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Modelling an Efficient Hybrid Optimizer for Handling Vehicle Routing Problem

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Vehicle Routing Problem (VRP) like total routing distance, number of serve provisioning vehicles, and vehicles' waiting time are determined as the multi-objective constraints. Investigators pretend to handle these multi-constraint issues with the time window and fail to attain a prominent solution. Thus, there is a need for a global multi-objective vehicle routing solution. Here, a novel Particle Positioning Particle Swarm Optimization (P^3SO) approach is designed to predict the robust route with the elimination of non-linearity measures. The linearity measure includes the movement of the vehicles, service time, and status of the move towards a particular direction. The lack of exploration and exploitation conditions during optimization is addressed with the inclusion of Grey Wolf Optimization (GWO). Therefore, the models attain a global solution with the least error rate. Simulation is done in MATLAB 2016b environment, and the experimental outcomes are compared with various approaches in large-scale and small-scale instances. The model intends to attain robustness and stability towards the measure in a linear manner. The model's time consumption and computational complexity are reduced with the adoption of a global routing-based optimization approach.

Keywords: Grey wolf optimization, Linear measure, Multi-constraint problem, Particle swarm optimization, Routing distance

Introduction

In the modern era, the basic requirements of life are highly dependable on fragile goods like delicatessen products, food, milk, meat, fresh fruits and vegetables, meat and aquatic. The product quality constantly reduces because of its perishable nature.[1] For instance, maintaining meat quality and shelf life is influenced by factors like micro-organisms, holding temperature, endogenous enzymes, atmospheric oxygen, moisture, light and it results in detrimental variation in the odour, colour, flavour, and texture. Thus, the value of the delivered products is influenced based on their freshness. It is general to characterize the perishability to enhance the delivery activity. Considering the customer demand, the optimal solution for VRP is a challenging task; however, it diminishes the overall relevant costs.

While considering the perishability of the goods, some are anticipated to be delivered during desirable time interval. To handle this huge loss, cancellations of specific orders are generally not allowed.[2]

Similarly, when time windows are also imposed, VRP is provided as VRP with time windows. Various researchers in the literature also study it. Moreover, the real issue is the traffic flow over urban region and it is not so specific and generally varies with time. For instance, during peak hours (morning/evening), massive traffic loads slowdown vehicle speed where this consistent phenomenon is identified by examining the traffic data. Generally, the vehicle routing scheme determines the changing travelling time with valid stochastic information to deal with unwanted traffic jams specifies time-dependent VRP.

Some unavoidable disruptive events may still occur and lead to the massive vehicle travelling routes like vehicle breakdown and terrible traffic blocks. When these disruptions happen, a disruption recovery strategy is produced rapidly based on instant situations. However, re-sorting towards advanced communication and experimental technologies include GPRS/GIS/GPS, site data is related to vehicles, traffic data is acquired from the real-time environment, and practical vehicle re-routing decision is provided for drivers at the crucial time.[3]

Generally, split delivery is unavoidable as on customer's demand inequality. Naturally, to enhance complete customer satisfaction, essential requirements in disrupted routes are expected with priority by the available vehicle. Even though split delivery is extensively used in various reviews like it is considered only in the preliminary routing generation and routing plan, which is constrained by vehicle

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capacity. It is divergent from split delivery executed for disruption recovery in various works. On the contrary to that literature, this research concentrates on linearity measure of the time-dependent VRP in preliminary routing plan of delivery by measuring the vehicles movement, service time, and status of the movement over the particular direction in the real-traffic network by validating various paths among the connected nodes. While executing the preliminary routing schemes, the concept behind the route optimization is designed with meta-heuristic optimization to reduce the negative consequences of transportation delay and other related factors.

GWO is depicted as a unique meta-heuristic optimizer inspired based on grey wolves' hierarchical leadership and hunting mechanism. This heuristic approach was initially modelled in 2014, which includes diverse wolves known as alpha, beta, delta, and omega. The simulated chains of commands are shown in Fig. 1. Here, the dominance of the model is decreased from top to bottom and the outcomes are attained in a multi-modal or unimodal manner based verification process with exploration and exploitation ability of GWO. Being a novel and well-defined optimizer, it is extensively used by various researchers in different applications based on the review. Demir *et al.*[4] employ the GWO approach for optimal selection of feature subset selection process where the model's performance is evaluated against Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) The author acquired superior results with this optimizer; similarly, adopts improved GWO for training the radial basis functionality of neural networks. Competitive outcomes are acquired and compared with other approaches. In this research, linear Support Vector Machine (SVM) concept is considered along with the GWO approach for measuring the linearity of the model to handle regression and classification problems.

Fig. 1 — Simulated chain of GWO

Materials and Methods

Related Works

This section discusses three variants of VRP known as capacitated VRP, routing problems with timing windows, and intermittent routing problems. The researcher's ideas towards these approaches are provided elaborately to acquire better insight into the VRP.

Reviews on Capacitated VRP

VRP is an essential application during delivery of various perishable materials proximately after the enormous adversity in case of the critical and emergency condition. Nuzzolo *et al.*[5] provide some nominal invariants of capacitated VRP adopting a single vehicle to perform multiple trips. The author anticipates a novel approach for predicting a reduced arrival time. Some nominal computational evaluations are tested with the anticipated model, and experimentations are evaluated with problem instances of routing issues as elaborated by Zhou *et al.*[6] and Qiu *et al.*[7] They discussed a prominent model for reducing the arrival time of vehicles dispatched from customer location, leading to some aggregative capacitated VRP. The travelling salesman problem is determined as a Non-Deterministic Polynomial Time (NP) hard problem and triggers other constraints like homogeneous fleet and vehicle capacity. Song *et al.*[8] resolves Capacitated Vehicle Routing Problem (CVRP) and classified by the homogeneous fleet with depot. Mu *et al.*[9] provide solution with the adoption of Tabu search approaches.

Reviews on Routing Problem with Timing Windows

Yuan *et al.*[10] discuss routing problem-based timing windows by restricting travel cost and time independent of the timing function. The author anticipates GA composed of three modules: management module to validate the system state, strategic model to validate information attained by management module, and optimization model. An iterative process runs among two phases termed localization optimization framework that is initiated by Ichoua *et al.*[11] The authors model a localized GA using a routing problem with timing windows as domain space. Solomon *et al.*[12] designed novel VRP variants that constrain timing windows and heterogeneous fleets. Here, a two-phase tabu search approach is utilized to resolve the issue. The preliminary phase comprises an improved version of a particular process as anticipated by Ding *et al.*[13]

Reviews on periodic routing problem

Some preliminary features and corresponding combinations give rise to various literature variants, as shown in Table 1.

Model Formulation

Before allocating vehicles for any specific purpose, an initial routing strategy is generated to assist vehicle travelling. During the execution process, when delay is discovered, Disruption Recovery Plan (DRP) needs to be responded. Vehicle visits are related with present traffic condition. The arc travelling time is used to attain an effectual disruption recovery strategy with traffic information. Here, time-dependent road network and time-dependent travelling time evaluation is introduced. Subsequently, DRP and Initial Routing Plan (IRP) is constructed effectually.

Time-Dependent Network Model

Under certain traffic condition, the path is measured with constant travelling time. The shortest path among two road-side network model is extremely definite and related with least distance. Therefore, the selection of optimal path with least travelling time relies on time (over a day).[16] Here, road-based network is modelled with multi-graph design to demonstrate the time-dependent characteristics. Generally, the multi-graph model is composed of more edges among the nodes and this work considers triple directed edges (i, j, h) where first and second number is related to source and destination and the third specifies edge identifier. Initial departure generally guarantees the earlier arrival of destination based on First In First Out (FIFO) manner. Here, travel speed is specified based in the pricewise linear function and the speed seem to be stable during certain period v_{ijh} and time $T_{ijh\,(u+1)}$ which initiates the starting and ending of time. When vehicle departs, the arc is completely longer and travelling is done for a period of time and travelling time is evaluated based on Eq. (1):

$$\tau_{ijh}\left(l_j, t_{current}\right) = \begin{cases} t_{res} + \tau_{ijh}(\ell_j - \ell_{res},\ t_{current} + t_{res}0 & \ell_{res} < l_j \\ \ell_j / v_{ijhu} & \ell_{res} \geq l_j \end{cases} \quad \ldots (1)$$

Here, $t_{current}$ and t_{res} specifies the current time and remaining time, ℓ_j and ℓ_{res} specifies length from present location to vertex j and distance covered within t_{res}. The recursive function is used for evaluating the travelling time of traversing length from present time.

Routing Model

The expression for initial routing is given below in Eq. (2):

$$\min F = \theta_1 \sum_{i \epsilon O} t_i + \theta_2 \sum_{i \in C} t_i D_i \quad \ldots (2)$$

Here, D_i specifies product demand, t_i specifies departure time, O specifies set of vertices specifies depot copies, θ_1 and θ_2 specifies variable cost during transportation operation and deterioration loss/unit, and C specifies set of vertices based on customer nodes. The objective is to reduce weighted sum of deterioration loss and transportation cost. Here, vehicle travelling time is used to evaluate the transportation cost while product loss is connected with order delivery time.

Disruption Recovery Plan

Generally, when transportation is delayed in successive routes; then it leads routing plan to be infeasible, vehicle transmission needs to be re-scheduled to diminish loss from service failure. The disruption management system helps to deal with this issue and the model tries to recover initial routing

Table 1 — Real-time application of variants of VRP

Ref.	Constra-int	Solution	Real-time applications
5	Pyramid route	Branch and cut	Transportation
6	Fuel consumption	Simulated annealing	Transportation
7	Cumulative model	Neighbourhood search	Job scheduling
8	Fuzzy demand	Clustering model	Post-disaster management
9	Multi-depot	Local search and greedy heuristics	Collaborative transportation
10	VRP with central depot	Tabu search	Formal description
11	VRP + soft timing window	IP	Shortest path algorithm
12	Multi-objective VRP +TW	Goal programming + GA	Transportation
13	Time-dependent	Linear programming model +ACO + Insertion	Transportation

plan and recovers IRP and reduces negative consequences of recovered route. The recovery scheme needs to reduce the sum of weighted service dissatisfaction. It is expressed as in Eq. (3)

$$F_1 = \sum_{i\in C'} w_i \left(\mu_1 \left(\sum_{j\in N'} \sum_{h\in H_{ij}} \sum_{k\in IK} + \mu_2 \sum_{k\in IK} \frac{x_{ijh}^{k} - 1}{\frac{\max\{t_{ik} - l_i, 0\}.\, q_{ik}}{D_i\,(l_i - e_i)}} \right) \right) \quad \ldots (3)$$

Here, w_i specifies the significance of customer degree i; μ_1 and μ_2 is measured as the relative weight among the frequency and service initiated time and $'l\,'$ is specified as the constraint of maximal tolerable delay limit. Subsequently, the company needs to take care of customers and reduce the deterioration and transportation cost. In case of alternative routes, then it leads to increase in charge. Thereby, the company intends to reduce the delivery cost and deviation is the cost expressed as in Eq. (4):

$$F_2 = \theta_1 \sum_{i\in O} \sum_{k\in IK} t_{ik} + \theta_2 \sum_{i\in C'} \sum_{k\in IK} t_{ik} q_{ik} \quad \ldots (4)$$

Finally, the drivers are completely aware of the delivery route and the recovery plan is initiated with route adjustments even in case of issues. Some new routing schemes are maintained with initial routing scheme to reduce the deviation and it is expressed as in Eq. (5):

$$F_3 = \sum_{i\in C'UP} \sum_{j\in N'} \sum_{h\in H_{ij}} \sum_{k\in IK} \max\,\{x_{ijh}^{-k} - x_{ijh}^{k}, 0\} \quad .. (5)$$

The routing issues related with all these three-folds are considered and it is handled efficiently by GWO optimizer and particle-positioning PSO model. Thus, these two optimization approaches play substantial role to attain global solution and the detailed investigation is given below.

Grey Wolf Optimizer for VRP

This work examines the vehicle routing problem using time window with the target to reduce the routing cost, delay and so on. To solve the problems in a practical dimension, grey wolf optimization is adopted where the optimizer attains high-quality solutions. In this research, GWO is used for handling VRP. For this purpose, the hunting behaviour of grey wolves is inspired by the researchers to acquire best solution to the problem statement.

There are four diverse levels of leadership hierarchy specified as Alpha ($\propto$), Beta (β), Gamma (δ) and Omega(Ω). The $\propto$ wolf is leader who occupies the higher position and leads the group. β wolf occupies the successive level and it is used for decision-making. The third position is occupied by δ wolves, and it is depicted as the weakest one among the group. These wolves are less permitted and dominated by other dominant members. Some wolves not coming under these categories are Ω wolves and it dominate δ wolves. However, it is dominated by $\propto$ and β wolves. Prey hunting is guided by $\propto$, β and δ groups and it is made of three stages like 1) prey encircling, 2) prey hunting and 3) prey attacking.

The first two stages are accountable for exploration while the last is accountable for exploitation. The searching process is modelled by reducing the hunting nature of wolves and its hierarchy as shown in Fig. 2. The algorithm for GWO is given in Algorithm 1.

Prey Encircling

Wolves of definite numbers are positioned randomly in diverse search places. Thus, prey encircling is expressed in Eqs (6) & (7):

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \quad \ldots (6)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \quad \ldots (7)$$

Here, $'t'$ is number of iterations, x_p is prey's position, x is grey wolves location. $\vec{A}$ and $\vec{C}$ are vector coefficients, $\overrightarrow{X_p}$ is prey position vector, $\vec{X}$ is grey wolf position. The vector coefficients $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad \ldots (8)$$

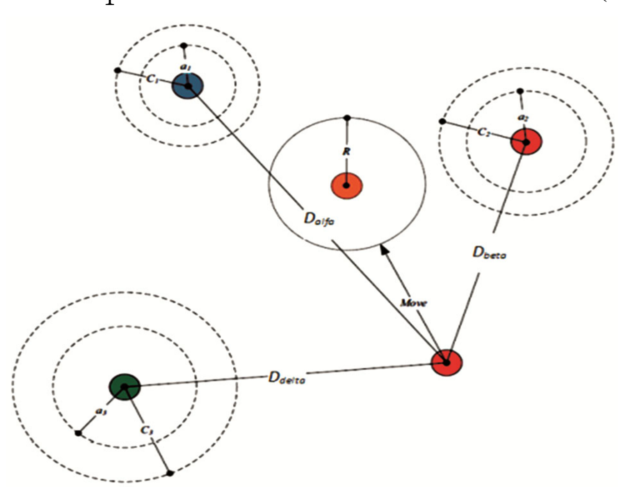

Fig. 2 — Grey wolf positioning for routing prediction

$$\vec{C} = 2.\vec{r}_2 \quad \ldots (9)$$

Here, $\vec{a}$ vector has linear reduction from 2 to 0, $\vec{r}_1$ and $\vec{r}_2$ are random vectors in [0, 1].

Hunting

Grey wolves predict prey's situation and surround the prey for hunting. They α, β, δ are best solutions and the other solutions also will be updated based on β, δ . In general, alpha (α), beta (β) and gamma (δ) evaluate prey situation and other wolves update the solution based on the three wolves. The formula for updating the process is given below:

$$\vec{X}(t+1) = (\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3})/3 \quad \ldots (10)$$

$$\begin{cases} \overrightarrow{X_1} = \overrightarrow{X_\alpha} - A_1\,(\overrightarrow{D_\alpha}) \\ \overrightarrow{X_2} = \overrightarrow{X_\beta} - A_2\,(\overrightarrow{D_\beta}) \\ \overrightarrow{X_3} = \overrightarrow{X_\delta} - A_3\,(\overrightarrow{D_\delta}) \end{cases} \quad \ldots (11)$$

$$\begin{cases} \overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}| \\ \overrightarrow{D_\beta} = |\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}| \\ \overrightarrow{D_\delta} = |\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}| \end{cases} \quad \ldots (12)$$

where, $\overrightarrow{X_1}, \overrightarrow{X_2}, \overrightarrow{X_3}$ are the three best wolves solution over the given iteration 't'and $\overrightarrow{A_1}, \overrightarrow{A_2}, \overrightarrow{A_3}$ are computed as in Eq. (11). Similarly, $\overrightarrow{C_1}, \overrightarrow{C_2}, \overrightarrow{C_3}$ are computed using Eq. (12).

Attacking Prey

Prey hunting by wolves is accomplished, when they pretend to attack. To reach prey, $\vec{A}$ vector value reduces by reducing the $\vec{a}$ vectors value. Subsequently, $'A'$ vector is random value among $[-a, a]$, $\vec{a}$ Value changes from 2 to 0. The random value of $\vec{A}$ lies between $[-1, 1]$, where the successive iteration for searching lies among the current prey's situation.

Particle Swarm Optimization

The novelty of the proposed P^{3}SO relies on handling the real-time version of swarm for handling the vehicle routing problem with concurrent pickup and deliver. This research intends to explain the routing mechanism based on vehicle positioning for resolving the vehicular route and demonstrates the efficiency of the anticipated model. Consider a particle population $'m'$ in $n-$ dimensional search space where the particles provides solution in search space. The $'i'^{th}$ particle comprises of $n-$ dimensional position and velocity vector which is represented as $x_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,n})^T$ and $v_i = (v_{i,1}, v_{i,2}, \ldots, v_{i,n})^T$ respectively. The particles update the position and velocity which is expressed as in Eq. (13) & Eq. (14):

Algorithm 1 Grey Wolf Optimization

Input: Initialize the necessary parameters like the population of wolves, solution dimensions, range of solutions, Max_iter

Output: best solution

1. Begin
2. Initializea, $\vec{A}$, $\vec{C}$, and t = 1
3. Evaluate fitness of search agents of the population
   a. $\overrightarrow{X_\propto}$ = dominant search agent among the population
   b. $\overrightarrow{X_\beta}$ = dominant search agent among the population next to α wolves6
   c. $\overrightarrow{X_\delta}$ = dominant search agent among the population next to β wolves
4. While (i < Max_iter)
5. For each search agents
6. Current search agent position is updated;
7. end for
8. update a, $\vec{A}$, $\vec{C}$
9. Evaluate fitness of all search agents;
10. update $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$, $\overrightarrow{X_\delta}$
11. i = i+1
12. End while
13. Return Best solution $\overrightarrow{X_\alpha}$
14. End

$$v_{i,j} = v_{i,j} + c_1 r_{1,j}\left(x_{i,j}^{pbest} - x_{i,j}\right) + c_2 r_{2,j}(x_j^{gbest} - x_{i,j}) \quad \ldots (13)$$

$$x_{i,j} = x_{i,j} + v_{i,j} \quad \ldots (14)$$

Here, $i = 1,2, \ldots, m; j = 1,2, \ldots, n$ where $'m'$ and $'n'$ are population size and search space dimensions. Where as $x_{i,j}$ is position and v_{ij} is velocity of j^{th} is particle $'i'$ dimensions. $x_i^{pbest} = \left(x_{i,1}^{pbest}, x_{i,2}^{pbest}, \ldots, x_{i,n}^{pbest}\right)^T$ is the best positions' history. $r_{1,j}$ and $r_{2,j}$ are uniformly distributed random numbers with [0,1] for j^{th} dimension, c_1 and c_2 are acceleration coefficients. $v_j^{max}$is the maximal velocity to deal with the particle velocity. The exploitation and exploration of the population based on velocity is expressed as in Eq. (15):

$$v_{i,j} = wv_{i,j} + c_1 r_{1,j}\left(x_{i,j}^{pbest} - x_{i,j}\right) + c_2 r_{2,j}(x_j^{gbest} - x_{i,j}) \quad \ldots (15)$$

Particle-Positioning PSO (P^3SO)

P^3SO is an ‘intelligent movement mechanism’ proposed by Song *et al.*[14] for generating a temporary position like $r = (r_1, r_2, \ldots, r_n)^T$ and $h = (h_1, h_2, \ldots, h_n)^T$ for all particles. It is expressed as in Eq. (16) & Eq. (17):

$$h_j = x_{i,j} + wv_{i,j} + c_1 r_{1,j}(x_{i,j}^{pbest} - x_{i,j}) \quad \ldots (16)$$

$$r_j = x_{i,j} + wv_{i,j} + c_2 r_{2,j}(x_j^{gbest} - x_{i,j}) \quad \ldots (17)$$

Here, $'r'$ and $'h'$ specifies social learning and self-cognitive components. It is applied over $'r'$ and $'h'$ for acquiring successive position $'x'$ and particle velocity is attained based on the difference among current $'x'$ and new position x'. Song *et al.*[15] anticipated a novel mechanism for particles’ discovery and population best solution. The positioning strategy uses this mechanism by merging x_i^{pbest} and x^{gbest} for developing learning exemplar for all particles, x_i^{ol} is substituted with x_i^{pbest} and x^{gbest} to carry out particle searching. Here, particles’ velocity updation is expressed as in Eq. (18):

$$v_{i,j} = wv_{i,j} + c_1 r_{1,j}(x_{i,j}^{ol} - x_{i,j}) \quad \ldots (18)$$

Some essential information like x_i^{pbest} and x^{gbest} relies on x_i^{ol} to eradicate oscillation from learning exemplar. x_i^{ol} is an exemplar for number of generation till it acquires maximal best particle position. When learning exemplar attains maximal movement strategy, then new learning exemplar is reconstructed. Here, k_i is considered as stagnation generation. When particles’ best solution is not updated, then k_i is incremented by 1. When $k_i > K$, then new learning exemplar is construced and it avoids oscillation learned with best searching efficiency. Here, dimensional learning is inspired to maintain particle information where x_i^{pbest} is learnt from x^{gbest} dimensionally for learning exemplar x_i^{dl} construction. It facilitates x^{gbest} to pass to the exemplar. Assume, the target is to minimize 5-dimensional sphere with $f(x) = x_1^2 + x_2^2 + x_3^2 + x_4^2 + x_5^2$ with a global minimum point $(0,0,0,0,0,0)^T$. the personal best position is $x_i^{pbest} = (1,0,3,2,4)^T$.

Similarly, the current best position $x^{gbest} = (2,4,2,2,0)^T$. Based on the given an example $x_i^{pbest} = 30$ and $f\left(x^{gbest}\right) = 28$. Then, x_i^{pbest} learns from x^{gbest} overall dimensions to form learning exemplar. Here, x^{temp} is temporary vector, i.e., $x^{temp} = x_i^{pbest} = (1,0,3,2,4)^T$.

1) Dimension 1: $x_1^{temp} = x_1^{gbest} = 2, x^{temp} = (2,0,3\ ,2,4)^T, f(x^{temp}) = 33 > f\left(x_i^{dl}\right) = 30.$ Therefore, $x_{i,l}^{dl}$ remains the same; $x_{i,l}^{dl} = (1,0,3,2,4)^T; f\left(x_i^{dl}\right) = 30.$
2) Dimension 2: $x^{temp} = x_i^{dl}, x_2^{temp} = x_2^{gbest} = x_2^{gbest} = 2, x^{temp} = (1,4,3,2,4)^T,\ \ f_x^{temp} = 46 > f\left(x_i^{dl}\right) = 30$; Therefore, $x_{i,2}^{dl}$ remains the same; $x_{i,l}^{dl} = (1,0,3,2,4)^T; f\left(x_i^{dl}\right) = 30$
3) Dimension 3: $x^{temp} = x_i^{dl}, x_3^{temp} = x_3^{gbest} = x_3^{gbest} = 2, x^{temp} = (1,0,2,2,4)^T, f_x^{temp} = 25 < f\left(x_i^{dl}\right) = 30$; Therefore, $x_{i,l}^{dl} = (1,0,2\ 2,4)^T; f\left(x_i^{dl}\right) = 25$
4) Dimension 4: $x^{temp} = x_i^{dl}, x_4^{temp} = x_4^{gbest} = x_4^{gbest} = 2, x^{temp} = (1,0,3,2,4)^T, f_x^{temp} = 30 < f\left(x_i^{dl}\right) = 25$; Therefore, $x_{i,4}^{dl}$ remains the same; $x_{i,l}^{dl} = (1,0,3,2,4)^T; f\left(x_i^{dl}\right) = 25.$
5) Dimension 5: $x^{temp} = x_i^{dl}, x_5^{temp} = x_5^{gbest} = x_5^{gbest} = 2, x^{temp} = (1,0,3,2,0)^T, f_x^{temp} = 14 < f\left(x_i^{dl}\right) = 25$; Therefore, $x_{i,5}^{dl}$ remains the same; $x_{i,l}^{dl} = (1,0,3,2,0)^T; f\left(x_i^{dl}\right) = 14.$

Finally, $x_i^{dl} = (1,0,3,2,0)^T$ where the dimensions are learnt from $x^{gbest} = (2,4,2,2,0)^T$. The dimensional learning process, x_i^{pbest} learns from x^{gbest} to construct x_i^{dl}, which is developed by integrating x_i^{best} where dimensional components are learnt from x^{gbest}. However, learning strategy ensures that x_i^{dl} is finest than x_i^{pbest}. With PSO variants, it is known as position learning based particle swarm optimization (P^3SO). The velocity updated (improved) is expressed as in Eq. (19):

$$V_{i,j} = wv_{i,j} + c_1 r_{1,j}\left(x_{i,j}^{dl} - x_{i,j}\right) + c_2 r_{2,j}\left(x_j^{gbest} - x_{i,j}\right) \quad \ldots (19)$$

With reference to the above given example, the comparison is made among current & temporary exemplar for all dimensions. This one is updated regularly. If the temporary exemplar is somehow higher than the current state, then the learning process gets updated. If not, for all the dimensions, the current learning exemplar remains the same. The dimension of population's best position is considered. Therefore, the fitness is improved. During the learning process, the performance is improved a lot. The flow diagram of P[3]SO is given in Fig. 3.

Algorithm 2: P³SO

Update $'x_i'$, and $'v_i'$ (position and velocity) of particles $'i'$.
Compute $'x_i'$ fitness value
if $f(x_i) < f\left(x_i^{pbest}\right)$ then
$x_i^{pbest} = x_i$ //temporary exemplar is better than current learning exempler = 1;
$else$
current learning exemplar remains the same for all successive dimensions =0;
$endif$
if temporary learning exemplar = = 1 then
update x_i^{pbest};
end if;//updation of learning exemplar
$x_i^{pbest} = x_i^{dl}$;
$foralldimensionsdo$ //dimension = 5;
$temp = x_i^{dl}$
$iftemp(j) = x^{gbest}(j)$;
$continuelearningprocess$;
$endif$
$temp(j) = x^{gbest}(j)$;
$iff(temp) < f\left(x_i^{dl}\right)$
$x_i^{dl}(j) = x^{gbest}(j)$
end if
end for
update position of particles using the moving mechanism
Perform particle positioning;
update fitness value
end
output best fitness value

Results and Discussion

This section shows the numerical outcomes of the anticipated model, and the simulation is done in MATLAB 2016b environment over core i3 processor, 2.13 GHz CPU, and 4 GB RAM. The parameters are set as:

$$p_{size} = 10, \propto = 0.20, q = \left[\sqrt{n}\right], andNoimp = 50.$$

Based on the review, it is noted that there is no proper dataset for handling the vehicle routing problem. This research considers Solomon's Vehicle Routing Problem with a Timing Window (SVRPTW) with 100 randomly chosen customers. Based on the geographical location of the customers, the samples are partitioned into three different categories like R-type (uniformly distributed), C-type (clustered), and RC-type (integration of both).

In this work, six instances are constructed based on the customer's geographical location with three large-time windows and three narrow-time windows. Next, the successive form of test instances are composed of 48 instances (200, 400, 600, and 800 customer instances), and these two instances are randomly sampled for all groups with customer scale. For a specific set of instances, the provided data is connected to the customer's remains dimensional-less. Some modifications are done to acquire essential information like time-dependent travelling speed and a couple of nodes. The network nodes possess approximately 2–3 arcs in the routing model and λ is the distance measure among them. For simplicity, three equal intervals are considered with time-dependent speed function with patterns like $(1-\varepsilon, 1+\varepsilon, 1-\varepsilon)$ where ε value is related with the speed profile as shown in Table 2.

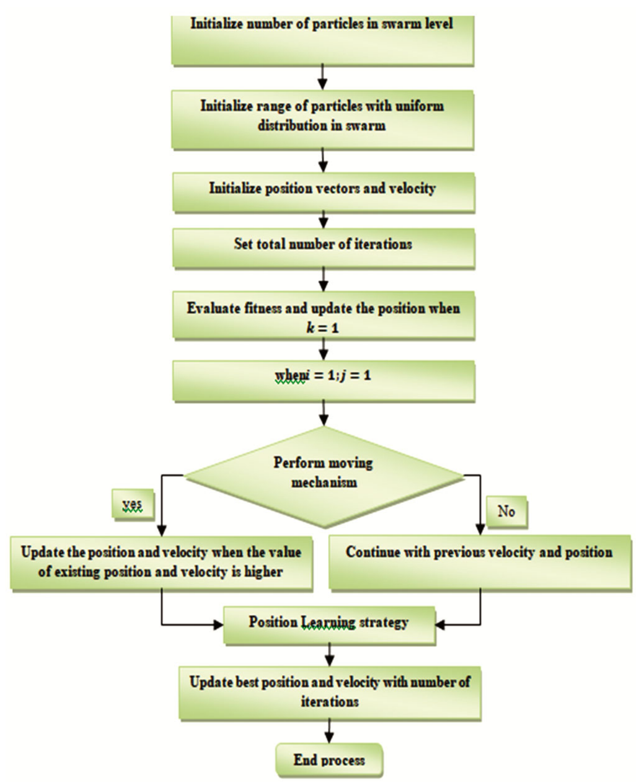

Fig. 3 — Flow diagram of P[3]SO

Based on the pre-determined routes ‘p’, seven vehicles are considered for delivering the order, and the dispatched vehicles travel over a specific region. It is observed that vehicles 4 and 6 are affected due to massive traffic conditions, and transportation delay is measured as 31 and 27, respectively. It is proven that the initial routing plans are not suitable for evaluation, as shown in Table 3.

Based on the disruption recovery process, the best recovery plan is revealed based on Table 3. The superior outcomes based on the five repetitive computations with average delivery consumption time are 39 seconds. The objective function (disruptive routing model) values are $F_1 = 1.4373, F_2 = 1578.3$ and $F_3 = 12$. The coefficients μ_1, μ_2, and L are set as 0.2, 0.10, and 30. Moreover, the vehicle re-routing scheme is evaluated based on the global scheduling method, which performs re-execution of routing model as in Table 4. Therefore, the company concentrates on the recovery scheme of all customers. The objective function attained with the global rescheduling method is $F_1 = 11.4590,\ F_2 = 1496.3, and\ F_3 = 14$.

Table 2 — Initial Routing plan

No	Routing plan
1	0-11-8-19-1-0
2	0-13-15-5-12-0
3	0-22-4-5-24-0
4	0-12-18-9-18-0
5	0-6-8-19-11-0
6	0-3-16-23-25-0
7	0-22-0

Table 3 — Recovered routing plan

No	Routing Plan
1	0-11-p_1-19-1-0
2	0-13-p_2-5-12-0
3	0-p_3-22-4-5-24-0
4	0-12 (p_4)-18-9-18-0
5	0-6-p_5-8-19-11-0
6	0-3-p_6-16-23-25-0
7	0-22-p_7-0

Table 4 — Global re-scheduling routing plan

No	Routing plan
1	0-11-p_1-10-19-1-0
2	0-13-p_2-5-6-12-0
3	0-p_3-22-4-24-0
4	0-12 (p_4)-18-9-6-0
5	0-6-p_5-8-19-11-0
6	0-3-p_6-16-23-4-0
7	0-22-p_7-0

The rescheduling nodes are provided for best solutions, and the objective functions are compared with disruptive recovery schemes and show negative influence over customers with approximately equal cost. In contrast, the global rescheduling process leads to massive influence over the customer with reduced cost savings. It is noted that the disruption recovery more is highly suited for real-time applications. The anticipated GWO-P^{3}SO is compared with existing Ant Colony Optimization (ACO) to achieve disruption management. Therefore, ACO fits for handling the issue with slight modification to constraint the supply quality of every vehicle equal to left load. The initial solutions of the optimization algorithm are designed to fulfil all customers' requirements when the current route is not so sufficient. The search criteria for GWO are the same alike as ACO with slight modifications. The ant population size is set as 20, and the significance of heuristic information is set as 1.5 and 5, respectively. The customer requirements need to with resolved in lesser time while computing the instances with more essential requirements. Based on the prioritization objective, the computational outcomes are evaluated hierarchically. The index rate is set to measure the model superiority

$Rate_{GWO\,+\,P^2SO} = \frac{F_{*,ACO} - F\_(*,GWO\,+\,P^2SO)}{\max\,(F^*,\ ACO,\ F*,\ GWO + P^2SO)}$ where $*$ specifies priority level

From the above Table 5, it is observed that the outcome of the customer instances gives superior results over the prevailing ACO model. The former model attains an exceptional impact in 16/18 cases where only two instances offer a worst solution. Based on the scaling of instances, the benefit of the prevailing ACO begins to fade. The statistical analysis of the provided model is compared with GWO + P^{2}SO on various scale instances. From the research, the anticipated model shows a slight improvement of about 45% approximately for 100–200 customers, and the model's functionality seems to be lesser in the case of above 200 customers.

Over various disruption events, the model's efficiency is analyzed with multiple instances chosen randomly from the test set in the disruption recovery model. For handling the scaling problem, the instances are composed of 100 customers (3 instances), 200 customers (3 instances), and 400, 600, and 800 customers (3 instances). The disruptive event occurs at times t_1 and t_2 to produce two diverse situations and set as 0.3 and 0.6, respectively. The customer distance measure and distance from source to destination are shown in the Figs 4 & 5. The initial route scheduling and rescheduling measure are shown in the Figs 6 & 7. The possible combinations and experimental and theoretical analysis are shown in the Figs 8 & 9. The most satisfactory solution is attained with both ACO and GWO + P^{3}SO models in these scenarios, as shown in Table 6. The recovery rate of maximal and total delay time is expressed as in Eq. (20) & Eq. (21):

$$RR_{MDT} = \frac{MDT^0 - MDT^1}{MDT^0} \quad \text{... (20)}$$

$$RR_{TDT} = \frac{TDT^0 - TDT^1}{TDT^0} \quad \text{... (21)}$$

Based on the analysis, it is noted that the disruption recovery plan reduces the maximal delay time during the disruption event, and the maximal delay time of a single disruption event is reduced by huge variations, as shown in Table 7. The disruption scheme may diminish the total delay time significantly. Moreover, it is not sure that the higher delay time is saved during a single disruption event. It is more feasible during the recovery plan for earlier events where the vehicles move near depot region with short distance and the

Table 5 — Evaluation with GWO+P^{3}SO with existing ACO

Instances	Original problem	ACO			GWO+P^{3}SO			$Rate_{GWO+P^3SO}$
		F1	F2	F3	F1	F2	F3	
S_C100_1	C103	0	9490.8	19	0	9397.2	9	−0.08%
S_C100_2	C104	0	7786.8	14	0	7990.7	15	0.10%
S_C100_3	C105	1.2	9023.1	17	0.8	8733	17	37.5%
S_C100_4	C106	0	8117	13	0	8305.4	17	−1.2%
S_C100_5	C205	1.0	7240.6	10	0.7	7082.5	13	34.3%
S_C100_6	C206	4.3	7725.8	15	1.4	6818.2	19	70.0%
S_R100_1	R101	5.8	3609.8	7	1.7	3604.10	5	73.10%
S_R100_2	R102	2.2	4718.3	10	1.2	5006.4	14	48.6%
S_R100_3	R104	3.7	6491.4	16	2.4	7695.4	20	36.2%
S_R100_4	R105	1.6	4712	11	0	4639.6	14	100%
S_R100_5	R204	10.5	5373.8	10	8.8	5397.4	12	17.3%
S_R100_6	R206	9.2	4915.3	18	5.3	4616.9	20	43.9%
S_RC_100_1	RC102	3.8	2943.5	11	1.10	3363	5	49.6%
S_RC_100_2	RC103	0	2415.6	4	0	2301.6	4	0.6%
S_RC_100_3	RC106	9.4	3288.9	6	5.5	3362.3	9	42.10%
S_RC_100_4	RC201	7.2	9012.2	10	6.6	8521.4	15	8.6%
S_RC_100_5	RC202	4.8	5870.3	12	3.2	5692.7	6	35.0%
S_RC_100_6	RC206	8.3	8330.5	10	5.9	6814.7	13	29.4%

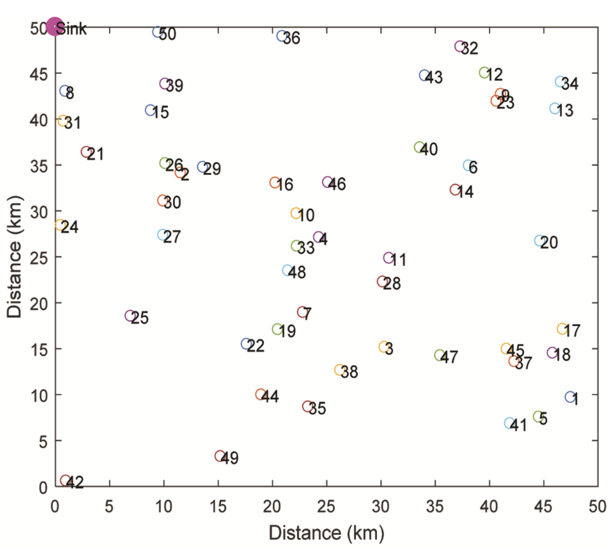

Fig. 4 — Customer distance measure

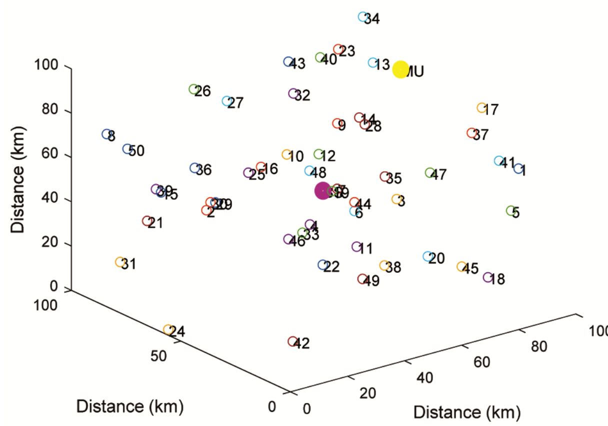

Fig. 5 — Distance measure from source to destination

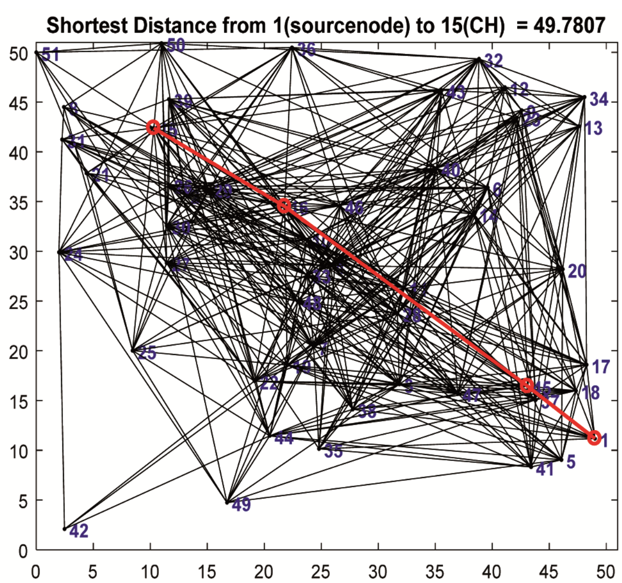

Fig. 6 — Initial route scheduling

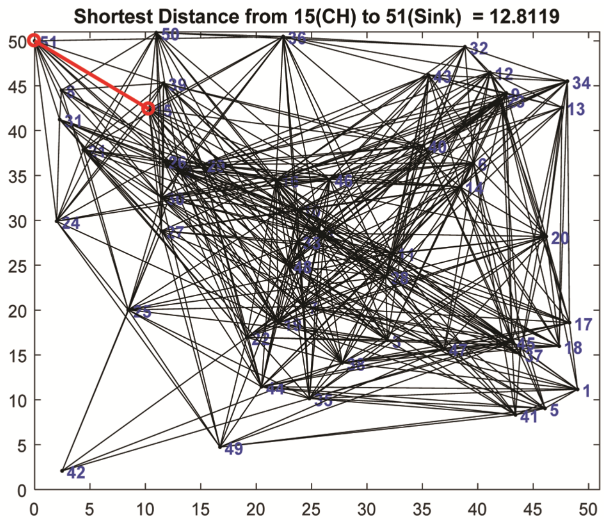

Fig. 7 — Rescheduling due to traffic scenario

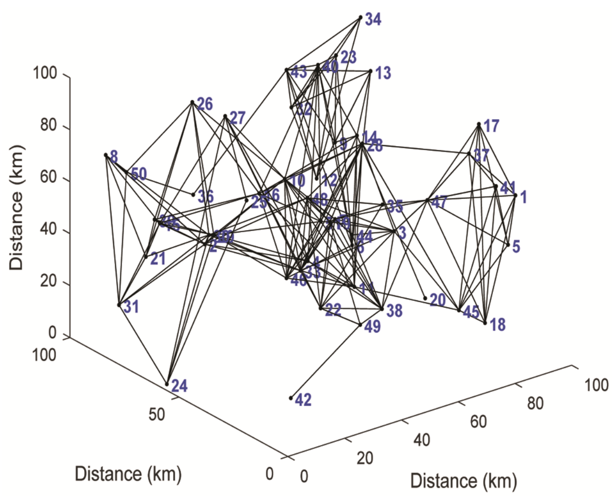

Fig. 8 — Possible combinations to reach the destination

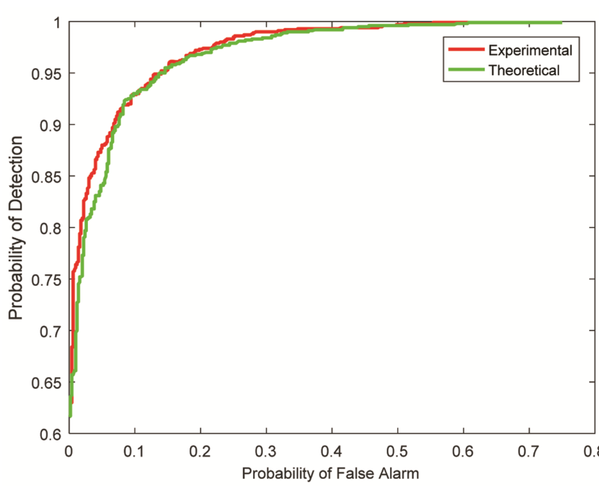

Fig. 9 — Experimental and theoretical analysis for predicting the vehicle route to reach the destination

Table 6 — Evaluation with GWO+P^{3}SO with existing ACO

Instances	ACO			GWO+P^{3}SO			$Rate_{GW}$
	F1	F2	F3	F1	F2	F3	
GH_C200_1	0	1058	19	0	1037	24	−9.6%
GH_C200_2	0.5	9600.2	16	0	9544.2	20	100%
GH_C200_3	1.2	16200.8	22	0.8	16153.8	20	37.5%
GH_C200_4	2	1652.5	20	2.2	1571.5	25	−9.6%
GH_R200_1	2.4	15999.2	36	1.7	15908.2	32	31.4%
GH_R200_2	1.4	14300.8	21	0	14218.8	17	100%
GH_R200_3	8.5	19805.9	25	5.7	19745.9	26	34.4%
GH_R200_4	6.4	17900.8	29	4.4	17897.8	20	32.8%
GH_RC200_1	4	14319.2	16	0	14312.2	22	100%
GH_RC200_2	7.3	17990.7	22	8.2	17982.7	17	−12.2%
GH_RC200_3	3.2	16958.5	20	3.1	16825.5	24	−6.0%
GH_RC200_4	5	20365.9	27	5.7	20214.9	22	−29.7%
GH_C400_1	0	31789	28	0	31518	30	−5.2%
GH_C400_2	4.9	36165.1	31	5.2	36139.1	22	6.8%
GH_C400_3	10.10	40169.5	25	9.4	40154.5	32	15.8%
GH_C400_4	5.4	294987.6	34	5.9	294871.6	29	−8.7%
GH_R400_1	7.5	31900.5	25	8.7	31874.5	21	50%
GH_R400_2	7.2	3700.2	21	7.9	3689.2	18	88.6%
GH_R400_3	10	41158.5	24	5.5	41085.5	33	−21.9%
GH_R400_4	3.3	38589	32	0.3	38095	29	93.3%
GH_RC400_1	7.7	31365.3	31	9.7	31210.3	36	9.6%
GH_RC400_2	12.9	34685.6	27	8.4	34585.6	31	−36.7%
GH_RC400_3	3.3	40300.8	20	5.7	40125.8	22	−29.3%
GH_RC400_4	4.8	31356.5	35	4	31254.5	39	−39.4%
GH_C600_1	8	39489.1	30	10.2	39452.1	32	36.5%
GH_C600_2	6.5	42300.6	36	0.6	42152.6	27	14.6%
GH_C600_3	6.4	48258.6	25	5.8	48145.6	32	8.2%
GH_C600_4	9.5	50879.8	36	14.7	50127.8	34	29.9%
GH_R600_1	10.3	5	28	14.3	5	40	−23.1%
GH_R600_2	10.9	43658.5	42	17.6	43561.5	38	37.2%
GH_R600_3	23.9	50895.5	38	14.9	50551.5	56	−28.4%
GH_R600_4	11	54300.5	41	9.9	54251.5	44	−35.2%
GH_RC600_1	0	46256.5	29	0	46198.5	42	29.7%
GH_RC600_2	11.5	481485.6	40	7.5	481365.6	37	26.5%
GH_RC600_3	9.3	39200.7	47	11.9	39158.7	49	−47.5%
GH_RC600_4	15.4	42458.5	30	9.3	42389.5	44	29.7%
GH_C800_1	27.1	40365.5	32	16.8	40215.5	37	−32.2%
GH_C800_2	7.3	51356.5	38	11.3	51325.5	49	−30.9%
GH_C800_3	9.2	53285.5	48	6.8	53125.5	44	13.6%
GH_C800_4	24.6	46985.2	41	17.4	46850.2	38	8.5%
GH_R800_1	3	47852.2	42	5.7	46980.2	53	29.9%
GH_R800_2	23	37895.2	31	16.7	37685.2	38	−35.1%
GH_R800_3	7.4	50856.2	27	10.6	50725.2	50	−100%
GH_R800_4	12.8	63365.5	51	18.4	63205.5	62	−0.1%
GH_RC800_1	8	45258.5	57	14	45125.5	50	36.2%
GH_RC800_2	45.6	53895.5	53	15.3	53256.5	40	39.9%
GH_RC800_3	14.8	54789.2	38	14.2	54824.2	53	−32.1%
GH_RC800_4	12.1	42256.2	30	11.2	42156.2	39	−30.9%

Table 7 — Minimal and total delay time computation

Instances	ACO				GWO+P^{3}SO			
	MDT^0	TDT^0	MDT^1	TDT^1	MDT^0	TDT^0	MDT^1	TDT^1
S_C100_1	42.4	234.8	24.7	162.4	58.3	413.7	37.9	294.5
S_C100_2	20.7	74.6	13.8	43.9	33.7	190.3	29	140.9
S_C100_3	53.4	494.4	42.10	382.9	107.4	897.7	105.3	555.2
S_C100_4	38.10	140.6	22.7	95.3	50.9	190.4	38.8	151.5
S_C100_5	43.2	165.9	28.10	106.3	80.3	614.9	64.4	480.4
S_C100_6	28.9	142.4	20.6	105.2	104.7	330.8	82	278.2
S_R100_1	62.6	261.4	44.9	105.3	69.2	1017.3	57.4	742.5
S_R100_2	30.4	302.9	21.4	180.7	44.5	285.2	36.2	227.9
S_R100_3	60.8	214	40.4	143.8	50.3	307.6	38.5	258.7

vast volume of product load. However, this work does not consider the double disruptive events.

Conclusions

In this research route, the discovery and route disruption model during product delivery is discussed. Some persistent nature of the proposed optimization approaches is considered to characterize the VRP accurately. The vehicle routing is measured in the traffic hours with an edge connecting pair of network nodes. In this research, the routing objective is to diminish the total cost, including transportation and product costs. Thus, the disruption recovery model is designed to fulfil various other constraints. The anticipated optimization approach is provided to handle the multi-objective restriction, and the work attains global best solution with these optimization approaches. The GWO pretends to work effectually by fulfilling the exploration and exploitation condition, and the P^{3}SO model selects the network patterns to perform the route discovery process effectually. The model initiates its discovery process in the initial routing phase by establishing the connectivity among the neighbourhood search. The significance of the model is validated with the comparison of computational outcomes attained with the anticipated P^{3}SO and GWO models. This objective is limited with the initial routing and disruption mechanism and not extended further, leading to substantial computational complexity. Thus, some other factors like split delivery are considered in the future, and the routing issues associated with those split delivery are analyzed. The primary research constraint is the selection of benchmark datasets and validation with the dataset.

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References

1 Ou Z L, Wu Z, Zheng J, Lyu R, Przesmitzki S & He X, *A study of China's explosive growth in the plug-in electric vehicle market* (US Dept Energy, Oak Ridge, TN, USA) 2017, 6283–37831.

2 Hermann R, Hartl F, Puchinger J & Vidal T, Routing a mix of conventional, plug-in hybrid and electric vehicles, *Eur J Oper Res*, **272(1)** (2019) 235–248.

3 Yu Z, Yang Z & B Z Yao, A hybrid algorithm for vehicle routing problem with time windows, *Expert Syst Appl*, **38(1)** (2008) 435–441.

4 Demir T, Bekta Ş & Laporte G, An adaptive large neighbourhood search heuristic for the pollution-routing problem, *Eur J Oper Res*, **223(2)** (2012) 346–359.

5 Nuzzolo & Comi A, Advanced public transport and intelligent transport systems: New modelling challenges Transportmetrica A, *Transp Sci*, **12(8)** (2016) 674–699.

6 Zhou, Yu H, Li Z, Su J & Liu C, Robust optimization of a distribution network location-routing problem under carbon trading policies, *IEEE Access*, **8** (2020) 46288–46306.

7 Qiu, Wang L, Fang X, Pardalos P M & Goldengorin B, Formulations and branch-and-cut algorithms for production routing problems with time windows, Transportmetrica A, *Transp Sci*, **14(8)** (2018) 669–690.

8 Song & Ko Y D, A vehicle routing problem of refrigerated and general-type vehicles for perishable food products delivery, *J Food Eng*, **169** (2016) 61–71.

9 Mu & WEglise R, Disrupted capacitated vehicle routing problem with order release delay, *Ann Oper Res*, **207(1)** (2013) 201–216.

10 Yuan & Jiang Z, Disruption management for the real-time home caregiver scheduling and routing problem, *Sustainability*, **9(12)** (2017) 2178.

11 Ichoua, M Gendreau & Potvin J Y, Vehicle dispatching with time-dependent travel times, *Eur J Oper Res*, **144(2)** (2003) 379–396.

12 Solomon, Algorithms for the vehicle routing and scheduling problems with time window constraints, *Oper Res*, **35(2)** (1987) 254–265.

13 Ding, Hu X & Jiang Y, A model of disruption management based on prospect theory in logistic distribution, *J Manage Sci China*, **17(11)** (2014) 1–9.

14 Song, Sun W, Xiao F, Peng S, An J & Wang D, A novel coordinated control algorithm for distributed driving electric vehicles, *J Européen des Systèmes Automatisés*, **50(4–6)** (2017) 405–421.

15 Song, Gao S & Chen C, A novel vehicle feature extraction algorithm based on wavelet moment, *Traitement Signal*, **35(3–4)** (2018) 223–242.

16 Schneider, Stenger A & Hof J, An adaptive VNS algorithm for vehicle routing problems with intermediate stops, *Or Spectr*, **37(2)** (2015) 353–387.