The TS algorithm

Vehicle no.	Route	Vehicle capacity (cm)	Route length (m)	Demand (cm)	Vehicle occupancy rate %	Route cycle time (min)
1	[0 15 13 11 14 16 0]	400	203	332	83%	19
2	[0 6 0]	400	16	213	53%	9
3	[0 5 4 0]	400	58	336	84%	15
4	[0 1 2 19 18 0]	400	228	396	99%	23
5	[0 8 10 17 12 3 0]	400	199	352	88%	20
6	[0 7 9 0]	400	60	310	78%	14
Total		2400	764	1939	81%	100

Table 8. The SA algorithm

Vehicle no.	Route	Vehicle capacity (cm)	Route length (m)	Demand (cm)	Vehicle occupancy rate %	Route cycle time (min)
1	[0 16 1 4 0]	400	187	365	91%	20
2	[0 9 10 0]	400	80	352	88%	16
3	[0 18 2 19 0]	400	132	371	93%	19
4	[0 3 15 13 12 11 17 14 7 0]	400	199	385	96%	21
5	[0 8 0]	400	20	178	45%	7
6	[0 6 5 0]	400	35	288	72%	12
Total		2400	653	1939	81%	96

Table 9. The HTS algorithm

Vehicle no.	Route	Vehicle capacity (cm)	Route length (m)	Demand (cm)	Vehicle occupancy rate %	Route cycle time (min)
1	[0 9 10 0]	400	80	352	88%	16
2	[0 7 8 0]	400	21	244	61%	10
3	[0 16 15 13 12 11 17 14 3 0]	400	226	398	100%	23
4	[0 6 0]	400	16	213	53%	9
5	[0 18 19 1 2 0]	400	222	396	99%	23
6	[0 4 5 0]	400	58	336	84%	15
Total		2400	623	1939	81%	95

The results obtained using the four solution methods are compared in Table 10. It can be seen that the proposed HTS algorithm determines distribution routes with shorter route lengths and shorter cycle times than the other solution methods.

Table 10. Comparison of solution results for a homogeneous vehicle fleet

Solution methods	Length of route (m)	Cycle time of route (min)
Mathematical model	691	97
TS algorithm	764	100
SA algorithm	653	96
HTS algorithm	623	95

In addition, meta-heuristic algorithms were tested for scenarios involving both homogeneous and heterogeneous vehicle fleets. In Scenario 1, which represents the current situation with six homogeneous vehicles, the HTS algorithm provided the best result with a routing distance of 623 m and vehicle occupancy rate of 81%. The obtained results are presented in Table 11.

Scenario 2, which utilized a heterogeneous vehicle fleet, resulted in shorter route length than Scenario 3, which used a homogeneous fleet with the same total vehicle capacity. Scenarios 4 and 5 also employed heterogeneous fleets with different total capacities. These scenarios demonstrate that adjusting the total vehicle capacity and using a heterogeneous fleet can reduce the route distance. It was determined that using a heterogeneous vehicle fleet can improve the number of distribution vehicles and route length.

A graphical representation of the material-distributing routing length of the HTS, SA, and TS algorithms is shown in Figure 7. Based on Figure 7, the HTS algorithm provided the optimal solution for all scenarios.

The current situation and results of the methods used in this study are compared in Table 12. It was found that the proposed HTS algorithm determines material distribution routes with the minimum route length to serve all assembly lines. In addition, it was shown that the rate of vehicle capacity utilization (97%) was improved using the suggested meta-heuristic algorithms, and the route distance could be reduced using a heterogeneous vehicle fleet. As a result of the study, a 78% improvement in the route length and a 46% improvement in the material distribution cost were achieved using the HTS algorithm for the heterogeneous vehicle fleet.

Table 11. Comparison of results between homogeneous and heterogeneous vehicle fleets

Test no.	Number of vehicles	Capacity of each vehicle	Total vehicle capacity	Vehicle occupancy rate %	SA	TS	HTS	Gap% (SA-HTS)	Gap% (TB-HTS)
1	6	[400 400 400 400 400 400]	2400	81%	653	764	623	4.8%	22.6%
2	5	[380 380 400 400 440]	2000	97%	629	844	626	0.5%	34.8%
3	5	[400 400 400 400 400]	2000	97%	714	936	658	8.5%	42.2%
4	5	[380 400 420 420 440]	2060	94%	629	844	607	3.6%	39.0%
5	5	[400 400 420 420 440]	2080	93%	630	861	607	3.8%	41.8%

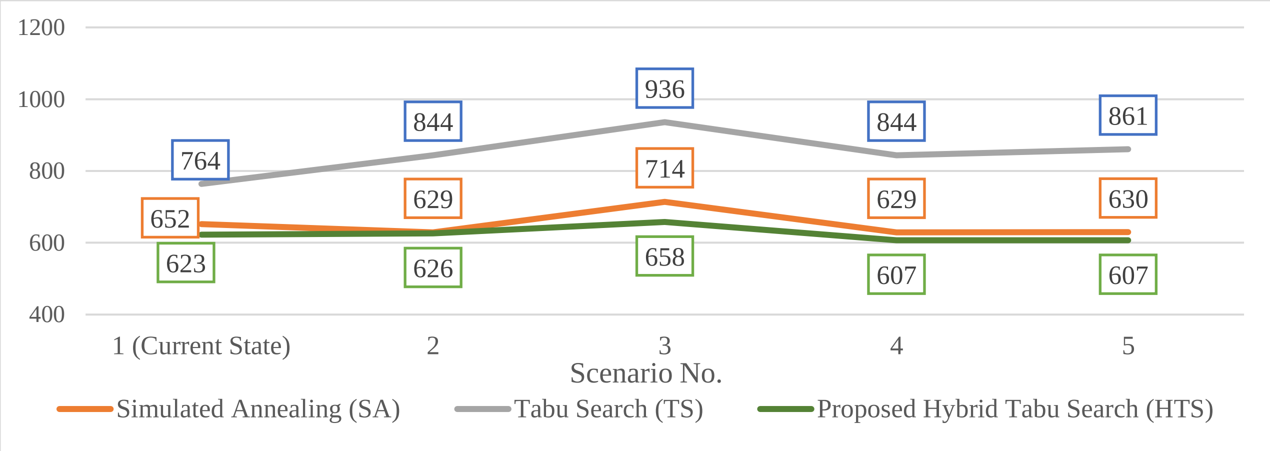

Figure 7. Comparison of solution results

Table 12. Comparison of solution results

Solution method	Current state	Homogeneous vehicle fleet				Heterogeneous vehicle fleet		
		MM of CVRP	SA	TS	HTS	SA	TS	HTS
Capacity of each vehicle	V = [400 400 400 400 400 400] Total = 2400	V = [400 400 400 400 400 400] Total = 2400				V = [380 380 400 400 440] Total = 2000		
Route length (m)	2880	691	652	764	**623**	629	844	**626**
Distribution cycle time (min)	168	97	96	100	**95**	**95**	102	**95**
Number of vehicles (units)	6	**6**	**6**	**6**	**6**	**5**	**5**	**5**
Daily delivery time (h)	61.3	35.4	35.0	36.5	**34.7**	**34.7**	37.2	**34.7**
Daily vehicle preparation time (h)	11	11	11	11	11	9	9	9
Number of operators	10	6.3	6.3	6.5	**6.2**	**6.0**	6.3	**6.0**
Total monthly cost (€)	5276	3667	3644	3735	**3622**	**3377**	3535	**3377**
Rate of capacity utilization (%)	81%	81%	81%	81%	81%	97%	97%	97%
Gain in the route length (%)		76%	77%	73%	**78%**	**78%**	71%	**78%**
Gain of material distribution cost (%)		30%	**31%**	29%	**31%**	**36%**	33%	**36%**

3.4. Statistical analyses

Regression analysis is a statistical method used to examine the relationship between a dependent variable and one or more independent variables, and to quantitatively evaluate this relationship. It is employed to understand the relationship between variables, predict the value of the dependent variable, and measure their degree of influence [45].

The effects of the HTS algorithm parameters on the outcomes were analyzed by calculating the initial route length using various parameters. Multiple regression analyses were performed. The results are presented in Table 13.

Independent variables were defined as follows:

MaxIt1: Maximum number of iterations at each temperature
MaxIt2: Maximum number of iterations
TLs: Coefficient used to navigate tabu list size (Tabu list Size=round (TLs*nAction))
T0: Initial temperature
Alpha1: Cooling coefficient of initial solution algorithm (cooling formula T=alpha1*T)
Alpha2: Cooling coefficient (cooling formula T=alpha2*T)
Means and standard deviations for all variables are presented in Table 14.

Table 13. Route lengths for different parameters

No	MaxIt1	MaxIt2	TLs	T0	Alpha1	Alpha2	Route length
1	20	300	0.1	200	0.99	0.99	642
2	20	300	0.1	250	0.99	0.99	797
3	20	300	0.2	200	0.99	0.99	642
4	20	300	0.3	200	0.9	0.99	754
5	20	500	0.2	200	0.9	0.99	730
6	20	500	0.2	200	0.95	0.99	657
7	20	500	0.3	200	0.9	0.99	731
8	20	500	0.7	200	0.9	0.99	807
9	20	700	0.3	200	0.9	0.99	731
10	30	300	0.2	200	0.99	0.99	640
11	30	500	0.1	200	0.95	0.9	642
12	30	500	0.3	200	0.9	0.99	702
13	50	300	0.1	200	0.98	0.98	629
14	50	300	0.2	100	0.95	0.9	629
15	50	300	0.3	100	0.95	0.9	629
16	50	500	0.5	150	0.98	0.9	700
17	50	500	0.5	200	0.9	0.9	679
18	90	300	0.2	150	0.9	0.95	758
19	90	300	0.2	200	0.7	0.99	837
20	90	300	0.3	200	0.9	0.95	783
21	90	300	0.3	200	0.95	0.99	655
22	90	300	0.5	200	0.7	0.99	802
23	90	500	0.2	100	0.99	0.99	626
24	90	500	0.2	200	0.98	0.99	636
25	90	500	0.2	200	0.99	0.99	626
26	90	500	0.3	200	0.95	0.99	636
27	90	500	0.3	250	0.99	0.99	640
28	90	500	0.5	150	0.99	0.9	626
29	90	500	0.7	100	0.99	0.99	629
30	90	700	0.3	200	0.95	0.99	636

The ANOVA results are presented in Table 15. The significance value (Sig.) in the table was less than 0.05, indicating a significant impact of the independent variables on the dependent variable (Route Length).

Table 16 shows the significant relationships between MaxIt1, MaxIt2, TLs, T0, Alpha1, and Route Length. However, no statistical significance between Alpha2 and Route Length. Based on these findings, we recommend eliminating the Alpha2 parameter. Additionally, the 'Beta' values could determine whether a negative or positive correlation exists between independent and dependent variables. An increase in the TL and T0 values can increase the standard deviation of the Route Length. On the other hand, increasing the MaxIt1, MaxIt2, and Alpha1 parameters decreased the standard deviation of Route Length.

The Beta value indicates the change in the standard deviation of the dependent variable when the independent variable shifts by one unit while the other variables remain constant in the model [46]. According to the beta value shown in Table 15, Alpha1 had the most significant impact on the route length parameter. Specifically, when Alpha1 increases by one unit, the standard deviation of route length decreases by 0.655.

Table 14. Descriptive statistics

	Mean	Std. deviation	N
Route length	687.7000	67.4599	30
MaxIt1	56.3333	31.56639	30
MaxIt2	426.6667	122.98958	30
TLs	0.2933	0.1596	30
T0	185	39.71884	30
Alpha1	0.9333	0.07341	30
Alpha2	0.9969	0.03652	30

Table 15. ANOVA results

Model	Sum of squares	df	Mean square	F	Sig.
1 Regression	89117.45	6	14852.908	7.971	0.000
Residual	131974.3	23	1863.341		
Total	42856.85	29			

Table 16. Coefficients

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	95% Unstandardized coefficients		Correlations			Collinearity statistics	
	B	Std. error	Beta			Lower bound	Upper bound	Zero-order	Partial	Part	Tolerance	VIF
1 (Constant)	1122.11	263.2		4.267	0.00	577.69	1666.53					
MaxIt1	-0.44	0.27	-0.21	-1.65	0.11	-0.99	0.11	-0.15	-0.33	-0.2	0.9	1.11
MaxIt2	-0.1	0.07	-0.18	-1.35	0.18	-0.25	0.05	-0.22	-0.27	-0.16	0.83	1.21
TLs	90.78	57.87	0.22	1.57	0.13	-28.92	210.49	0.17	0.31	0.19	0.75	1.33
T0	0.39	0.25	0.23	1.56	0.13	-0.12	0.89	0.33	0.31	0.19	0.67	1.49
Alpha1	-600.68	119.04	-0.65	-5.05	0.00	-846.9	-354.43	-0.73	-0.73	-0.60	0.84	1.19
Alpha2	97.64	250.1	0.05	0.39	0.7	-419.8	615.08	0.19	0.08	0.05	0.77	1.3

4. Conclusions

The aim of this study was to optimize the distribution routes of semi-finished goods to assembly lines in an automotive factory. This study addressed inefficiencies in labor caused by the absence of job descriptions for distribution operators by using VRP techniques to determine the most efficient material distribution routes.

The SA and TS algorithms, in conjunction with the CVRP mathematical model, were employed to determine the distribution route for semi-finished goods. In addition, a hybrid algorithm that combines the TS and SA algorithms was proposed to solve CVRP. The proposed hybrid algorithm provides the optimal solution for homogeneous vehicles in the factory, generating a route 141 m shorter than the TS and 29 m shorter than the SA, resulting in 18.5% and 4.4% improvements, respectively. Analysis of the distribution routes of the hybrid algorithm showed that assigning operators to specific lines and distributing tasks evenly can reduce distribution costs by 31%.

Furthermore, the proposed algorithms were tested on both homogeneous and heterogeneous vehicle fleets. The use of a heterogeneous vehicle fleet for in-factory logistics systems reduced the number of vehicles required and the total distance traveled. Specifically, using heterogeneous CVRP achieved a 17% reduction in the number of vehicles, a 36% reduction in distribution costs, and a 78% reduction in route length. The capacity utilization rate increased from 81% to 97% when using the proposed HTS algorithm.

In this study, the applicability of CVRP in in-plant logistics systems was demonstrated through the proposed hybrid algorithm using a heterogeneous fleet. The study provided concrete data on improving the distribution routes of semi-finished products, particularly in automotive factories, by comparing homogeneous and heterogeneous fleets. The results showed that heterogeneous fleets are more efficient in terms of both cost and route length. his study contributes to the literature by presenting a new solution for utilizing heterogeneous fleets and demonstrating the effectiveness of meta-heuristic algorithms in logistics systems.

Comparing the obtained results with the current situation shows that the proposed approach enables more efficient vehicle usage while reducing unnecessary activities and transportation costs. Thus, this study provides evidence that VRP solutions are appropriate for in-plant logistics systems and can lead to significant improvements.

Future studies could explore the application of fuzzy logic methods to optimize distribution routes by minimizing travel distance and vehicle usage while accounting for uncertainties in customer demand. The proposed hybrid algorithm could also be applied to different industries and more complex case studies to enhance its generalizability and validate its performance across diverse logistical settings. Furthermore, Furthermore, integrating ergonomic considerations into route optimization could alleviate physical strain on workers, improving both operational efficiency and worker well-being.

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The Declaration of Research and Publication Ethics
The authors of the paper declare that they comply with the scientific, ethical, and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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