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A genetic algorithm model for optimizing vehicle routing problems with perishable products under time-window and quality requirements

Anil Kumar Agrawal [a], Susheel Yadav [b,*], Amit Ambar Gupta [c], Suchit Pandey [a]

[a] Department of Mechanical Engineering, Indian Institute of Technology (BHU) Varanasi, 221005, India
[b] Jindal Global Business School, O.P. Jindal Global University, Sonipat, India
[c] GITAM School of Business, GITAM University, Bengaluru, India

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ABSTRACT

The Vehicle Routing Problem (VRP) has recently piqued the interest of researchers seeking to improve the efficiency and efficacy of the transportation system in distributing commodities. Many scholars have proposed using a heterogeneous fleet in vehicle routing to minimize distribution costs further. When perishable items need to be distributed at numerous demand points during specific time intervals, the situation becomes more difficult. This paper discusses this variant of VRP and the restriction on accepting products with a minimum stated quality level. This research aims to create and optimize a mathematical model that incorporates the quality issue of a perishable commodity into the distribution process. The given product's worth is decreasing as its quality deteriorates. This problem is mathematically represented as a Mixed Integer Non-Linear Programming Problem (MINLP). A Genetic Algorithm-based heuristic is also recommended due to the computational complexity required in applying the model to solve real-world situations. The proposed approach is used to solve numerical cases and perform sensitivity analysis.

1. Introduction

A supply chain includes entities such as suppliers, manufacturers, distributors, retailers, and purchasers involved in the supply, manufacture, distribution and sale of products or services with the objective to serve customers while earning a profit. Supply chain management (SCM) is all about efficiently integrating suppliers, manufacturers, warehouses and stores to achieve the objectives of the supply chain [1]. Fig. 1 depicts the linkage of supply chain management with the other critical related functions. Modern supply chains are complex and entail transporting raw materials, semi-finished items, and finished products.

The collaborative development of logistics and the economy is crucial to any country's development [2,3]. Logistics management increases the efficiency of the entire supply chain [4,5] and is thus an essential component of any supply chain. It is about the acquisition of resources, their storage and transportation to their final destination. In Fig. 2, different functions associated with logistics management are shown.

In recent years, the logistics industry has grown significantly and is also expected to grow at a faster rate for some years [6,7]. Logistics play a critical role in the distribution of perishable products, which includes vegetables, fruits, dairy products, bakeries, medications and vaccines etc. [8]. The distribution problem of perishable products is a difficult task not only because of their limited shelf life but because, even during the transportation itself, they deteriorate [9]. In addition, consumers these days are more concerned than they have ever been about the quality of products that have a short shelf life. If the required minimum level of quality of perishable products cannot be maintained, then buyers will not purchase those products. Finally, such products have to be sold at discounted prices, and in some cases, they will not find any buyers. In order to avoid such cases, retailers pay extra precautions while accepting the delivery of perishable products. Thus, the distribution of perishable products is different from the other products in that it focuses on not only the minimum cost of the distribution but also the quality of the product.

A recent trend is to focus on the transportation part of logistics management as it accounts for the major cost. Hence vehicle planning and routing are attracting plenty of attention from researchers nowadays. In a logistics network, the Vehicle Routing Problem (VRP) aims to efficiently resolve the distribution problem for a product or commodity. VRP creates the routes with the lowest possible cost for the vehicles to distribute the product or commodity to a group of customers. In VRP, the start and end nodes for all routes are the same. VRP is a complex combinatorial optimization problem where optimal routes for different vehicles are designed to distribute the product from the warehouse

* Corresponding author.
E-mail addresses: akagrawal.mec@iitbhu.ac.in (A.K. Agrawal), susheel.bbd@gmail.com (S. Yadav), amitambargupta@gmail.com (A.A. Gupta), suchitp.mec16@itbhu.ac.in (S. Pandey).

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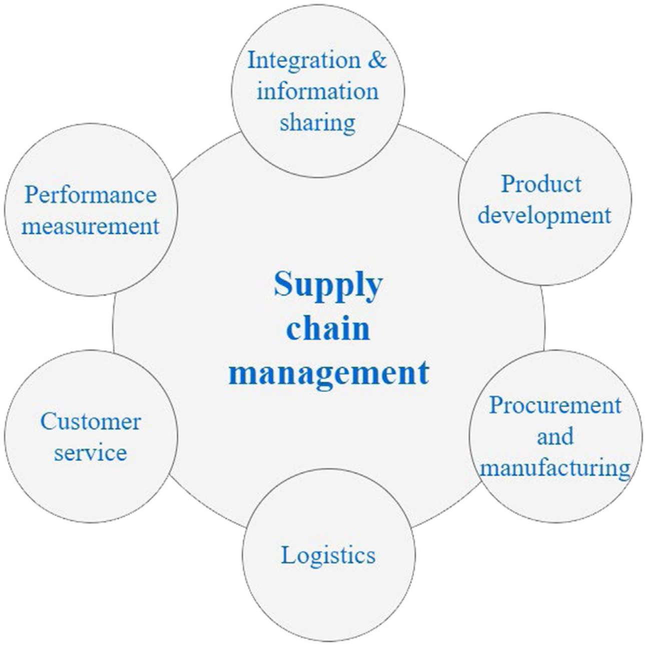

Fig. 1. Linkage of supply chain management with other functions.

to a finite set of customers. Due to its complexity, VRP is referred to as an NP-hard problem which is generally difficult to solve [10–12]. Researchers have used heuristics and exact strategies to tackle complex VRP problems [13,14], and while these methods are capable of providing the optimal solution, they usually take a long time to do so. In such a scenario, metaheuristics play a crucial role because they can deliver a comparable quality solution while requiring a much shorter duration. This study focuses on modelling as an important distribution problem of a perishable product which deteriorates with time and where the retailers are concerned with the quality of the product. A metaheuristics-based solution approach is proposed for solving the problem along with the exact solvers.

The paper is organized as follows: The literature review is presented in Section 2. Section 3 describes the problem and presents the associated mathematical model. Section 4 contains details of the proposed Genetic Algorithm-based heuristic to solve the Heterogeneous fleet Vehicle Routing Problem with a Time Window (HVRPTW). Section 5 illustrates the use of the proposed model with the help of numerical examples. The results of sensitivity analyses are also presented in Section 5. Section 6 is devoted to presenting the conclusions and scope for future work.

2. Literature review

Travelling Salesman Problem (TSP) is a classic problem of routing in which a salesman has to visit each of the cities starting from one and returning to the same while minimizing the total length of the trip or the total travel cost. This problem is equivalent to the one where a single vehicle serves single or multiple products to different retail stores in a single visit or a single vehicle collects a variety of products from all the nodes in a single visit. The vehicle's capacity must be at least equal to the cumulative demand of all the nodes covered in a single trip. Fig. 3 depicts a possible result for TSP where a vehicle starts from the depot and first reaches node 5 and then covers all the remaining 7 nodes as shown in the figure before returning to the depot from node 4.

The classical Vehicle Routing Problem (VRP) aims to find a set of routes at a minimal cost beginning from and ending the trip at the depot so that the known demand of all customers is fulfilled [15]. In the past, many researchers have studied VRP [16]. The main objective of the VRP is to minimize the total distance travelled by all vehicles, which constitutes a significant part of delivery costs. The depot and customers are collectively represented as nodes, and the complexity of the VRP increases with the number of nodes [17]. In Fig. 4, a possible variation of the vehicle routing problem is shown where three routes and hence three vehicles are needed to cover all the demand nodes, and every vehicle starts and ends its journey at node '0'.

VRP is a general name given for a class of combinatorial optimization problems. There are various subclasses of VRP differing from each other. Some of these variations are presented below.

Goel and Gruhn [18] proposed a General VRP (GVRP) model incorporating various real-life application complexities. Their problem involved time window restrictions, a heterogeneous fleet of vehicles with different travel times, travel costs and capacity, order-to-vehicle compatibility constraints, orders with multiple services, pickup and delivery locations, different starting and ending locations for every vehicle, route restrictions for different vehicles and limit on drivers' working hours. They suggested an iterative improvement approach based on changing the neighbourhood structure during the search for the solution. The results of the computational experiments involving several vehicles and transportation requests signified their method's effectiveness. Sadouni [19] proposed a Tabu search-based heuristic algorithm to solve HVRP with time windows and nonlinear penalized delays. The objective function included the weighted sum of the cost of vehicles used, the cost of total distance travelled, and a nonlinear penalty cost of delays. Méndez et al. (2008) formulated a mixed-integer linear programming model (MILP) to solve HVRP with time window constraints and multiple vehicle visits to pickup and delivery nodes. They used Branch and Cut algorithm-based commercial software package to find optimal vehicle routes. Penna et al. [21] proposed an Iterated Local Search (ILS) metaheuristic using a variable neighbourhood descent procedure to find an optimal solution for HVRP. They tested their developed heuristics on five variants of HVRP with varying numbers of customers and limited and unlimited fleet sizes. Kritikos and Ioannou [22] addressed a new variant of HVRP with permissible overloads where a penalty cost due to overloads, lesser than the pre-defined limit, is considered. They proposed a sequential insertion-based heuristic to solve the benchmark data sets of Solomon [23]. Mungwattana et al. [24] considered a practical case study of a third-party logistics firm in Thailand and modelled an HVRP with time windows, multi-product deliveries and limited availability of vehicles and drivers. They used the Genetic Algorithm and Branch and Bound approaches to find the optimal solution. Cheng et al. [25] introduced a green inventory routing problem (IRP) with a heterogeneous fleet. A mixed-integer linear mathematical programming model (MILP) was developed to minimize the total cost, including load-dependent fuel consumption and emission cost. Numerical tests were conducted to quantify the benefits of this comprehensive study.

Logistics of deteriorating items

Logistics management of deteriorating items has received increasing research attention in recent years. Hsu et al. [26] proposed a vehicle routing problem with the time windows (VRPTW) model to find optimal delivery routes, loads and fleet departure times to deliver deteriorating food from the distribution centre to customers. Algorithms were developed to solve the proposed model that considered time-dependent travel time and temperature. Osvald and Stirn [27] have used the Tabu search approach to solve the VRPTW of fresh vegetables and considered the deterioration of product quality in terms of the associated cost. They applied this model to solve modified versions of Solomon's problems. Rong et al. [28] provided a quality degradation function showing the importance of temperature settings on product quality and assigned a cooling cost to maintain the desired quality level. A mixed-integer linear programming model (MILP) was developed to study production and distribution planning. Yu and Nagurney [29]

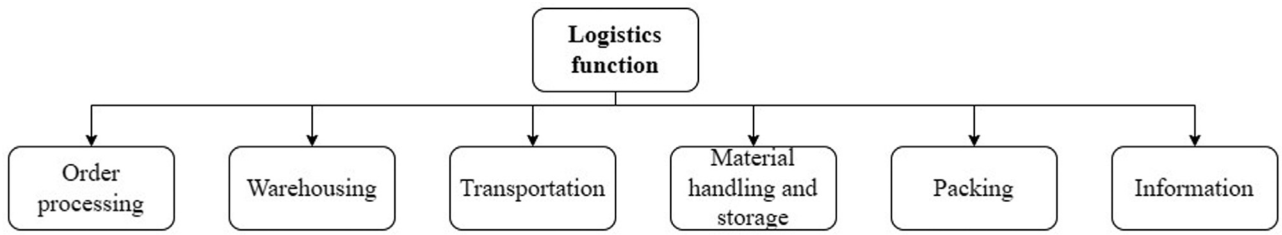

Fig. 2. Different functions associated with logistics.

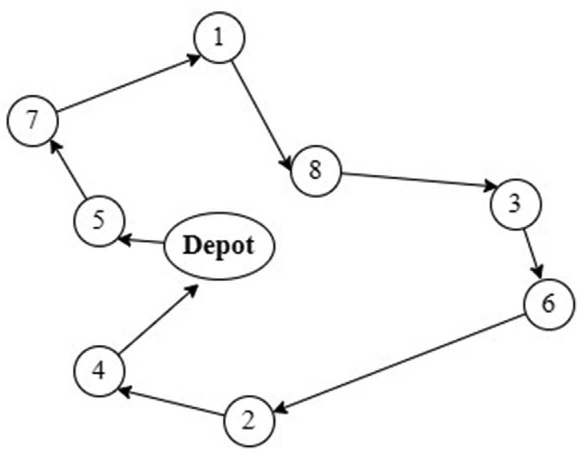

Fig. 3. An example of travelling salesman problem.

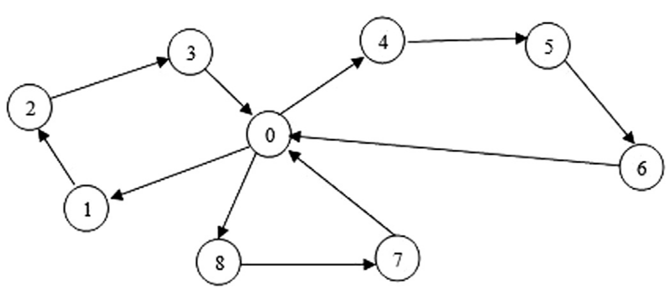

Fig. 4. A variation of vehicle routing problem.

developed a network-based food supply chain model where food deterioration and discarding costs were considered. The model was used to find the solution to a real-life problem. Nakandala et al. [30] consider the storage temperature settings of trucks and the transportation period as decision variables in their multi-product supply chain model. They proposed three approaches, Genetic Algorithm (GA), Fuzzy Genetic Algorithm (FGA) and Simulated Annealing (SA), with a repair mechanism for solving the problem. The performance evaluation showed that the FGA had performed better than the other two approaches. Jafari Nozar and Behnamian [31] studied a multiobjective optimization problem of perishable products considering vehicle routing and scheduling where they want to minimize the cost while maximizing the customer's purchase probability. They used the non-dominated sorting genetic algorithm-II (NSGA-II) for the solution. Ghasemkhani et al. [32] considered a multi-product case of perishable items with multi-period time horizons. They considered the fleet of vehicles as heterogeneous. They proposed two evolutionary heuristics for the solution.

Distribution of deteriorating items under a heterogeneous fleet of vehicles

A heterogeneous fleet of vehicles gives rise to another version of VRP. Many a time distributor or third-party fleet operator owns a fleet with vehicles of different capacities [33,34]. Qiang and Jiuping [35] formulated a fresh agricultural products vehicle routing problem with a heterogeneous fleet of vehicles (HVRPTW) to minimize total cost and maximize customer service level in terms of acceptable delivery time. They proposed a random fuzzy multiobjective Dependent Chance Programming (DCP) model to account for randomness in demand. To solve it, they designed a hybrid intelligent algorithm (integrating random fuzzy simulation and genetic algorithm).

Amorim et al. [36] focused on a heterogeneous fleet vehicle routing problem with multiple time windows as a case study for a Portuguese Food Distribution Company. They used an adaptive extensive neighbourhood search framework to find the optimal solution. Rabbani et al. [37] proposed a mix-integer nonlinear programming model to maximize the distributor's profit and the freshness of the delivered products. They solved their proposed model with the TH method [38]. Genetic Algorithm and Simulated Annealing algorithm-based approaches were also proposed for large-sized problems. Shahabi-Shahmiri et al. [39] studied a scheduling and routing problem with the consideration of cross-docking for heterogeneous vehicles which carry perishable products. Their study was inspired by a real case of a supermarket chain. They also considered a deadline for pickups and deliveries. Máximo et al. [40] also studied HFVRP and implemented an adaptive iterated local search (AILS) heuristic for solving the HFVRP. AILS is nothing but an adaptive version of iterative local search (ILS). Küçük and Yildiz [41] considered a capacitated vehicle routing problem where they considered the capacity of the vehicle while solving the vehicle routing problem.

This paper addresses the problem of distributing a deteriorating item from a warehouse to several retail stores. A mixed integer nonlinear programming model is proposed for the Heterogeneous fleet Vehicle Routing Problem with Time Window (HVRPTW), subjecting the acceptance of the product to some minimum specified quality level. The objective is to minimize the total cost consisting of fixed costs of hiring the vehicles and drivers, the variable cost of transportation, loss in value because of diminishing quality of supplied product and a penalty cost on being late from the allowed time. This allowed time is within the specified time window. The penalty must be borne if the item is supplied after this time. In no case will the item be accepted beyond the specified time window.

3. The problem and formulation

This paper considers the problem of distributing a deteriorating item from a warehouse to several retail stores. The distribution is to be carried out using a heterogeneous fleet of vehicles with different travel times, travel costs and storage capacities. The hiring cost of vehicles is also considered. The cost of hiring drivers is the same and is independent of the type of vehicle they would operate.

Retail stores have varying demands for the product, which can be met in a single supply by some vehicle types. Retail stores would accept the product only when it is of some acceptable quality level. The product quality keeps falling with time, but it must reach a store by some specified time by the retailer. After this time, the distributor has to pay a fine based on how late they were up until the latest time and how many units were ordered. There is no restriction on the early supply of products to any retail store.

The route that a vehicle will follow is the sequence of visiting the retail stores. Such sequences determined serve the purpose of routing decisions. Vehicles start and end their trip at the warehouse only, and these cannot carry items in quantity more than their capacity at any time.

Opportunity cost due to loss in products' quality is based on the consideration of Rong et al. [28], who described the change in food quality q over time t as:

$$\frac{dq}{dt} = -k'q^n \tag{1}$$

where q = quality of the product

k' = rate of decay in quality, and

$n = 0$ for a fresh product such as foods and vegetables

From Eq. (1), $q = -k't + q_0$
where q_0 = quality of product at time $t = 0$.

The expression for the cost corresponding to the loss in quality of the product will be:

$$\text{Unit product devalue cost} = C_q(q^\beta - 1) \tag{2}$$

where C_q represents the value of one unit of the product with no deterioration and β is a constant ($\beta < 0$). Therefore, the total opportunity cost due to the loss in the value can be computed by multiplying the unit product devalued cost with the total number of units of the product supplied to that retail store.

For the mathematical formulation of the problem, the following notations have been used.

Indices

i : Avehicle type
j, k : Nodes

Parameters

β : A constant
I : Number of different types of vehicle
k' : Rate of decay/degradation in product' s quality
N : Total number of nodes
q' : Minimum acceptable quality level
C_d : Cost of hiring a driver
C_p : Penalty cost per unit of product per unit time for being late than the allowed time
C_q : Devalued cost per unit product due to quality lost
D_k : Demand for the product at node $k(D1 = 0)$
P_i : Capacity of vehicle type i
v_i : Speed of vehicle of type i
V_i : Number of vehicles of type i used
C_{hi} : Cost of hiring a single vehicle of type i
C_{it} : Transportation cost per unit time for vehicle type i
d_{jk} : Distance between nodes j and k
L_{ak} : Time for product's arrival at node k without any penalty ($k = 2, 3, \dots, N$)
L_k : Latest time for receipt of the product by node k ($k = 2, 3 \dots, N$)

Decision Variables

$$p_k : \begin{cases} 1 \text{ When the product arrives at node k} \\ \quad \text{later than the allowed time} \\ 0 \text{ Otherwise} \end{cases}$$

q_k : Quality level of the product when it reaches node k ($k = 2, 3 \dots, N$)
t_k : Arrival time of products at node k ($k = 2, 3 \dots, N$)
W_{ik} : Number of units of product left in vehicle type $i$after serving node k ($k = 2, 3, \dots, N$)

$$X_{ijk} : \begin{cases} 1 \text{ if vehicle type } i \text{ travels from node } j \text{ to } k \\ 0 \text{ Otherwise} \end{cases}$$

Using the above notations, the mathematical programming formulation of the problem is as follows:

$$Minimize\ Z = \sum_{i=1}^{I}\sum_{j=1}^{N}\sum_{k=1}^{N}\left[\left(\frac{djk}{vi}\right) C_{it}X_{ijk}\right] + \sum_{i=1}^{I}[(C_{hi} + C_d)V_i] + \sum_{k=2}^{N}[C_q(qk^\beta - 1)D_k] + \sum_{k=2}^{N}[(t_k - L_{ak})C_p p_k D_k] \tag{3}$$

Subject to constraints:

$$qk \geq \left\{qj - \left(\frac{djk}{vi}\right)k'\right\} X_{ijk} \qquad \forall i, \forall j, k = 2, 3, \dots, N \tag{4}$$

$$qk \geq q' \qquad k = 2, 3, \dots, N \tag{5}$$

$$q_1 = 1 \tag{6}$$

$$tk \geq \left\{tj + \left(\frac{djk}{vi}\right)\right\} Xijk \qquad \forall i, \forall j, k = 2, 3, \dots, N \tag{7}$$

$$t_k \leq L_k \qquad k = 2, 3 \dots, N \dots \tag{8}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{N} Xijk = 1 \qquad k = 2, 3, \dots, N \tag{9}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{N} Xijk = \sum_{i=1}^{I}\sum_{j=1}^{N} Xikj \qquad k = 1, 2, \dots, N \tag{10}$$

$$\sum_{k=2}^{N} Xi1k = V_i \qquad \forall i \tag{11}$$

$$W_{i1} \leq P_i \qquad \forall i \tag{12}$$

$$Wik \geq [(Wij - Dk)\,Xijk] \qquad \forall i, \forall j, k = 2, 3, \dots, N \tag{13}$$

$$(t_k - L_{ak})\,(p_k - 1) \geq 0 \qquad k = 2, 3 \dots, N \tag{14}$$

$$Wik \geq 0 \qquad \forall i, k = 2, 3 \dots, N \tag{15}$$

$$X_{ijk} \in \{0, 1\} \qquad \forall i, \forall j, k = 2, 3 \dots, N \tag{16}$$

$$p_k \in \{0, 1\} \qquad k = 2, 3 \dots, N \tag{17}$$

The objective function (3) has four terms. The first term shows transportation cost, while the second term represents the total cost of hiring various vehicles and drivers. The third term is the opportunity cost due to deterioration in the quality of the product supplied to the retail store. The fourth term represents penalty cost due to late arrival. Constraint (4) finds out the resulting quality of the product arriving at a retail store. Constraint (5) will help ensure the product's final quality reaching a retail store is greater than the minimum specified quality level. Constraint (6) states that the product quality level is the best when it is dispatched from the warehouse (i.e., from node 1) for distribution to different retail stores. Constraint (7) finds the time of arrival of the product at a retail store, while constraint (8) makes sure that this arrival time must be within the latest time for the receipt of the product. Constraint (9) ensures that a retail store is visited by only one vehicle of any of the available types. Constraint (10) takes care of flow conservation to ensure that every vehicle reaching a node must also leave it. Constraint (11) finds out the total number of a type of vehicles put into use. Constraint (12) represents the total number of units of the product in a vehicle once it departs from the warehouse, while constraint (13) determines the number of units of the product left after a retail store has been served. Constraint (14) is used in determining whether a vehicle is reaching a node in time or not. It will help in penalty cost computation in the case of the late supply of the product. Constraint (15) makes sure that the total number of units of product remaining in any vehicle after serving any node cannot be negative Constraints (16) and (17) show that the related decision variables can have only binary values.

4. Genetic algorithm-based heuristic

Genetic Algorithm (GA) is one of the popular optimization metaheuristics. It is based on Charles Darwin's theory of natural selection

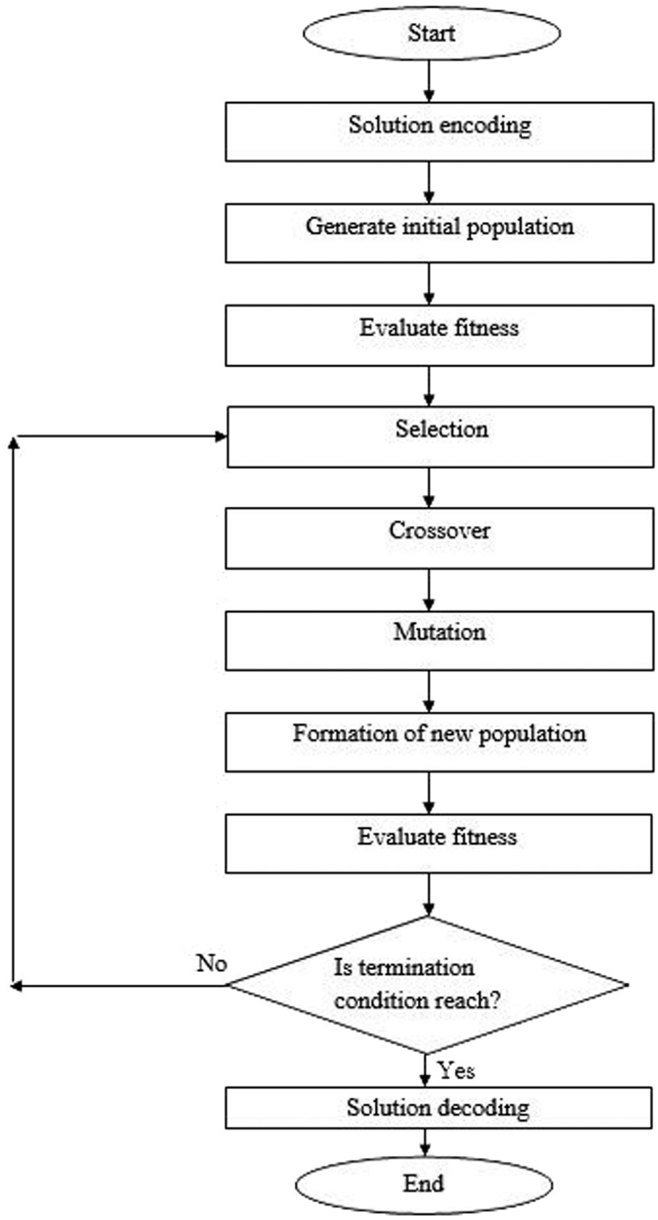

Fig. 5. Structure of the Genetic Algorithm.

and evolution. GA works on the principle of survival of the fittest over many generations. Each generation has a population of chromosomes. An individual chromosome, made of a number of genes, represents a solution for the problem. These chromosomes are exposed to the process of evolution, where genes from good individuals combine to form offspring. This process continues in successive generations, and one gets the fittest chromosome or an optimal solution for the problem in the last. The overall structure of GA is shown in Fig. 5. Various steps of the proposed heuristic are described below.

Solution Encoding

The chromosome chosen is a non-binary number string, with the number of genes equal to three times the number of retail stores (excluding warehouse). For a better understanding of the solution representation, this string in 3 parts is shown in Fig. 6. For a problem with seven nodes, node 1 is the warehouse, and the other nodes represent the retail stores. In the first row, all the nodes are randomly filled up. The second row is filled up by randomly deciding vehicle types used for serving them. The third row mentions the vehicle index of a vehicle type mentioned in row 2. If the quality, capacity and reaching time constraints are violated, then an additional copy of the same vehicle type is added to the third row. The same will be obvious from Fig. 6. According to the information in row 2, vehicle type 1 was planned for meeting the requirement of nodes 3, 2 and 4 in order. On noticing that some of the above-mentioned constraints are violated in the use of this vehicle type to meet the requirements of node 4, an additional vehicle of type 1 is then employed to serve node 4. This vehicle index is mentioned as 2 in row 3. This process is detailed in Fig. 7.

Generate initial population

Following the scheme for the solution encoding, a good number of chromosomes are generated, and the same form the initial population.

Fitness evaluation

Before performing the selection operation, every individual chromosome's fitness is evaluated using a fitness function, which is nothing but the objective function itself. The fitness value for any chromosome is the total cost of distributing the products to various nodes.

Selection

The roulette-wheel selection mechanism is used to select individuals for further operations. The total number of chromosomes selected is equal to the population size.

Crossover

Crossover is an operator used to produce offspring by combining the genetic information of two chromosomes. The number of individuals that take part in the crossover operation is obtained by multiplying the crossover rate by the population size. Here, the single-point crossover is used to produce offspring, and a rationalization procedure is adopted to convert infeasible offspring, if any, into feasible ones. Even though it may appear that the multi-point crossover strategy is being adopted, the fact is that single-point crossover is used with a slight variation. The logic followed is described below with the help of Fig. 8.

Fig. 8 (a) shows the two parent chromosomes to be used for the crossover. Let the cross-site be 2. This cross-site will be applicable to all three rows. In case the three rows are taken as one single array, then the cross-site values will be 2, (N + 2), and (2N + 2). After the crossover, the two resulting chromosomes will be as shown in Fig. 8(b). From this figure, it can be seen that some of the nodes are missing while some are repeated. For example, in offspring 1, nodes 5 and 3 repeats, while nodes 2 and 7 are missing. A procedure is adopted to overcome this problem by substituting missing nodes in place of repeated nodes. After this operation, the two offspring will be, as shown in Fig. 8(c). It is the outcome of a rationalization procedure (detailed in Fig. 9) that converts an infeasible solution into a feasible one. In the flowchart of Fig. 13, "3 constraints" refer to constraints (5), (8) and (12).

Mutation

The mutation operator is used to maintain diversity in the population by changing the value of the randomly selected genes. Here mutation operation is performed on the genes of the first two rows only. Mutation sites are determined by multiplying population size with mutation rate and twice the value of $(N-1)$. If the randomly selected gene belongs to row 1, then its value is interchanged with any of the randomly selected nodes except with node 1. If it is in row 2, then the genes' value is changed to any of the vehicle type. Feasible chromosomes may become infeasible after undergoing a mutation operation. The rationalization procedure detailed in Fig. 9 is adopted to make them feasible.

Formation of a new population

Each of the new offspring's fitness values obtained after crossover and mutation is determined at this stage. In the new population, to be of the same size, those from old chromosomes of the current population

Row 1:	5	7	3	2	4	6
Row 2:	2	2	1	1	1	3
Row 3:	1	1	1	1	2	1

Fig. 6. Representation of a chromosome.

Table 1
Data related to different types of vehicles.

Vehicle type	Capacity (units)	Fixed hiring cost ($)	Speed (km/h)	Transportation cost ($/h)
1	12	1200	30	30
2	08	900	40	25
3	04	600	50	20

Table 2
Data related to various nodes.

Node	Demand (Units)	Allowed time (h)	Latest time (h)
1	0	–	–
2	1.1	4	8
3	1.4	4	8
4	1.8	4	8
5	2.1	4	8
6	1.2	4	8
7	1.9	4	8
8	1.9	4	8
9	1.4	4	8
10	1.6	4	8
11	1.8	4	8
12	1.6	4	8
13	2.5	4	8
14	2.1	4	8
15	2.2	4	8
16	2.6	4	8

and new offspring are retained that have superior fitness value than those that will be rejected.

Termination

The selection, crossover, mutation and formation of the new population is continued for some specified number of generations. The chromosome with the best value in any generation is taken to represent the optimal solution.

5. Results and discussion

The proposed model in Section 3 is used to solve an illustrative example using LINGO Lindo Systems Inc [42] software for solving optimization problems. Sensitivity analysis has also been carried out by changing the values of certain parameters of the example problem.

5.1. Illustrative example

The example problem is with a warehouse and 15 retail stores. Data regarding the distance between two nodes (Table 3) and the demand at various retail stores (Table 2) is taken from the work of Qiang and Jiuping [35]. A heterogeneous fleet of 3 types of vehicles is taken to be available with the distributor. The capacity of different vehicle types, their hiring cost, speed and unit time transportation cost are shown in Table 1. Table 2 shows the time window for various retail stores along with their demand. Additional data are as follows:

Penalty cost per unit time per unit product (C_p) = \$40

Cost of hiring one driver (C_d) = \$400

Cost of a single unit of the product without any deterioration (C_q) = \$500

$\beta = -1$

The rate of deterioration in product's quality (k') = 2% per hour, which is defined as the rate of degradation which may depend upon environmental factors like temperature etc., and a rate of 2% means that the quality drops by 2% in an hour.

Minimum acceptable quality level (q') = 80%

The example problem was solved with the above data using the mathematical model. The resulting routes from the warehouse to other retail stores are shown in Fig. 10. From this figure, the following can be noticed.

- Three vehicles (one of type 1, two of type 2 and none of type 3) are used.
- Vehicle type 1 starts from node 1 and delivers the product to nodes 16, 11, 15, 9, 12 and 14 in sequence before returning to node 1. It is utilizing 97.5% of its capacity.
- First, the vehicle of type 2 goes from node 1 to node 3 and then to nodes 2, 6, 4 and 13 in sequence, and then returns to node 1. Its capacity is fully utilized.
- The second vehicle of type 2 moves from node 1 to node 5, and then to nodes 7, 8 and 10 in sequence before returning to node 1. It is utilizing 93.75% of its capacity.

Table 4 shows the arrival time and quality of products arriving at the retail stores. All the nodes are visited before the latest time. However, nodes 9, 12, 13 and 14 are served after no-penalty time. Table 5 shows resultant values for various cost elements.

5.2. Validation of the proposed model

In this section, some of the problem parameters, such as minimum acceptable quality level, latest time and quality deterioration rate, are modified to visualize their impact and whether it is in line with the general and shared understanding.

Effect of increased acceptable quality level

Once the acceptable quality level is increased, the routing solution has to ensure that the deterioration in quality is comparatively less to meet the requirement on the increased quality level. This may ask for a greater number of vehicles for the quick supply of the product to the retail stores. This feature of the model is explained with the help of the example problem. The quality of the product served to nodes 9, 12 and 14 is less than 90%. On increasing the minimum acceptable quality level from 80% to 90% and solving the example problem once again, a routing solution shown in Fig. 11 is obtained. From this figure, it can be seen that nodes 9, 12 and 14 are now served with vehicle type 2 instead of type 1. At the same time, a type 3 vehicle is also used along with one type 1 and two types 2 vehicles to match the quality constraint. This solution shows a change in the mix of vehicles and their total number put into operation. Table 6 shows the time and quality of products arriving at various retail stores, while Table 7 shows optimal values for various cost elements. From the two tables, the following observations can be made.

- The hiring cost of vehicles and drivers increased as the vehicle of type 3 is being hired now.
- The penalty cost was reduced due to less time taken by the vehicles to serve the nodes.
- Quality deterioration cost also decreased as the product is served in lesser time with higher quality.
- The overall cost increased from \$6621 to \$6734.

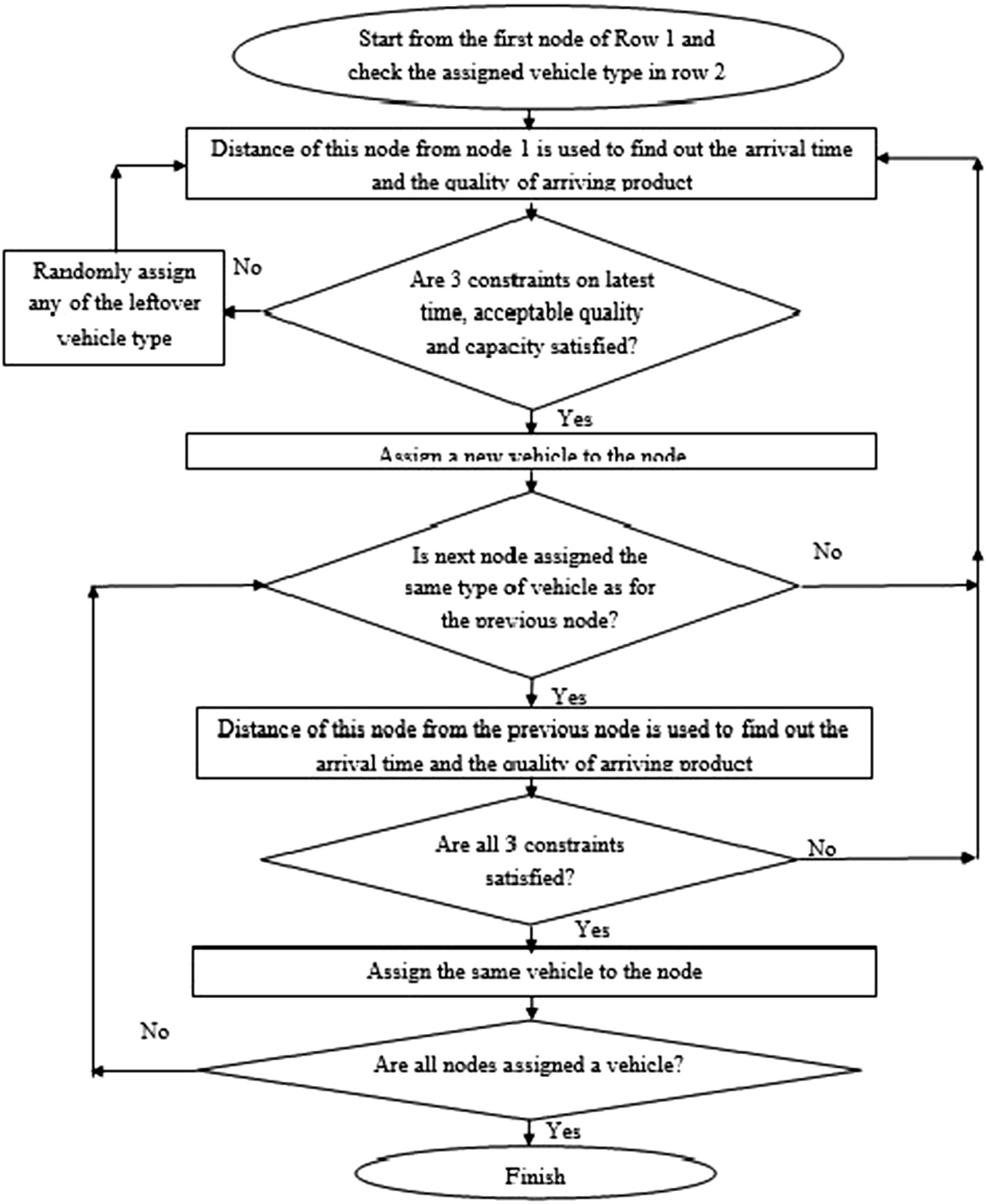

Fig. 7. Procedure to assign a vehicle to various nodes.

Row 1	5	3	2	6	4	7
Row 2	2	2	1	1	3	1
Row 3	1	1	1	1	1	2

Parent 1

Row 1	2	7	5	4	6	3
Row 2	1	1	2	3	3	2
Row 3	1	1	1	1	2	2

Parent 2

(a) Before crossover

Row 1	5	3	5	4	6	3
Row 2	2	2	2	3	3	2
Row 3	1	1	1	1	2	2

Off-spring 1

Row 1	2	7	2	6	4	7
Row 2	1	1	1	1	3	1
Row 3	1	1	1	1	1	2

Off-spring 2

(b) After crossover

Row 1	5	3	2	4	6	7
Row 2	2	2	2	3	3	2
Row 3	1	1	1	1	2	2

Off-spring 1

Row 1	3	7	2	6	4	5
Row 2	2	2	2	3	3	2
Row 3	1	1	1	1	2	2

Off-spring 2

(c) Final off-springs

Fig. 8. Crossover operation.

Table 3
Node to node distance (km).

Node	Node 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0	39.0	37.5	39.5	38.5	40.0	80.0	85.5	86.5	90.5	92.5	136.5	140.0	137.5	53.0	49.5
2	39.0	0	7.5	13.0	35.5	30.5	40.0	48.5	76.5	57.5	60.0	151.5	106.5	156.5	25.5	20.5
3	37.5	7.5	0	15.0	13.5	38.5	55.5	89.0	40.5	105.5	115.5	99.5	158.0	111.5	20.0	26.5
4	39.5	13.0	15.0	0	15.5	21.5	46.5	43.5	78.5	51.5	45.5	155.5	109.5	157.0	21.0	18.5
5	38.5	35.5	13.5	15.5	0	14.5	58.5	75.5	42.0	84.0	81.5	100.5	160.5	107.5	23.5	21.5
6	40.0	30.5	38.5	21.5	14.5	0	45.0	105.5	45.0	88.5	79.5	101.5	159.0	106.5	21.5	24.0
7	80.0	40.0	55.5	46.5	58.5	45.0	0	23.5	45.5	42.5	42.5	75.5	65.5	98.5	30.5	34.5
8	85.5	48.5	89.0	43.5	75.5	105.5	23.5	0	25.0	25.0	38.5	78.5	62.5	100.0	34.0	33.5
9	86.5	76.5	40.5	78.5	42.0	45.0	45.5	25.0	0	21.4	65.5	58.5	80.5	56.5	35.5	36.0
10	90.5	57.5	105.5	51.5	84.0	88.5	42.5	25.0	21.4	0	22.5	75.0	66.5	97.5	38.0	32.5
11	92.5	60.0	115.5	45.5	81.5	79.5	42.5	38.5	65.5	22.5	0	60.5	59.5	95.0	34.5	31.5
12	136.5	151.5	99.5	155.5	100.5	101.5	75.5	78.5	58.5	75.0	60.5	0	25.5	20.5	88.5	95.5
13	140.0	106.5	158.0	109.5	160.5	159.0	65.5	62.5	80.5	66.5	59.5	25.5	0	25.5	90.5	93.5
14	137.5	156.5	111.5	157.0	107.5	106.5	98.5	100.0	56.5	97.5	95.0	20.5	25.5	0	85.0	96.5
15	53.0	25.5	20.0	21.0	23.5	21.5	30.5	34.0	35.5	38.0	34.5	88.5	90.5	85.0	0	97.0
16	49.5	20.5	26.5	18.5	21.5	24.0	34.5	33.5	36.0	32.5	31.5	95.5	93.5	96.5	97.0	0

Effect of decreased quality deterioration rate

When the rate of quality deterioration is low, the quality of a product reaching a node should be less of a problem than when the rate of quality deterioration is high because the first product is likely to be of better quality, even if both take the same amount of time to get there. As a result, the number of required vehicles may decrease with the possibility of each vehicle utilizing more of its capacity. This feature of the model is explained with the help of the same example problem by decreasing the quality deterioration rate from 2% per hour to 1% per hour. For this case, the optimal vehicle route obtained is shown in Fig. 12. Although the vehicles used are the same, the stores covered by them differ. Understandably, there is a considerable decrease in the quality-deterioration cost. Table 8 shows the arrival time and quality of products arriving at the retail stores, while Table 9 shows optimal

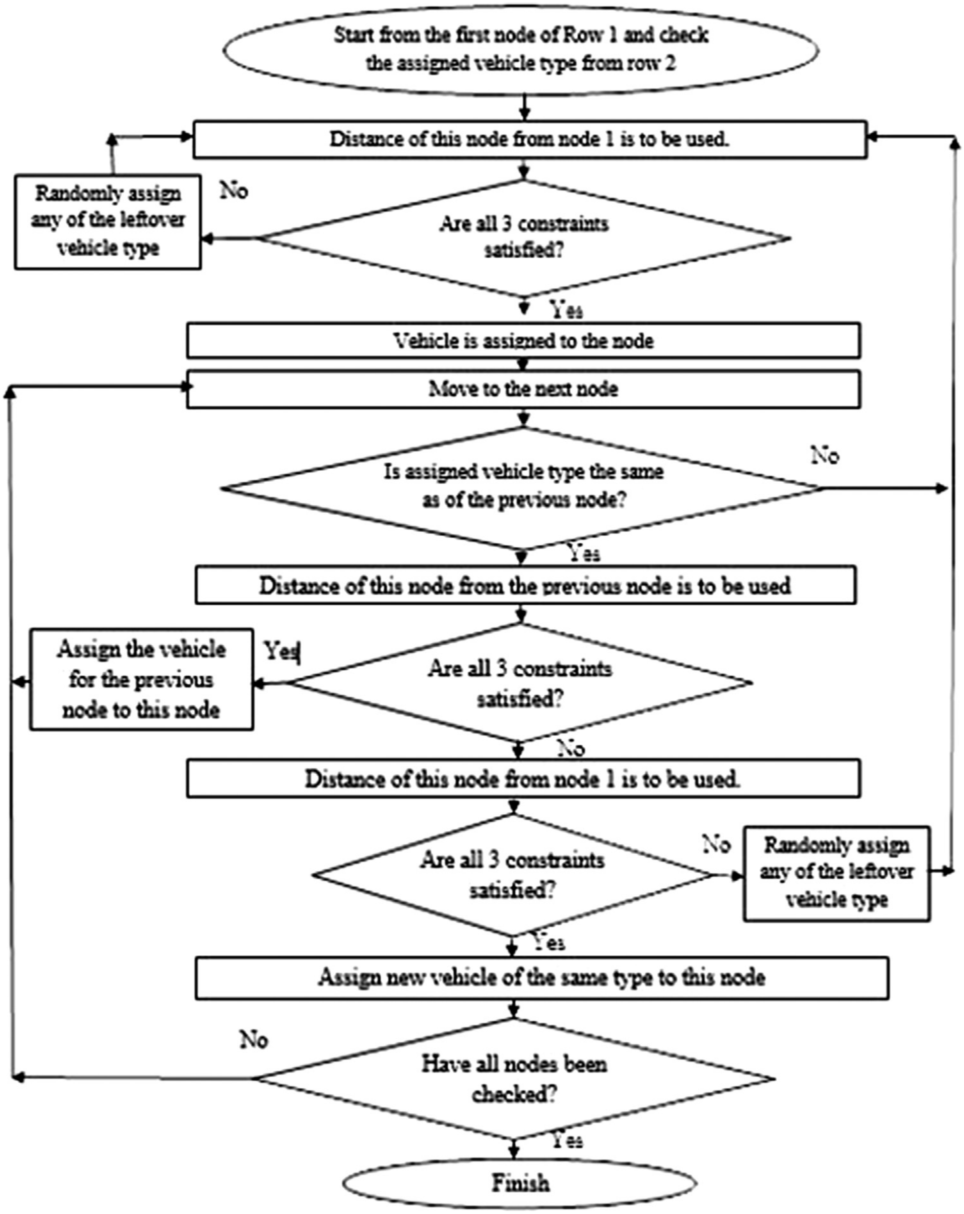

Fig. 9. Rationalization procedure.

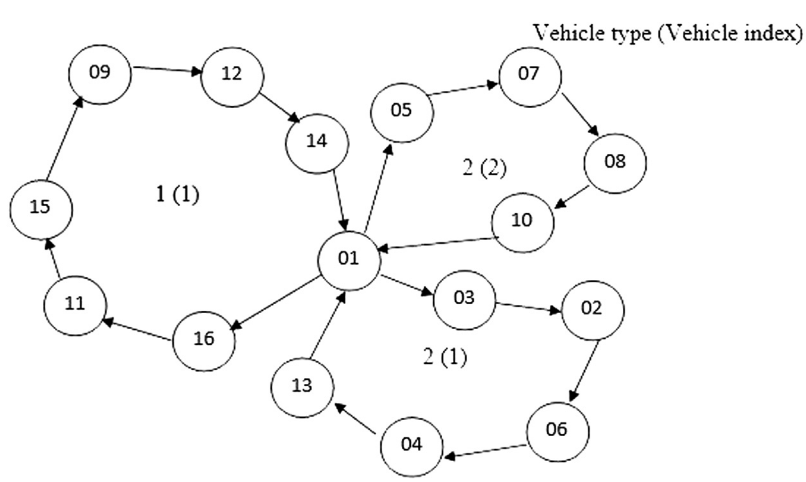

Fig. 10. Optimal routes (original problem).

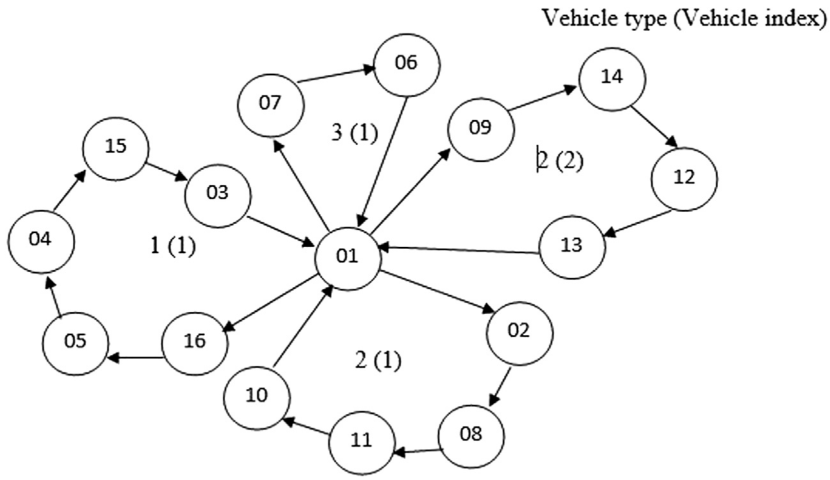

Fig. 11. Optimal routes (modified version A).

Table 4
Arrival time and quality of the product (original problem).

Nodes	Arrival time of product (h)	Quality of shipped product (%)
2	1.12	97.76
3	0.94	98.12
4	2.42	95.16
5	0.96	98.08
6	1.89	96.22
7	2.42	95.16
8	3.01	93.98
9	5.03	89.94
10	3.64	92.72
11	2.70	94.60
12	6.98	86.04
13	5.16	89.68
14	7.67	84.66
15	3.85	92.30
16	1.65	96.70

Table 5
Resultant cost values (original problem).

Cost element	Value ($)
Vehicle hiring cost	3000
Driver hiring cost	1200
Transportation cost	731
Quality deterioration cost	1018
Penalty cost	672
Overall cost	6621

Table 6
Arrival time and quality of the product (modified version A).

Nodes	Arrival time of product (h)	Quality of shipped product (%)
2	0.97	98.06
3	4.25	91.50
4	2.88	94.24
5	2.37	95.26
6	2.63	94.74
7	1.73	96.80
8	2.19	95.62
9	2.16	95.68
10	3.71	92.58
11	3.15	93.70
12	4.09	91.82
13	4.72	90.56
14	3.58	92.84
15	3.58	92.84
16	1.65	96.70

values for various cost elements. From the two tables, the following can be observed.

Table 7
Resultant cost values (modified version A).

Cost element	Value ($)
Vehicle hiring cost	3600
Driver hiring cost	1600
Transportation cost	588
Quality deterioration cost	855
Penalty cost	91
Overall cost	6734

Table 8
Arrival time and quality of the product (modified version B).

Nodes	Arrival time of product (h)	Quality of shipped product (%)
2	1.30	98.70
3	1.55	98.45
4	0.98	99.02
5	1.38	98.62
6	7.30	92.70
7	5.80	94.20
8	3.55	96.45
9	2.16	97.84
10	4.38	95.62
11	3.41	96.59
12	5.32	94.68
13	4.17	95.83
14	4.81	95.19
15	4.27	95.73
16	2.43	97.57

- The hiring cost of the vehicles and drivers is the same as no additional vehicle is hired.
- Since the quality deterioration cost has been decreased, which shows that the product served to the retail stores was of higher quality.
- The low deterioration rate implies that the product deteriorates at a slower rate and has more time to degrade below a certain level, which means the constraint on the quality requirement can easily be achieved, and the model will therefore try to reduce the transportation and penalty costs further. The same is being observed here in this case.
- Transportation cost and penalty cost reduced.
- The overall cost has decreased from $6622 to $5832.

Effect of decrease in the latest time for receipt of the product

If the latest time for receipt of the product at retail stores is somewhat less, it may force more vehicles to be put into operation. This feature of the model is explained with the help of the same example problem. Let this time (L_k) is reduced from 8 h to 5 h.

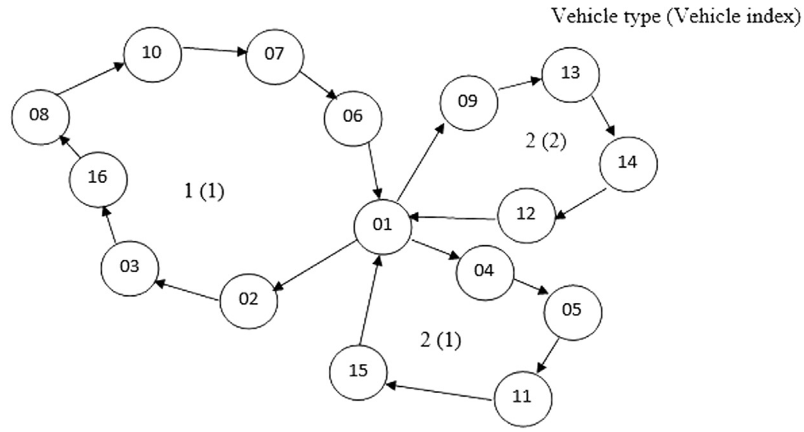

Fig. 12. Optimal routes (modified version B).

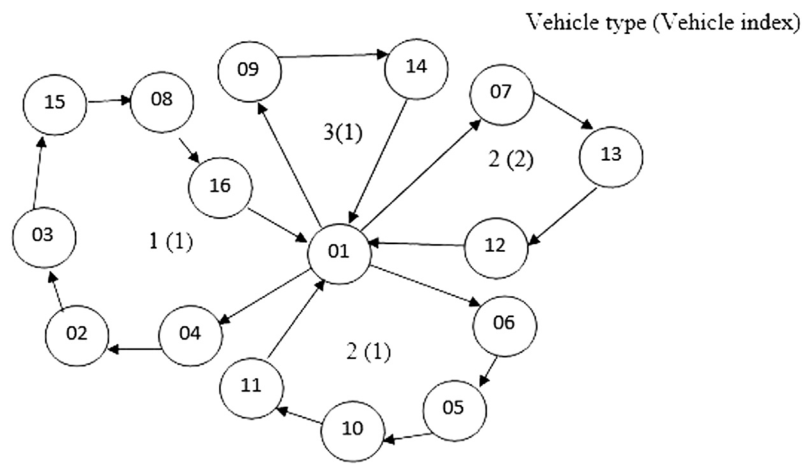

Fig. 13. Optimal routes (modified version C).

Table 9
Resultant cost values (modified version B).

Cost element	Value ($)
Vehicle hiring cost	3000
Driver hiring cost	1200
Transportation cost	617
Quality deterioration cost	513
Penalty cost	502
Overall cost	5832

In solving this example, the optimal vehicle route obtained is shown in Fig. 8. From this figure, it can be seen that four vehicles are now used instead of three in the earlier case. Table 10 shows the arrival time and quality of products arriving at different retail stores, while Table 11 shows optimal values for various cost elements. From the two tables, the following can be observed.

- Initially, the arrival time of products at nodes 12, 13 and 14 was more than 5 h. Once the latest time was decreased from 8 h to 5 h, node 12 is served with vehicle type 2 and node 14 was served with vehicle type 3 instead of vehicle type 1.
- The hiring cost of the vehicle and drivers increased as a separate vehicle of type 3 is hired.
- The penalty cost for late supplying the product is now less reduced due to the shortening of the latest supply time, making the penalty period length smaller.

Table 10
Arrival time and quality of the product (modified version C).

Nodes	Arrival time of product (h)	Quality of shipped product (%)
2	1.75	96.50
3	2.00	96.00
4	1.32	97.36
5	1.36	97.28
6	1.00	98.00
7	2.00	96.00
8	3.80	92.40
9	1.73	96.54
10	3.46	93.08
11	4.02	91.96
12	4.27	91.46
13	3.64	92.72
14	2.86	94.28
15	2.67	94.66
16	4.92	90.16

- Quality deterioration cost decreased as the product could no more be supplied late because of the shortening of the permissible latest time for the receipt of the product.
- The overall cost increased from $6621 to $6810.

The sensitivity analyses carried out hereinabove are sufficient to prove the model's validity as the changes made in the problem parameter values force the optimal routing decision to change as was expected and understood.

The vehicle routing model proposed in Section 2 is NP-hard and was found to take hours of CPU time when the example problems

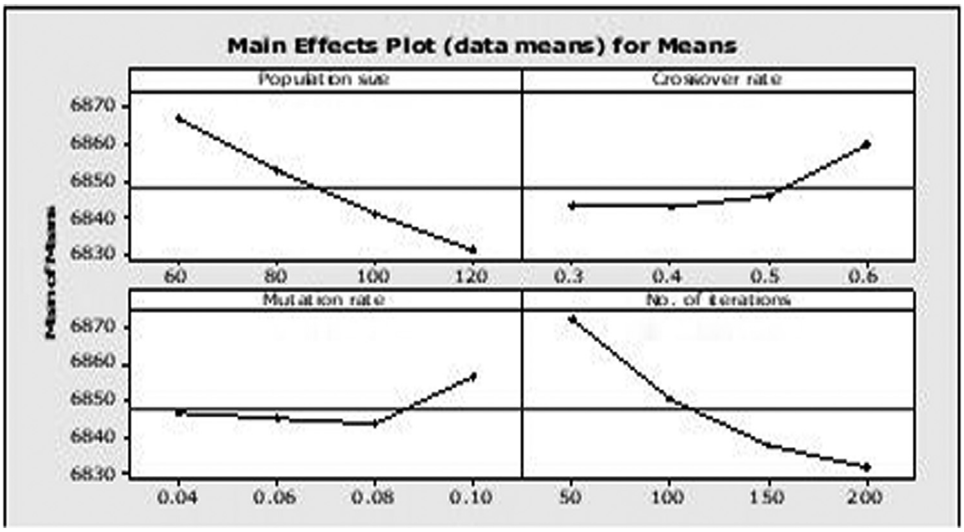

Fig. 14. Results of Taguchi experiments.

Table 11
Resultant cost values (modified version C).

Cost element	Value ($)
Vehicle hiring cost	3600
Driver hiring cost	1600
Transportation cost	659
Quality deterioration cost	837
Penalty cost	114
Overall cost	6810

Table 12
Taguchi L16 combinations.

Population size	Crossover rate	Mutation rate	No. of iterations	Total Cost
120	0.4	0.04	50	6840
120	0.5	0.06	100	6835
120	0.6	0.08	150	6829
120	0.3	0.10	200	6820
60	0.4	0.06	150	6850
60	0.5	0.04	200	6848
60	0.6	0.10	50	6918
60	0.3	0.08	100	6851
80	0.4	0.08	200	6834
80	0.5	0.10	150	6840
80	0.6	0.04	100	6867
80	0.3	0.06	50	6870
100	0.4	0.10	100	6848
100	0.5	0.08	50	6860
100	0.6	0.06	200	6825
100	0.3	0.04	150	6832

described in Section 5.1 were solved using LINGO software to find out an optimal solution. Therefore, a Genetic Algorithm (GA) is proposed to find solutions in a computationally efficient manner.

5.3. Determination of robust parameters of the GA based heuristic

Effect analysis was carried out to find out the robust values for the parameters for the proposed heuristic. For this purpose, L16 combinations, as shown in Table 12, were used. The result in terms of the total cost for the example problem of Section 4 is also shown. Using the data of Table 12, the main effect analysis has been carried out, and the results are shown in Fig. 14.

Fig. 14 shows that the best results are obtained for a population size of 120, a crossover rate of 0.4, a mutation rate of 0.08, and a number of generations (iterations) of 200.

5.4. Performance evaluation of proposed heuristic

In this section, efforts are being made to find out the computational efficiency of the proposed heuristic. For this purpose, the same example problems are solved with an exact solver LINGO, and these solutions are compared with that of the heuristics. The results for the example problems of Section 4 are recorded in Table 13. From this table, it is clear that the proposed GA heuristic successfully finds out a solution in much lesser time in comparison to ones from the use of LINGO. It may be noted that the CPU time requirement mentioned herein is for a computer with Intel i7 3.4 GHz microprocessor.

LINGO is, in general, providing better results. However, the difference does not seem to be very high. Mann–Whitney test was performed using MINITAB software to evaluate the significance of the difference. The test results find the differences to be statistically insignificant. This analysis suggests that one should favour the GA-based heuristic for solving the related problems to get the results much quicker without any significant loss in the solution quality.

Since GA-based heuristic takes much less CPU time and yields solutions very close to the optimal ones, it is suggested to use the proposed heuristic to find a reasonably good upper bound value for the objective function and use them while solving the problem using LINGO software. This will help in fathoming many of the branches of the branch and bound procedure adopted by the software for yielding integer solutions and thus helping in resulting the optimal solution very quickly. For this approach, named as Hybrid Approach, the CPU time requirement has also been mentioned in Table 13. It can be seen from this table that the time required is very less (around 8%), and the hybrid approach yields the optimal solution.

6. Conclusion

In this paper, the problem of distributing a deteriorating item from a warehouse to various retail stores with the help of a heterogeneous fleet of vehicles has been considered with a restriction on supply during the customer specified time-window and the same being of specified minimum quality level. The problem is formulated as a mathematical programming model. This model can solve distribution problems related to products, even those with a short shelf life, like milk, fruits, vegetables, etc. Sensitivity analyses were carried out to prove the validity of the proposed model. Whether it is the increase in the quality level requirement, the decrease in the latest time for supply or the increase in the deterioration rate, it is expected that a greater number of vehicles will be required in the distribution operation. The results obtained

Table 13
Comparison between LINGO and GA results.

Illustrative examples	LINGO solver		Genetic Algorithm (GA)		[(B-A)/A] ∗ 100	HYBRID APPROACH	
	Resultant cost (A)	CPU time (s)	Resultant cost (B)	CPU time (s)		Resultant Cost	CPU time (s)
Original problem	$6622	28 800	$6720	0.84	1.47%	$6622	2330
Modified version A	$6735	24 600	$6849	0.82	1.68%	$6735	2140
Modified version B	$5832	24 300	$5960	0.80	2.19%	$5832	2035
Modified version B	$6810	25 500	$6950	0.82	2.03%	$6811	2195

from the proposed model were exactly in this line, asking for more vehicles when constraints become more stringent on the quality and the time or with the increased deterioration rate. A Genetic Algorithm based heuristic was proposed to find out the optimum set of routes in a computationally efficient manner. Efforts have also been made to determine the most suitable values of GA parameters. The output from the GA-based heuristic can be used as an upper bound on the objective function value to yield the optimal solution in a very computationally efficient manner. Statistical test performed shows that the proposed heuristic provides a solution computationally quite efficiently with statistically insignificant loss in the quality of the solution.

Traffic congestion and variability in demand for retail stores can be incorporated to make the problem more realistic. The problem can be extended to consider the distribution of multiple items instead of a single one. In the present work, only the case of dropping products at retail stores is considered. One can extend this work to address those problems where retail stores get the supply and, also from these, some products are picked up. Products picked up may be required to be stored at the warehouse or may be demanded by other stores.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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