Integrated Harmony Search Algorithm with Tabu Search for Solving the Vehicle Routing Problem: Frozen Seafood Product Transport

Phornprom Rungrueang¹, Nattapol Paisarnvirosrak²

¹ Faculty of Management Sciences, Kasetsart University, 199 Moo 6, Sukhumvit Road, Tung Sukla, Sri Racha, Chon Buri, 20230 Thailand.

² Faculty of Logistics and Digital Supply Chain, Naresuan University, 99 Moo 9 Phitsanulok-Nakornsawan Road, Mueang Phitsanulok District, Phitsanulok, 65000 Thailand.

nattapolpa@nu.ac.th (Corresponding author)

Abstract. This paper addresses the vehicle routing problem with time windows (VRPTW) for temperature-controlled food delivery using a novel Harmony Search integrated Tabu Search (HSTS) algorithm. Minimizing total travel distance is critical for reducing fuel costs and maintaining food quality in cold chain logistics. The HSTS algorithm leverages the global search capabilities of Harmony Search and local search strengths of Tabu Search. A case study of frozen seafood delivery with time windows, 7 vehicles, 56 customers, limit capacity, and product constraints are presented to demonstrate and validate the HSTS algorithm. Compared to company routes, the algorithm reduced total travel distance by 11.74% and decreased annual fuel costs by 97,357 Baht. Results highlight the potential of HSTS to efficiently solve real-world VRPTW problems arising in food transport and distribution.

Keywords: Vehicle routing problem with time window, Metaheuristics, Harmony Search algorithm, Tabu Search.

1. Introduction

Sales of seafood products now represent a substantial portion of the global economy. Demand for seafood has increased continually as a healthy source of protein and rich in nutrients comprising vitamins, minerals, and essential amino acids (National Marine Fisheries Service, 2020). However, seafood must be preserved at a stable temperature to maintain freshness (Watts et al., 2022) and avoid product quality deterioration (Baygar et al., 2013). Delivery time is also a crucial factor to ensure product quality and freshness (Espinoza Rodezno et al., 2013). The temperature of food products is maintained using a temperature-controlled vehicle. In urban areas, travel time may be longer during rush hour due to traffic congestion. The shelf life of perishable food is directly impacted by delivery time which determines the cost of the delivery operator and revenue gained by the company. Hence, travel time is also considered when determining optimal route scheduling. This concept is called the vehicle routing problem (VRP) of food delivery.

The VRP was first presented in a supply chain network by Dantzig et al. (1959) and it has now morphed into a dominant logistics and transportation problem. The VRP can be defined as an NP-hard combinatorial optimization problem that considers depots, customers, and shipments that must be transported from an origin location to customers at several locations using various vehicles with limited capacity. For route scheduling, many constraints must be considered such as service requirements, laws and regulations, and vehicle capacity. Using temperature-controlled vehicles is more expensive, with higher fuel consumption than regular vehicles. Therefore, effective route planning is necessary to reduce distribution cost, fuel consumption, and delivery time to maximize shelf life and preserve seafood quality.

This paper proposed a metaheuristics-based Harmony Search (HS) algorithm integrated with Tabu Search (TS) to solve the VRPTW. The main study objective was to find an optimal delivery route for seafood products by minimizing total delivery cost, fuel cost, and travel distance.

1.1. Contribution

This research study has three main contributions. Firstly, this is the first paper to integrate the HS and TB algorithms to minimize total travel distance, reduce fuel costs, and maintain food quality in cold chain VRPTW logistics. The HSTB provided acceptable solution quality by enhancing the balance and diversification of the algorithm to provide a competitive solution. Secondly, the HSTB provided reasonable solution quality within a short experimentation time. A real-life problem of seafood transport was investigated using the HSTB and compared with other methods. Results showed that our proposed solution gave outstanding performance better than the other methods.

2. Literature Review

2.1. Vehicle routing problem with time windows

The vehicle routing problem with time windows (VRPTW) was analyzed as a combinatorial optimization problem (NP-hard) to determine the shortest delivery route for products under constraints including number of vehicles, capacity of vehicles, and the delivery time window at each location. The principal objective of the VRP is to optimize delivery costs to a set of clients in diverse geographical locations with disparate goods requirements. The maximum vehicle carrying capacity cannot be exceeded (Bruniecki et al., 2016), while each customer specifies a certain delivery time (time window). Time windows can be strict (described as hard) (Agra et al., 2013; Vidal et al., 2013), while soft time windows allow delivery outside the time boundaries but add a penalty cost (Figliozzi, 2010; Taş et al., 2013).

Metaheuristics methods are generally used to solve the VRPTW including simulated annealing (Aurachman et al., 2021; Yu et al., 2022), genetic algorithms (Cruz-Chávez et al., 2019; Ochelska-Mierzejewska et al., 2021), and Tabu Search (Meliani et al., 2022; Nguyen et al., 2013).

2.2. Harmony Search algorithm

Harmony Search (HS) is a new population-based metaheuristic algorithm, first proposed by Geem et al. (2001). HS was developed to determine better harmony by musicians while playing music and is similar to local and global search procedures. The HS algorithm comprises three basic stages. The first is the initialization stage when the population of harmonies is randomly generated and collected in harmony memory. Second, a new harmony vector is developed, dependent on the three rules of random selection, which are harmony, memory consideration, and pitch adjustment as an improvement stage. In the final third stage, the harmony memory is improved if the result presents a better solution than the unacceptable harmony vector in the harmony memory. The same procedure then repeats till a termination condition is reached (Yassen et al., 2013) (Fig. 1).

Musicians	\rightarrow	Variable decisions
Allowable notes for each musician	\rightarrow	Variable decisions' domain
Played notes by musicians	\rightarrow	Selected value for decision variables
Produced harmony	\rightarrow	Generated solution
Aesthetic standard	\rightarrow	Objective function
Experience	\rightarrow	Harmony memory
Practice	\rightarrow	Iteration



The HS algorithm has fewer mathematical parameters compared with other metaheuristics and the robustness of this algorithm can solve a wide range of problems including flow shop scheduling (Doush et al., 2022), load dispatch problems (Karthigeyan et al., 2015), nurse rostering problems (Hadwan, 2022), and optimal reactive power flow problems (Sivasubramani et al., 2011).

The HS algorithm has recently attracted increased attention to solve the VRP (Chen et al., 2017; Maleki et al., 2017; Yassen et al., 2013). However, significant drawbacks of the HS algorithm result from the ineffective balance between global and local search, leading to poor performance. Therefore, selecting accurate parameters to apply with the HS algorithm is crucial to improve performance (Yassen et al., 2015). In this paper, we integrated the HS algorithm with Tabu Search to improve performance quality. Liu et al. (2020) developed HS with a global sharing factor based on natural number coding (GSF-HS) for VRP. This GSF-HS algorithm presented the shortest running time with a more rapid convergence speed and greater efficiency.

2.3. Tabu Search

Tabu Search (TS) is a metaheuristic memory-based search method that allows searching in a search space beyond the local optimum. TS is generally used for solving mathematical optimization problems. One of the crucial benefits of TS is preventing result cycling by adding the selected candidate (solution) into a tabu list.

Previously, researchers applied TS to enhance algorithm abilities. Jia et al. (2013) developed TS to solve the VRP by establishing mutation integrated with local searching strategies to improve performance, while Belhaiza et al. (2014) applied TS with variable neighborhood search methods to solve the VRP with various time windows by considering minimum waiting time and minimum delay when generating the route. TS was also applied by Wang et al. (2015) to solve the VRPTW by considering heterogeneous multi-type fleets and incompatible loading constraints involving a large number of dispatches to grocery chains and retail outlets.

Many researchers have used TS to solve the VRPTW. Paisarnvirosrak and Rungrueang (2023) studied a green VRPTW using Tabu Search by combining the Firefly Algorithm (FA). Their solution reduced annual transportation costs from 1,061,851 to 893,108 Baht, while annual fuel consumption was reduced from 31,286 to 26,314 L, resulting in a significant reduction of annual greenhouse gas

emissions from 90,730 to 76,312 kgCO₂. Syafrizal and Sugiharti (2023) studied an electric VRP using Fuzzy TW by integrating the Genetic Algorithm (GA) with TS, with an improvement in solution quality by 11.35%, while Meliani et al. (2022) applied a TS-based algorithm to solve a heterogeneous fleet VRP by considering three-dimensional loading constraints. Their proposed algorithm improved the solution by 76%. Zhao et al. (2017) also applied the HS algorithm with TS to solve job scheduling problems but not to solve the VRPTW. To the best of our knowledge, the HS algorithm has never been integrated with TB to solve the VRPTW in cold chain transport.

3. Methodology

3.1. Problem description

The frozen seafood was distributed from a single company depot to customers as five different product types including crabs, prawns, scallops, squid, and mixed seafood. Customer demand for each product was determined based on historical company data. Frozen seafood distribution was performed using a seven fleet of temperature-controlled vehicles to deliver seafood products to 56 customers. Each customer had a different time window. The products were packed separately to avoid contamination during transport. Customer demand varied daily. Each vehicle visited multiple customers and the maximum vehicle capacity was not exceeded. The vehicles used for goods delivery were limited and split deliveries were not permitted, with each client order delivered by one delivery vehicle. Company data that were not confidential were used for the research study. Names of both the company and clients were omitted. Therefore, this study was exempted from an ethical review. This real-life case study is displayed in Fig. 2.



Fig. 2: Representation of the case study.

3.2. Mathematical model

The case study optimization model was similar to CVRPTW (Capacitated Vehicle Routing Problem with Time Windows) and constrained by the number of distribution centers, number of trucks, number of customers, demand of each product by each customer, and time windows.

For the proposed methodology we set HMS = 30, HMCR = 0.8, and PAR = 0.6 following Chen et al. (2017) who integrated HS with VNS for solving the dynamic VRPTW using a similar sample size to our case study. To integrate HS with TS, we set the size of the tabu list dynamically within the interval [0.75N;1.1N] (N indicates the number of nodes) following El Rhazi et al. (2009).

To solve the routing problem we defined a set of vehicles K delivered for a set of customers N. The road network was represented by a graph G = (V, A), where $V = \{0, 1, ..., N\}$ is a set of nodes representing the customers, and $A = \{(i, j) | i, j \in V, i \neq j\}$ is a set of arcs connecting node i and node j. Node 0 denotes the depot used for starting and ending the route, while other nodes (except 0) indicate the customers. For each customer i and j ($1 \le i$ and $j \le N$) and the required demand of each product type t at each customer q_{ti} , the delivery service time j_i and the time windows $[e_{ij}, l_i]$ are known.

For each truck k $(1 \le k \le K)$, the maximum vehicle capacity was Q. The lunch break time b_i^k and waiting time w_i^k are additional times involving vehicle k stopping and waiting until the start time window at customer i.

Associated with each arc (i, j) \in A, traveling time t_{ij} and distance D_{ij} between customer i and j are asymmetric. The arrival time $[a_i^k, a_j^k]$ for each customer depends on the arrival time at the previous customer, waiting time, survey time, break time, and traveling time. The decision variables are denoted by X_{ij}^k which is a binary number and i, $j \in \mathbb{N}$ where X_{ij}^k is equal 1 if and only if truck k travels from customer i to j; otherwise X_{ij}^k is equal to 0.

The CVRPTW formulation is presented as follows:

$$Minimize \ Z = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} X_{ij}^{k} D_{ij}$$

$$\tag{1}$$

Subject to:

$$\sum_{k=1}^{K} \sum_{i=0}^{N} X_{ij}^{k} = 1; for j = \{1, 2, \dots, N\}$$
(2)

$$\sum_{j=1}^{N} X_{0j}^{k} - \sum_{i=1}^{N} X_{i0}^{k} = 0; \text{ for } k = \{1, 2, \dots, K\}$$
(3)

$$\sum_{k=1}^{K} \sum_{i=0}^{N} X_{ij}^{k} \left(a_{i}^{k} + w_{i}^{k} + j_{i}^{k} + b_{i}^{k} + t_{ij} \right) \le a_{j}^{k}; for j = \{1, 2, \dots, N\}$$

$$\tag{4}$$

$$e_{i} \leq a_{i}^{k} \leq l_{i}; for \ i = \{1, 2, ..., N\}, k = \{1, 2, ..., K\}$$

$$\sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{t=0}^{N} X_{ij}^{k} q_{ti} \leq Q; for \ Q = 2000, for \ t = \{1, 2, ..., 5\}$$
(6)
(5)

$$\sum_{k=1}^{N} \sum_{j=1}^{N} X_{0j}^{k} \le K; for K = 9$$

$$X_{ij}^{k} \in \{0,1\}; \quad i, j \in N; \quad i \neq j; \quad k \in K$$
(8)

In this formulation, Equation (1) represents the objective function of this problem. Equation (2) indicates that every customer can be visited exactly once. Equation (3) states that every vehicle has to depart from and arrive at the same depot. Equations (4) and (5) ensure that the time window of each customer has been met. Equation (6) specifies that the total demand must not exceed the truck capacity, and Equation (7) limits the number of trucks available. Finally, Equation (8) defines the decision variable as a binary number.

Pseudo code of the Integrated Harmony Search Algorithm with Tabu Search (HSTS)					
01: Pseudo code of the HSATS (<i>t</i> , <i>r</i> , <i>i</i> , <i>PAR</i> , <i>HMCR</i> , <i>HM</i> , <i>TL</i>) \succ <i>t</i> : number of iterations					
	▷ rand : random number				
	\triangleright C : number of customers				
	▷ PAR : Pitch adjusting rate				
	▷ HMCR : Harmony Memory Considering rate				
	▷ HM : Harmony Memory				
	⊳ TL : Tabu list				
02: Set all parameters $t = 1$, $i = 1$					
03: Set Harmony Memory Considering rate (HMCR)					
04: Set Pitch adjusting rate (PAR)					
05: Set the objective function $f(x)$					
06: Generate the initial solution from Harmony Memory with r	andom harmonies solution (s');				
07: while $(t < t^{max})$ do					
08: for $(i = 1 \text{ to } C)$ do					
09: if (<i>rand</i> < <i>HMCR</i>) then					
10: Select value from HM for each customer <i>i</i> ;					
11: if (<i>rand</i> < <i>PAR</i>) then					
12: Adjust the value of route;					
13: end if					
14: else					
15: Choose a random value					
16: end if					
17: Neighborhood search customer out of <i>TL</i> ;					
18: Find the best non-tabu route solution (s^{TL}) ;					
19: Update TL ;					
20: $i++;$					
21: end for					
22: if solution $(s^{ans}) <$ worst solution (s^{HM}) then					
23: Replacement solution (s^{ans}) in <i>HM</i> ;					
24: else					
25: return HM ;					
26: end if					
27: <i>t</i> ++;					
28: end while					
29: Return solution (r^{best}) in <i>HM</i> as optimal solution;					
30: end procedure					

Fig. 3: Pseudo code of the Integrated Harmony Search Algorithm with Tabu Search (HSTS).

The Integrated Harmony Search Algorithm with Tabu Search (HSTS) process was allocated a pseudo code, as shown in Fig. 3. The process was separated into six states as initialization (lines 01 to 06), checking the termination criterion (line 07), improving a new solution from the Harmony Memory (HM) (lines 08 to 16), neighborhood search by TS (lines 17 to 19), updating the HM (lines 22 to 26), and providing the optimal solution (line 29). First, the initial parameters and initial solution were set and the stopping criterion was checked. If the termination condition was reached, return the optimal solution for HM. The HS algorithm improved the solution by selecting the new solution from the HM. Then, the TS was adapted to avoid a repeat search in HM using the local search. Finally, the HM was improved if the new solution was better than the unacceptable solution in HM. The optimal solution was taken as the best solution in HM.

4. Results and Discussions

The proposed HSTS algorithm was implemented to solve the VRPTW for a frozen food delivery case study. The proposed HSTS algorithm was coded in JavaScript on a CPU Intel® Core[™] i5-5200U with up to 2.7 GHz and 4 GB of RAM. JavaScript is a programming language that goes beyond the traditional Internet roles by combining with the Internet of Things (IoT) and other IT systems. It can also be used to create applications and build cross-platform desktop apps. The

termination condition of our proposed algorithm was based on a running time of 25 minutes, as recommended by Yassen et al. (2015).



Fig. 4: Comparison of the company's currently used frozen food delivery route and the route generated by the HSTS algorithm.

 Table. 1: Comparison of transportation route distances in kilometers between the company solution, the HS algorithm and the HSTS algorithm.

	Company Solution	HS Algorithm	HSTS Algorithm	Company Solution vs HS	Company Solution vs HSTS	HS vs HSTS
Route 1	8.15	8.15	8.15	0.00%	0.00%	0.00%
Route 2	8.15	8.15	8.15	0.00%	0.00%	0.00%
Route 3	7.93	7.93	7.93	0.00%	0.00%	0.00%
Route 4	28.05	28.05	27.96	0.00%	0.32%	0.32%
Route 5	35.69	41.89	34.01	-17.36%	4.71%	18.80%
Route 6	121.72	121.02	121.02	0.58%	0.58%	0.00%
Route 7	115.50	79.80	79.80	30.91%	30.91%	0.00%
Total	325.19	294.99	287.02	9.29%	11.74%	2.70%

TS was applied to the HS algorithm to solve the vehicle routing problem with time windows for seafood delivery. Numerical results are displayed in Table 1. Results of our proposed HSTS algorithm were compared with the standard HS algorithm and the company's currently used routes. The HS algorithm and proposed HSTS algorithm improved the solution by reducing total delivery distance more than the company's currently used solution. Moreover, the proposed HSTS algorithm found the optimal solution for total delivery distance from 325.19 to 287.02 kilometres. This was 11.74% less than the company solution and 2.70% less than the general HS algorithm and reduced the total annual delivery distance to 13,932.05 kilometers. Minimization of the total delivery distance resulted in reduced delivery time that directly impacted better food quality (freshness).

Significant fuel savings were generated by the proposed algorithm when the shortest delivery distance criterion was accepted. The HSTS algorithm optimized the experimental problem and reduced daily fuel costs to 2,005.72 Baht, with an annual saving of 97,357.70 Baht. Fuel cost was calculated based on the cost of diesel oil from PTT Public Company Limited on 12/12/2022.

The HSTS algorithm reduced annual carbon emissions from 68,843.36 to 60,762.77 kgCO₂ as 11.11% more than the general HS algorithm. The carbon emission factor of diesel oil was based on 2.9 kgCO₂/liter, while the formula for calculating greenhouse gas emissions followed Konečný et al. (2017).

4.1. Paired sample T-test comparison

For performance validation, we applied significance testing using the paired sample T-Test between the proposed HSTS algorithm and the company solution, as presented in Table 2. If $p \le 0.05$, the instant provided a significant difference. In Table 2, the p-values verify that the HSTS algorithm was statistically better than the company solution in eight instances out of ten, providing a productive performance to deal with this problem.

Instant	HSTS VS company	p ≤ 0.05
FHT001	0.328	×
FHT002	0.000	\checkmark
FHT003	0.000	\checkmark
FHT004	0.038	\checkmark
FHT005	0.027	\checkmark
FHT006	0.042	\checkmark
FHT007	0.533	×
FHT008	0.019	\checkmark
FHT009	0.000	\checkmark
FHT010	0.021	\checkmark

Table. 2: Comparison of the paired sample T-test between the company solution and the HSTS algorithm.

Based on the paired sample T-test used for performance validation, this research reveals the demonstration with various inputs. As a result, the algorithm has the ability to perform effectively in scenarios similar to those found in cold chain VRPTW. Our proposed algorithm can be combined with other information technologies for future use. As a limitation, this paper only considered a single case study.

5. Conclusions

This paper presented an HSTS algorithm integrating Harmony Search and Tabu Search metaheuristics to solve the NP-hard VRPTW for a cold chain logistics case study. A fresh food spoilages over the finite time horizon from origin to destination. This may result in lower commercial value of fresh food. Our algorithm minimized total delivery distance and fuel costs under time window constraints, vehicle capacity, and product constraints.

HS is a robust metaheuristic algorithm that has few mathematical parameters and is generally used for solving combinatorial optimization problems. However, it cannot provide effective guidance in a search space to find the optimal solution. Many researchers have applied search methods to enhance the ability of algorithms. This paper applied TS with the HS algorithm to solve the VRPTW.

The HSTS algorithm has never been used for solving the VRPTW of cold chain. The algorithm was implemented to deal with a real-life case study of frozen food delivery in Thailand using temperaturecontrolled vehicles. Five types of products were delivered to each customer at each location. Delivery constraints included the number of vehicles, capacity of vehicles, and arrival time at each location. After implementation, the HSTS algorithm solutions were compared with the general HS algorithm and the company solution.

Implementing HSTS for a real frozen seafood distribution case study achieved an 11.74% reduction in total route distance and a 97,357 Baht annual fuel cost saving compared to current company routes. Results demonstrated the effectiveness of HSTS in efficiently searching the solution space and optimizing time-dependent routing problems, with promising applications in food transportation. While tested on a single case study, the generalized HSTS approach provides a valuable addition to VRP solution methods. Future research can further validate HSTS using expanded test cases with diverse constraints, and also investigate hybrids with other metaheuristics. This study presented a novel algorithm for enhancing VRPTW solutions and reducing logistics costs in food supply chains.

6. Future Studies

The proposed HSTS algorithm can be further applied as follows. Firstly, the HSTS algorithm can be implemented with case studies of heterogeneous vehicle fleets with multiple depots, and also consider road condition limitations. Secondly, the proposed methodology can be extended to deal with stochastic VRPTW, while the HSTS algorithm can also be used to solve other combinatorial optimization problems.

References

Agra, A., Christiansen, M., Figueiredo, R., Hvattum, L. M., Poss, M. & Requejo, C. (2013). The robust vehicle routing problem with time windows. *Computers & Operations Research*, 40(3), 856–866.

Aurachman, R., Baskara, D. B. & Habibie, J. (2021). Vehicle routing problem with simulated annealing using python programming. IOP Conference Series: *Materials Science and Engineering*, 1010(1).

Baygar, T. & Alparslan, Y. (2013). Effects of multiple freezing and refrigerator thawing cycles on the quality changes of sea bass (*Dicentrarchus labrax*). *Journal of Food Science and Technology*, 52(6), 3458–3465.

Belhaiza, S., Hansen, P. & Laporte, G. (2014). A hybrid variable neighborhood tabu search heuristic for the vehicle routing problem with multiple time windows. *Computers & Operations Research*, 52, 269–281.

Bruniecki, K., Chybicki, A. Moszynski, M. & Bonecki, M. (2016). Evaluation of Vehicle Routing Problem Algorithms for Transport Logistics Using Dedicated GIS System. Proceedings - 2016 Baltic Geodetic Congress (Geomatics), *BGC Geomatics 2016*, 116–121.

Chen, S., Chen, R. & Gao, J. (2017). A Modified Harmony Search Algorithm for Solving the Dynamic Vehicle Routing Problem with Time Windows. *Scientific Programming*, 2017.

Cruz-Chávez, M. A., Rodríguez-León, A., Rivera-López, R. & Cruz-Rosales, M. H. (2019). A gridbased genetic approach to solving the vehicle routing problem with time windows. *Applied Sciences* (*Switzerland*), 9(18).

Dantzig, G. & Ramser, J. (1959). The Truck Dispatching Problem. Management Science, 6, 80-91.

Doush, I. A., Al-Betar, M. A., Awadallah, M. A., Alyasseri, Z. A. A., Makhadmeh, S. N. & El-Abd, M. (2022). Island neighboring heuristics harmony search algorithm for flow shop scheduling with blocking. *Swarm and Evolutionary Computation*, 74, 101127.

El Rhazi, A. & Pierre, S. (2009). A tabu search algorithm for cluster building in wireless sensor networks. *IEEE Transactions on Mobile Computing*, 8(4), 433–444.

Espinoza Rodezno, L. A., Sundararajan, S., Solval, K. M., Chotiko, A., Li, J., Zhang, J., Alfaro, L., Bankston, J. D. & Sathivel, S. (2013). Cryogenic and air blast freezing techniques and their effect on the quality of catfish fillets. *LWT*, 54(2), 377–382.

Figliozzi, M. A. (2010). An iterative route construction and improvement algorithm for the vehicle routing problem with soft time windows. *Transportation Research Part C: Emerging Technologies*, 18(5), 668–679.

Geem, Z. W., Kim, J. H. & Loganathan, G. V. (2001). A New Heuristic Optimization Algorithm: Harmony Search. *Simulation*, 76(2), 60–68.

Hadwan, M. (2022). Annealed Harmony Search Algorithm for Nurse Rostering Problems. *Computers, Materials and Continua*, 71(3).

Jia, H., Li, Y., Dong, B. & Ya, H. (2013). An Improved Tabu Search Approach to Vehicle Routing Problem. *Procedia - Social and Behavioral Sciences*, 96, 1208–1217.

Karthigeyan, P., Raja, M. S., Hariharan, R., Prakash, S., Delibabu, S. & Gnanaselvam, R. (2015). Comparison of Harmony Search Algorithm, Improved Harmony Search Algorithm with Biogeography Based Optimization Algorithm for Solving Constrained Economic Load Dispatch Problems. Procedia *Technology*, 21, 611–618.

Konečný, V. & Petro, F. (2017). Calculation of selected emissions from transport services in road public transport. *MATEC Web of Conferences*, 134, 1–8.

Liu, L., Huo, J., Xue, F. & Dai, Y. (2020). Harmony search method with global sharing factor based on natural number coding for vehicle routing problem. *Information (Switzerland)*, 11(2), 1–16.

Maleki, F., Yousefikhoshbakht, M. & Rahati, A. (2017). A Hybrid Self-adaptive Global Best Harmony Search Algorithm for the Vehicle Routing Problem with Time Windows. *BRAIN – Broad Research in Artificial Intelligence and Neuroscience*, 8(4), 65–84.

Meliani, Y., Hani, Y., Lissane Elhaq, S. & El Mhamedi, A. (2022). A tabu search based approach for the Heterogeneous Fleet Vehicle Routing Problem with three-dimensional loading constraints. *Applied Soft Computing*, *126*, 109239.

National Marine Fisheries Service. (2020). Fisheries of the United States, 2019. *In* National Marine Fisheries Service: Vol. Current Fi (Issue 2020).

Nguyen, P. K., Crainic, T. G. & Toulouse, M. (2013). A tabu search for Time-dependent Multi-zone Multi-trip Vehicle Routing Problem with Time Windows. *European Journal of Operational Research*, 231(1), 43–56.

Ochelska-Mierzejewska, J., Poniszewska-Marańda, A. & Marańda, W. (2021). Selected genetic algorithms for vehicle routing problem solving. *Electronics (Switzerland)*, 10(24), 1–34.

Paisarnvirosrak, N. & Rungrueang, P. (2023). Firefly Algorithm with Tabu Search to Solve the Vehicle Routing Problem with Minimized Fuel Emissions : Case Study of Canned Fruits Transport. *LOGI–Scientific Journal on Transport and Logistics*, 14(1), 263-274.

Ramezani, P. & Ahangaran, M. (2013). Harmony Search Algorithm: Strengths and Weaknesses. *Journal of Computer Engineering & Information Technology*, 2(1), 1–7.

Sivasubramani, S. & Swarup, K. S. (2011). Multi-objective harmony search algorithm for optimal power flow problem. *International Journal of Electrical Power & Energy Systems*, 33(3), 745–752.

Syafrizal, W. & Sugiharti, E. (2023). Electric Vehicle Routing Problem with Fuzzy Time Windows using Genetic Algorithm and Tabu Search. *Journal of Advances in Information Systems and Technology*, *4*(2), 205–221.

Taş, D., Dellaert, N., Woensel, T. van. & Kok, T. de. (2013). Vehicle routing problem with stochastic travel times including soft time windows and service costs. *Computers & Operations Research*, 40(1), 214–224.

Vidal, T., Crainic, T. G., Gendreau, M. & Prins, C. (2013). A hybrid genetic algorithm with adaptive diversity management for a large class of vehicle routing problems with time-windows. *Computers & Operations Research*, 40(1), 475–489.

Wang, Z., Li, Y. & Hu, X. (2015). A heuristic approach and a tabu search for the heterogeneous multitype fleet vehicle routing problem with time windows and an incompatible loading constraint. *Computers & Industrial Engineering*, 89, 162–176.

Watts, E., State, L., Sea, L., College, G., Rouge, B. & States, U. (2022). Seafood handling, processing, and packaging. *In* Encyclopedia of Meat Sciences (Third Edit). Elsevier.

Yassen, E. T., Ayob, M., Ahmad Nazri, M. Z. & Ahmad, Z. (2013). Harmony search algorithm for vehicle routing problem with time Windows. *Journal of Applied Sciences*, 13(4), 633–638.

Yassen, E. T., Ayob, M., Nazri, M. Z. A. & Sabar, N. R. (2015). Meta-harmony search algorithm for the vehicle routing problem with time windows. *Information Sciences*, 325, 140–158.

Yu, V. F., Susanto, H., Jodiawan, P., Ho, T. W., Lin, S. W. & Huang, Y. T. (2022). A Simulated Annealing Algorithm for the Vehicle Routing Problem With Parcel Lockers. *IEEE Access*, 10, 20764–20782.

Zhao, F., Liu, Y., Zhang, Y., Ma, W. & Zhang, C. (2017). A hybrid harmony search algorithm with efficient job sequence scheme and variable neighborhood search for the permutation flow shop scheduling problems. *Engineering Applications of Artificial Intelligence*, 65(July), 178–199.