Vol. 05, No. S1 (2023) 47-54, doi: 10.24874/PES.SI.01.006

Proceedings on Engineering Sciences

www.pesjournal.net

OPTIMIZING VEHICLE ROUTING WITH A HYBRID SWARM-INTELLIGENT FROG JUMPING OPTIMIZATION ALGORITHM

Pramod Kumar Faujdar[1]
Ashish Simalti
Kannagi Anbazhagan

Received 21.04.2023.
Accepted 24.06.2023.

Keywords:

Vehicle routing problem, hybrid swarm-intelligent frog jumping optimization (HSIFJO), extremal optimization (EO).

A B S T R A C T

The issues in Vehicle Routing with Time Windows (VR-TW) are addressed in this study using a novel hybrid swarm-intelligent frog jumping optimisation (HSIFJO) algorithm. The method employs a diversity management strategy for developing memeplexes, which assists in preserving diversity and prevents the premature termination of the search. To increase population diversity and improve solution quality, an enhanced clone selection (CS) process is employed. To maximise the algorithm's potential, an enhanced and extended extremal optimisation (EO) strategy is used, coupled with different move operators. A proposed adaptive soft time windows (ASTW) surcharge approach acknowledges the possibility of impractical solutions during the evolution process. When compared to existing state-of-the-art heuristics, the suggested approach performs exceptionally well in performance evaluation.

1. INTRODUCTION

Logistics and transportation management require careful management of the vehicle routing (VR) problem. Order to deliver goods or render services to a group of clients entails determining the most effective routes for an inventory of vehicles (Sar et al. (2023)). The objective is to maximise resource utilisation, satisfy consumer demands, and save costs like fuel usage and vehicle wear and tear (Wang and Sheu (2019)). A combinatorial optimisation issue, known as VR-TW, involves choosing the best paths for a fleet of vehicles to take in order to deliver goods or services to a group of consumers within predetermined time periods. While making sure that all customers' needs are met, and deadlines are fulfilled, the objective is to reduce the overall distance travelled or the number of vehicles used (Mojtahedi et al. (2021)).

Each consumer in the VR-TW case has a unique request, as well as a time frame in which the delivery must occur. A route's maximum length, vehicle capacity, and beginning and end depot locations are also restricted. The vehicles begin and conclude their trips at the depot, and each customer must be serviced exactly once (Xu et al. (2019), Gayialis et al. (2020)). The problem becomes more challenging when considering TW because the solution must respect the temporal constraints. If a vehicle arrives too early or too late at a customer's location, the delivery may be impossible or result in penalties.

Solving the issues in VR-TW involves finding an arrangement of routes, determining the order of customer visits, and assigning a vehicle to each route. Various algorithms, such as heuristic approaches and

[1] Corresponding author: Pramod Kumar Faujdar
Email: pramod_kumar@vgu.ac.in

metaheuristic methods, are used to solve the issues in VR-TW and obtain near-optimal solutions. The issues in VR-TW are significant problem in logistics and transportation management, as it helps optimize the allocation of resources and improve the efficiency of delivery operations, ultimately reducing costs and improving customer satisfaction.

We propose a hybrid swarm-intelligent frog jumping optimisation (HSIFJO) to solve issues in VR-TW in this study. We introduce the diversity control (DC) mechanism used to build HSIFJO memeplexes (MPXs) as part of the suggested method. When applied to population evolution, the enhanced CS procedure proposes an enhanced and enhanced extremal optimisation (EEO) local search technique that makes use of different move operators. Additionally, the ASTW surcharge technique is created to hasten the algorithm's exploitation.

For the purpose of tackling issues in VR-TW, a brand-new hybrid heuristic built on ME is suggested. In order to maximise the algorithm's potential, a unique neighbourhood search based on an expanded and updated EO method with alternative move operators is provided. To prevent premature convergence, effective diversity management techniques are devised and used to promote the creation of memeplexes. These techniques include modified CS and the ASTW surcharge measure.

The remainder of this paper is arranged as follows: Part 2-related work, while part 3- methods, Part 4-Result and discussion, and part 5-conclusion.

2. RELATED WORKS

An innovative Municipal Solid Waste Management (MSWM) for a smart city and supply chain cost optimisation are presented by Akbarpour et al. (2021). This research uses the VRP idea in the first sub-model and plans LCV and HCV vehicles to collect waste in every spot and transfer it to the recovery centre. MSWM cost is minimised through objective function. Four metaheuristic algorithms and chance-constrained programming tested the presented difficulty. GAPSO had the best results and exhibited good metaheuristic consistency.

According to Qin et al. (2019), a complete "VRP-CSC (VR problem for cold chain logistics considering customer satisfaction and carbon emissions)" model with minimised cost of the unit satisfied customer as the aim function was constructed to optimise cold chain distribution channels. The model is solved using CEGA, an upgraded genetic method. The algorithm's efficacy is verified by numerical testing. Next, the method is applied with actual case data for conducting an automated experiment, which yields a highly cost-effective solution.

Marinakis et al. (2019) introduces the Multi-Adaptive PSO (MAPSO) for solving the VR Problem with TW. The algorithm uses a trio of adaptive strategies: the Greedy Randomised Adaptive Search Procedure (GRASP) for the solution of the initialization process, an Adaptive Memory process to substitute the Path Relinking method in the Combinatorial Neighbourhood Topology, and an adaptive strategy for PSO parameters computation.

Li et al. (2019) formulate a multi-depot green VR issue (MDGVRP) aimed to effectively address the challenge by maximising revenue while minimising expenses, time, and emissions. They proceeded to apply an improved ant colony optimisation (IACO) method to the problem. The IACO model used updates the pheromone in a distinctive manner that produces superior outcomes. When contrasted to the traditional ACO, the findings obtained using the IACO show satisfying performance and greater solution quality.

James et al. (2019) investigated the application of UAVs to reduce costs and fuel usage for last-mile deliveries, and they created a vehicle-UAV green routing model. A genetic algorithm called GVRP-GA has been developed with the goal of solving huge issue cases, and an ideal model to minimise the overall cost is also provided. The findings of the experiment demonstrate that the deployment of UAVs can assist in reducing fixed costs by minimising time to delivery and the number of vehicles necessary because UAVs and cars cooperatively deliver packages.

Zhang et al. (2019) present a unique neural combinatorial optimisation technique based on deep reinforcement learning. Specifically, they present a structural graph embedded pointer network to iteratively construct these tours, transforming the online routing issue into a vehicle tour manufacturing issue in the process.

Barma et al. (2019) presents a flexible time window multi-objective VR problem (MOVRPFlexTW). Ant colony optimisation and three mutation operators with Pareto optimality for multi-objective optimisation are proposed. Solomon's issues were used to test the proposed method. The recommended technique yields solutions comparable to the best-known findings, proving its efficacy.

In order to solve MDVRP, Zhang et al. (2019) suggested a 2-opt local exchange-guided discrete antlion optimisation method. In the instance of MDVRP, the combination of heuristics and local search produces satisfactory results.

Thus, a credibility-based fuzzy optimisation model was developed by Chen and Shi (2019) for a novel "fuzzy electric VR issue with TW and recharging stations." A modified large neighbourhood search (ALNS) technique combined with fuzzy simulation solves the model. For issues in VR-TW, the ALNS algorithm integrates four new removal techniques. The variable neighbourhood descent technique and five local search operators have been incorporated into the ALNS algorithm to boost speed. The ALNS algorithm was tested for the model solution.

3. METHODS

3.1 HSIFJO for issues in VR-TW

The “memetic evolution (ME)” of a population of foraging frogs served as the basis for HSIFJO, a metaheuristic optimisation method. The HSIFJO population is divided into a variety of parallel communities (MPXs) that are free to explore the cosmos and evolve on their own. Each MPX has frogs who have developed ideas about other frogs. They go through memetic growth as a result. ME improves a person's meme and boosts a frog's ability to accomplish well in a task. Frogs with superior memes (ideas) must contribute more to the creation of innovative ideas than frogs with inferior concepts in order to preserve competitiveness in the process of infection. The “triangular probability distribution” used for frog selection gives superior concepts a competitive edge. Information is shuffled across MPXs after a certain number of memetic development steps. After being infected by frogs from several MPXs, shuffling enhances the meme and ensures unbiased cultural progress toward any particular interest. When predetermined convergence requirements are met, the local search and shuffling operation is repeated.

The initial HSIFJO model is effective for dealing with continuous optimisation issues, but it is challenging to handle issues directly in VR-TW because it is a combinatorial optimisation issue with discrete solutions on every dimension. As a result, the problem's response requires to be encoded and adjusted so that the HSIFJO can calculate it. With M depots and N consumers, the data format of an HSIFJO solution to the VR-TW problems can be expressed as

$$Y_j = \{Y_{j1}, Y_{j2}, \dots Y_{jN}\}, Y_{jl} \in [0, L_1 + L_2 + \cdots + L_N), L = 1,2, \dots N \tag{1}$$

It describes the decoding process for the issues in the VR-TW solution represented by a data structure. The decoding procedure is divided into two phases. In the preliminary phase, the solution Y_j is grouped into several sets denoted as I_j. Each set I_j represents a vehicle route. The number of sets generated depends on the maximum vehicle number, L_d, for each depot d. The sets are created based on the values of Y_j, such that each element Y_{jl} in a set I_j satisfies the condition $1 \leq Y_{jl} < k$. In the second step, the elements of each set Y_j are sorted in ascending order based on the values of Y_{jl}. This sorting determines the sequence of customers in each vehicle route.

To assign the sets to the respective depots, the sets T_d are formed, where d belongs to the set of depots (1 to Mg). The set T_d includes all the sets Y_j. Overall, this decoding process organizes the solution representation into individual vehicle routes and assigns them to their respective depots, allowing for further analysis and optimization in the context of the issues in the VR-TW problem.

3.2 Development of MPXs using DC strategy

To find an improved response in each memeplex for the HSIFJO, a local search is conducted. The preliminary metric that produces the memeplex may cause the process to converge on a local optimum due to the similarity and lack of variety in the frog information (meme) across MPXs. Thus, it's critical to ensure that each memeplex has a variety of information. In this investigation, we provide a fresh DC method to develop MPXs. This strategy's primary goal is to keep each MPXs diversity as diverse as feasible.

In this analysis, differences between pairs of frogs are understood to exist when: To determine the variation between an MPX and a frog that is derived from Q_t, we use the following notation: frog is the $i-th$ frog in set T, s_n is the greatest number of references of the frogs in each MPX, and the frogs contained inside the targeted range remain in the Q_t temporary set.

$$Diversity(frog1, frog2) = \frac{N - \sum_{k=1}^{M} \left|\{d_l | s_j = s_j, j \in \{1,2,\dots,M\}|\}\right|}{N}, s_j \in frog1, s_k \in frog2 \tag{2}$$

In VR-TW, N - total number of customers,
M - the maximal amount of vehicles,
s_j - sequence of customers on the jth vehicle route, d_l is the customer's vertices for that route, and $s_j = s$ means that the visits for the two routes of vehicles are the same.

3.3 CS Procedure for HSIFJO

An integral part of the HSIFJO is the CS process. In HSIFJO, the method maintains records of a frog population and clones a portion of the population at the initial stage of each iteration. The CS process then chooses which clones are retained for the next round of reproduction. CS protocol according to the HSIFJO.

Cloning

The term "cloning" is used to describe the process of cell division or agamogenesis. Cloning in this work produced explorers (frogs) with higher antigen affinities and greater diversity; these characteristics were used to quantify the explorer’s ability to differentiate between one another. The fitness (objective) of explorers can be evaluated by their antigen affinity. Assuming the Explorers (frog) population is $Q(t) = \{Y_1(t), Y_2(t), Y_3(t), \dots, Y_G(t)\}$at t generation, the new explorer population Q' (t) can be produced by cloning in the following way:

$$Q'(t) = D(Q(t)) = \{j = 1,2,3, \dots . G\} = \{D(Y_1(t)), D(Y_2(t)), D(Y_3(t)), \dots, D(Y_G(t)), \dots, D(Y_3(t))\} \quad (3)$$

Where $D\left(y_j(t)\right) = S_j \times Y_j(t), j = 1,2,3, \dots., G, S_j$ is a 1D vector represented by $(1,1, \dots.,)^T$. S_j Stands for the total number of $y_j(t)$ for every explorer. Our research uses the following values for S_j:

$$\left|S_j\right| = Round\left(V \times \left(\frac{G \times f_a(y_j(t))}{\sum_{k=1}^{G} \ f_a(y_k(t))}\right)^{-1} \times \frac{Diversuty(y_j(t))}{Diversity_G}\right) \quad (4)$$

Where V is a variable associated with the overall scale of the explorers to be cloned, round (.) translates a real value to the closest integer, and $f_2(y_j(t))$ is the "fitness of frog" y_j in the t-th iteration. $Diversity(\ y_j(t))$ is the measure of $y_k(t)$'s uniqueness relative to the entire population, and it is described as

$$Diversuty\left(y_j(t)\right) = \frac{\sum_{j=1}^{G} \ Diversity(y_j(t), y_k(t))}{G} \quad (5)$$

A population's average variance is designated as $Diversity_G$.

$$Diversity_G = \frac{\sum_{j=1}^{G} \ \sum_{k=1}^{G} \ Diversity(y_j(t), Y_k(t))}{G \times (G-1)} \quad (6)$$

Therefore, the dimension of a cloning project for a given explorer is modified according to the explorer's specificity and affinity. The greater the affinity and variety of an explorer, the larger its scale for cloning.

EEO-based mutation

They hyper-mutate each member of the cloned population $Q'\ (t)$ with a probability equal to $Q_{mutation}(y_j(et))$. Our study employs the following parameters for the mutation probability rate:

$$Q_{mutation}\left(y_j(t)\right) = exp\ exp\ \left(\alpha \times \frac{f_a(y_j(t))}{\sum_{k=1}^{G} \ f_a(y_j(t))}\right) \quad (7)$$

Where α is a variable called determines the cloning proportion. We introduce an EEO and use it to optimise the CSP mutation mechanism, which speeds up convergence.

Selection

During the mutation functioning, every$Y_{dj}(t), j = 1,2,3, \dots G$, is then used to determine the most effective explorer (frog) with the optimum affinity. G, and is preserved with a probability of Q_{select} in the newly created explorer population. The optimal explorer for $Best\left(Y_{dj}(t)\right)$ for $Y_{dj}(t)$ is shown as follows:

$$Best\left(Y_{dj}(t)\right) = \{Y_{jk}(t) | k = arg_k\{k = 1,2, \dots . . |D_j|\}\} \quad (8)$$

In our research, the probability that the recently developed explorer $Best\left(Y_{dj}(t)\right)$ will succeed in the place of the original explorer $Y_j(t)$ is as follows:

$$Q_{select}\left(Y_j(t+1) = Best(Y_{dj}(t)\right) = \left\{1 \ 0 \ \left(exp\ exp\ \left(\frac{f_a\left(Best\left(Y_{dj}(t)\right)\right) - f_a(y_{jk}(t)))}{\beta}\right)\right)^{-1} if\ f_a(y_j(t)) \leq f_a(Best(y_{dj}(t)))) \ if\ f_a(y_j(t)) > f_z(Best(y_{dj}(t)))) \ and\ x_i(t)\ is\ not\ the\ best\ individual\ of\ Q\ \ f\ f_a(y_j(t)) > f_z(Best(y_{dj}(t)))) \ and\ x_i(t) is\ the\ best\ individual\ of\ Q \quad (9)$$

Consequently, the newly created population Q can be represented as

$$Q(t+1) = \{Y_1(t+1), Y_2(t+1), Y_3(t+1), \dots . Y_G(t+1)$$

$$Y_j(t+1) = \{Y_j(t) \ \ if\ s > q_{select}(Y_j(t+1) = Best\left(Y_{dj}(t)\right)) \ Best\left(Y_{dj}(t)\right) \ if\ \leq q_{\ select}(Y_j(t+1) = Best\left(Y_{dj}(t)\right)) \quad (10)$$

Where $[0, 1]$ is the range for the random number s. The fresh population of G individuals (frogs) is formed following the CS process. The newly created population is separated into m MPXs using the DC approach if the convergence requirement fails to be satisfied, and the local search is carried out in each MPXs.

The classic CS method has been changed in two ways: first, we accomplish the mutation more successfully using the EEO procedure; and second, we provide a novel DC approach to clone and choose the explorer, then produce the newly created population

3.4 EEO mutation process

This study enhances and broadens the extremal optimisation (EO) mutation. This process evolves a single chromosome S. The current individual S's decision variables are species in EO. In EO, only mutation exists. By repeatedly mutating the worst species, the individual can develop toward the best answer. This approach entails choosing a representation that assigns fitness to solution components. This differs from holistic methods like evolutionary algorithms, which give all solution sections equal fitness based on the algorithm's aggregated judgment of a desired function. It handles several continuous and discrete optimisation problems.

Customer element fitness

Asymmetric vehicle sub-paths are common issues in VR-TW. In addition to evaluating each path's capacity and overall length, we additionally verify to determine the TW for the current path is achieved. The customer's fitness λ_v is represented in this study as follows for a solution Y_j of the issues in VR-TW:

$$\lambda_v, 1 = (d(Y_{j,v\ min,}Y_{j,v}) + \left(d(Y_{j,v\ min,}Y_{j,submin})\right) - ((d(Y_{j,v-1,}Y_{j,v}) + (d(Y_{j,v,}Y_{j,v+1})) \quad (11)$$

$$\lambda_v, 2 = max(0, at_{v-1} + At_{v-1} + Tt_{v-1} + t_{v-1,v}))q_c \quad (12)$$

$$\lambda_v, 3 = max(0, e_{v-1} + At_{v-1} + Tt_{v-1} + t_{v-1,v}))q_c \quad (13)$$

$$\lambda_v = \lambda_v, 1 + \lambda_v, 2 + \lambda_v, 3 \quad (14)$$

The most adjacent and second-closest consumers to customer $Y_{j,v}$ are represented by $Y_{j,umin}$, and $Y_{j,vsubmin}$, respectively, and $\lambda_{v,1}$ is the distance variation level among the present path and the estimated optimal route. The customer service surcharge period is $\lambda_{v,2}$ for times that are earlier than the last interaction time permitted by the specified time frame. The fitness of this client should be penalised if the vehicle's arrival time arrives at the u customer after the v customer's latest service time and is the surcharge coefficient. The waiting time surcharge term is$\lambda_{v,3}$. When a vehicle arrives to a client sooner than the customer's earliest time, the fitness of that customer must also be penalised in some way. Q_c is the surcharge coefficient, which is often Q_b "Q_c. The client v's fitness is calculated as the product of $\lambda_{v,1}$,$\lambda_{v,2}$and$\lambda_{v,3}$. As a result, the probability distribution and fitness of every element can be used to predict the mutation consumer for each vehicle route.

Selection of most adjacent customer

Based on the TW data and the distances among the nodes, the adjacent fitness among two nodes, v, and w, is determined. The following formula is used to compute the closest fitness $\phi_{v,w}$:

$$\phi_{v,w} = \{d(v,w) + (0, f_v + Tt_v + t_{vw} - m_w)\ Q_b + \left(0, f_w - (f_w + Tt_v + t_{vw})\right)\ Q_c v \neq w\ T, \quad v \neq w \tag{15}$$

T is a significant enough constant. As a result, we may create a two-dimensional matrix that represents the adjacent fitness between each pair of algorithmic nodes. A novel two-dimensional can be created by sorting the components of each matrix row. Therefore, the probability distribution can be used to identify the best nearby customer w of a mutation the customer v.

Mutation process

The mutation operation aims to improve the solution by applying various points and segment moves. The following moves are utilized:

In “Two-opt move (TOM)," the enhanced two-opt technique is used to maintain the position of the standard two-opt procedure. Two routes and one link are eliminated in this modification. The main customer of one link is then connected to the end customer of another link, establishing two extra routes. This operator is better suited for problems with VR-TW since it keeps the link orientation. When the best nearby customer w and the mutation customer u are on the identical route, the two-opt move is employed. A customer gets integrated into a different route at a “merge point (MP)." "Merge segment (MS)” refers to the merging of a segment composed of numerous consumers into another route. In “Exchange routes in the same depot (ERSD)," the same depot, two routes from two initial locations ($v\ and\ w$) are exchanged with one another. Two segments from separate routes that are swapped within the same depot are referred to as "exchange segments in the same depot" (ESSD).

The move operators (MOs) are selected based on certain conditions. The MOs are chosen as follows:

- $MO = TOM\ if\ route(u) = route(v)$
- $MO = MP, MS, ERSD, ESSD\ if\ route(u) \neq (v) and\ depot(u) = depot(v)$
- $MO = MP, MS, ESDD\ if\ depot(u) \neq depot(v)$

Customers v and w are chosen in the mutation method, and a moving operator (MO) is then chosen at random using the predetermined rules. Applying the mutation procedure, the generated pathways are examined for viability in light of time window restrictions. The MO is chosen again, and the process is repeated until workable routes are found in the generated routes that fail to adhere to the TW.

Objectives surcharge function for ASTW

Fitness objective function calculation uses an ASTW surcharge measure. For delays, frog solutions are penalised. Problem-specific surcharge functions are utilised.

Two surcharge model functions are demonstrated. The TW objective function surcharge measurement model begins. When the explorer result surpasses the time frames, a big positive integer T is appended to the objective function. This significantly penalises the frog, signalling that solutions not fulfilling the TW are weak and picked for improvement in later iterations. Frogs that break the TW are unlikely to survive and provide little information to the evolutionary process as T is substantially bigger than the path cost.

However, it has been found that the majority of the factors contributing to frogs exceeding deadlines are often very important, and just a tiny percentage of the factors are detrimental. The study suggests the ASTW objective function surcharge measure as the second punitive measure in light of this observation.

The ASTW surcharge measure is calculated and considers the current number of shuffling iterations:

$$f_{a,it} = f_{e,it} + f_{q,it} \tag{16}$$

The total cost at the current iteration is used to determine the surcharge cost term and adaptively change it. The formula takes into account both the problem's customer number and the punishment coefficient.

Additionally, a number of factors are taken into account while calculating the surcharge term. Frogs who do not satisfy the TW have a better chance of taking part in the evolutionary process and contributing relevant information since the surcharge cost rises as the total cost falls. Infeasible solutions can contribute to the development of the algorithm and serve as information providers by using the ASTW surcharge measure, especially in the early phases of evolution.

4. RESULT AND DISCUSSION

In this section, we compare the performance of the suggested method to that of various existing methods (ABC+GA [14], HGA [15], and HPSO [16]). The factors include service level, Cost, travel time, and distance were analysed.

The term "distance" refers to the overall distance covered by the vehicles on a route. The result of the distance is shown in Figure 1. Our proposed approach (HSIFJO) is lower than the existing methods (HPSO, HGA, and ABC+GA), according to a comparison with the existing methods. Reducing the distance may reduce fuel use and travel time.

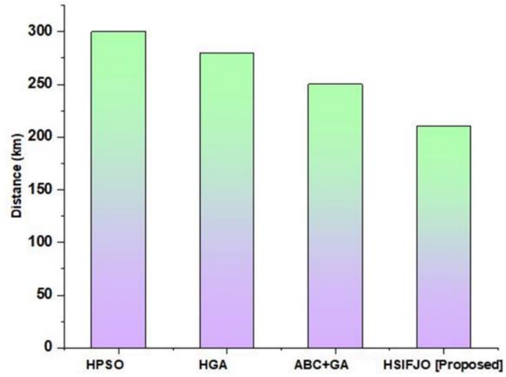

Figure 1. Result of the distance

Service level assesses the routing solution's capacity to satisfy customer requirements while maintaining predetermined service level standards. It evaluates on-time delivery, early or late deliveries, and customer satisfaction. The outcome of the service level is shown in Figure 2. Comparing the proposed (HSIFJO) with current methods (HPSO, HGA, and ABC+GA), it can be seen that our proposed method outperforms the existing method.

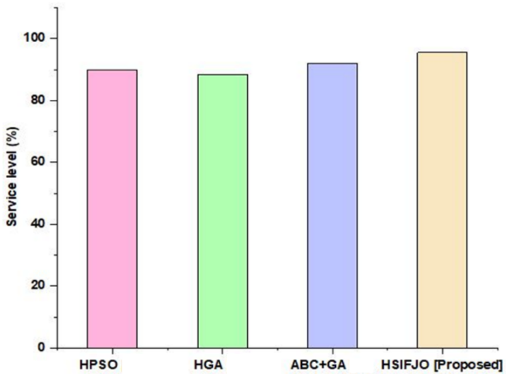

Figure 2. Service level outcome

The cost measure is a representation of the costs incurred by the VR system. The result of the cost is shown in Figure 3. Due to the fact that maximising profitability requires minimising expenses, our proposed approach (HSIFJO) is less expensive than the existing methods (HPSO, HGA, and ABC+GA).

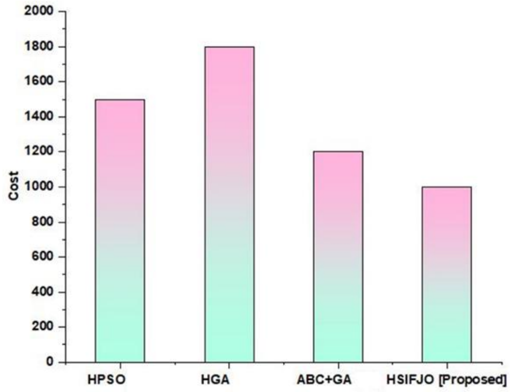

Figure 3. Cost outcome

The duration of the routes as a whole is represented by travel time. As a result, you can assess the time efficiency of several scenarios or routes and determine which ones resulted in the shortest trip durations. The travel time outcome is shown in Figure 4. It can be seen that our proposed approach (HSIFJO), which is lower than the existing methods (HPSO, HGA, and ABC+GA), is superior to them. It demonstrates how reducing travel time may improve customer satisfaction and improve the number of deliveries made every day.

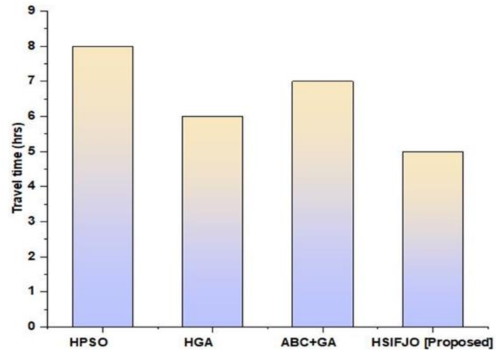

Figure 4. Travel time outcome

5. CONCLUSION

This paper presents a novel hybrid swarm-intelligent frog jumping optimization (HSIFJO) algorithm for solving the issues in VR-TW. The algorithm incorporates several innovative techniques, including a DC strategy, modified CS procedure, improved extremal optimization approach, and alternative move operators. It also introduces an ASTW surcharge measure to handle infeasible solutions. The experimental findings show that the suggested method outperforms other approaches. Overall, the HSIFJO algorithm shows promising potential for solving the issues in VR-TW and can be a valuable addition to the existing optimization methods for this problem. The proposed algorithm assumes a static problem environment where the problem instance does not change over time. Future research could explore dynamic variations of issues in VR-TW, where the problem parameters or constraints may change during the optimization process. Developing adaptive mechanisms within the algorithm to handle dynamic scenarios would be an interesting avenue for further investigation.

References:

Akbarpour, N., Salehi-Amiri, A., Hajiaghaei-Keshteli, M. and Oliva, D., 2021. An innovative waste management system in a smart city under stochastic optimization using vehicle routing problem. Soft Computing, 25, pp.6707-6727.

Barma, P.S., Dutta, J. and Mukherjee, A., 2019. A 2-opt guided discrete antlion optimization algorithm for multi-depot vehicle routing problem. Decision Making: Applications in Management and Engineering, 2(2), pp.112-125.

Chen, J. and Shi, J., 2019. A multi-compartment vehicle routing problem with time windows for urban distribution–A comparison study on particle swarm optimization algorithms. Computers & Industrial Engineering, 133, pp.95-106.

Davoodi, M., Malekpour Golsefidi, M. and Mesgari, M.S., 2019. A hybrid optimization method for vehicle routing problem using artificial bee colony and genetic algorithm. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 42, pp.293-297

Euchi, J. and Sadok, A., 2021. Hybrid genetic-sweep algorithm to solve the vehicle routing problem with drones. Physical Communication, 44, p.101236.

James, J.Q., Yu, W. and Gu, J., 2019. Online vehicle routing with neural combinatorial optimization and deep reinforcement learning. IEEE Transactions on Intelligent Transportation Systems, 20(10), pp.3806-3817.

Konstantakopoulos, G.D., Gayialis, S.P. and Kechagias, E.P., 2020. Vehicle routing problem and related algorithms for logistics distribution: a literature review and classification. Operational research, pp.1-30.

Li, Y., Soleimani, H. and Zohal, M., 2019. An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives. Journal of cleaner production, 227, pp.1161-1172.

Marinakis, Y., Marinaki, M. and Migdalas, A., 2019. A multi-adaptive particle swarm optimization for the vehicle routing problem with time windows. Information Sciences, 481, pp.311-329.

Mojtahedi, M., Fathollahi-Fard, A.M., Tavakkoli-Moghaddam, R. and Newton, S., 2021. Sustainable vehicle routing problem for coordinated solid waste management. Journal of Industrial Information Integration, 23, p.100220.

Qin, G., Tao, F. and Li, L., 2019. A vehicle routing optimization problem for cold chain logistics considering customer satisfaction and carbon emissions. International journal of environmental research and public health, 16(4), p.576.

Sar, K. and Ghadimi, P., 2023. A Systematic Literature Review of the Vehicle Routing Problem in Reverse Logistics Operations. Computers & Industrial Engineering, p.109011.

Wang, Z. and Sheu, J.B., 2019. Vehicle routing problem with drones. Transportation research part B: methodological, 122, pp.350-364.

Xu, Z., Elomri, A., Pokharel, S. and Mutlu, F., 2019. A model for capacitated green vehicle routing problem with the time-varying vehicle speed and soft time windows. Computers & Industrial Engineering, 137, p.106011.

Zhang, H., Zhang, Q., Ma, L., Zhang, Z. and Liu, Y., 2019. A hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows. Information Sciences, 490, pp.166-190.

Zhang, S., Chen, M., Zhang, W. and Zhuang, X., 2020. Fuzzy optimization model for electric vehicle routing problem with time windows and recharging stations. Expert systems with applications, 145, p.113123.

Pramod Kumar Faujdar
Vivekananda Global University,
Jaipur, India
pramod_kumar@vgu.ac.in
ORCID 0000-0002-0540-4771

Ashish Simalti
Teerthanker Mahaveer University,
Moradabad, Uttar Pradesh, India
ashusimalti@gmail.com
ORCID 0000-0001-7294-2791

Kannagi Anbazhagan
Jain (deemed to be) University,
Bangalore, India
a.kannagi@jainuniversity.ac.in
ORCID 0000-0003-3810-7500