Web Service-Based Capacitated Smart Vehicle Routing Problem with Time Window and Threshold Waste Level for Home Health Care Industry

Kubra Sar and Pezhman Ghadimi
Laboratory for Advanced Manufacturing Simulation and Robotics, School of Mechanical & Materials Engineering, University College Dublin, Belfield, Dublin, Ireland

Keywords: Web Service Interface, Vehicle Routing Problem, Waste Collection, Home Health Care Industry.

Abstract: In response to the significant rise of Home Health Care (HHC) due to technological advances, an expanding elderly demographic, and increased disease outbreaks—intensified by the COVID-19 pandemic—there is a pressing demand for better management of the resulting medical waste. This paper explores the development of a web-based decision support system designed to optimize medical waste collection in the HHC sector. The system is built using Flask for backend processes, with a user interface crafted from HTML and CSS, and employs JSON files for data management. It features dynamic routing enabled by two metaheuristic algorithms: the Strength Pareto Evolutionary Algorithm (SPEA-2) and the Non-Dominated Sorting Genetic Algorithm (NSGA-II). The application supports real-time adjustments to vehicle routes and waste production sites, enhancing the efficiency of medical waste management by minimizing human intervention. The design allows for easy adaptation to different sectors and can be expanded to test various scenarios.

1 INTRODUCTION

The Traveling Salesman Problem (TSP) is a well-known optimization problem in combinatorial mathematics and operations research, wherein a salesman is tasked with visiting a set of cities exactly once, and then returning to the starting city, all while minimizing the total travel distance or cost (Applegate, 2006). Building upon the foundation of TSP, the VRP expands the scenario by introducing multiple vehicles and demands in each node. In this context, the objective is to design optimal routes for each vehicle so that every node's demand is met and the overall operational costs are minimized (Hoffman, Padberg, & Rinaldi, 2013). Since Dantzig and Ramser (1959) first introduced the VRP in 1959, it has seen extensive application across various fields, initially concentrating on forward logistics and subsequently expanding to include reverse logistics operations. The waste collection process represents a key area within the scope of reverse logistics, focusing on optimizing routing strategies (Kubra Sar & Pezhman Ghadimi, 2023). Medical waste collection has emerged as a critical research topic within waste management, gaining increased significance in the wake of COVID-19 (Babaee Tirkolaee & Aydın, 2021; Ghannadpour, Zandieh, & Esmaeili, 2021; Govindan, Nasr, Mostafazadeh, & Mina, 2021). Recently, the generation points of medical waste have extended beyond hospitals and healthcare institutions to encompass the growing domain of home health care (HHC) services (K. Sar & P. Ghadimi, 2023). This development has introduced challenges in establishing robust coordination between decision-makers and system entities compounded by rising uncertainty and complexity. While the literature abounds with mathematical models addressing the waste collection routing problem, there is a distinct need for practical studies that offer sustainable and efficient routing plans capable of adaptively responding to the uncertainties of market conditions. In their comprehensive literature review, Vitorino de Souza Melaré, Montenegro González, Faceli, and Casadei (2017) highlighted the critical need for an intelligent Decision Support System (DSS) in the waste management area. They argue that such a system is essential for improving the efficiency, sustainability, and effectiveness of waste collection routing processes. Therefore, Burton Watson and John Ryan

Sar, K. and Ghadimi, P.
Web Service-Based Capacitated Smart Vehicle Routing Problem with Time Window and Threshold Waste Level for Home Health Care Industry.
DOI: 10.5220/0012640000003758

In *Proceedings of the 14th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2024)*, pages 185-191
ISBN: 978-989-758-708-5; ISSN: 2184-2841

(2021) introduced a web application interface designed to generate and showcase dynamic, resilient routes. This interface adapts to changes in the system by accessing updated data. The fluctuating nature of waste accumulation and disposal sites, which evolve rapidly over time, can be effectively captured and demonstrated through a practical study involving the design of a web interface application. The autonomous and dynamic features of web interface systems enhance the management of waste collection routes robustly by adjusting the number of vehicles required, driver assignments, and collection schedules. In practical scenarios, factors like travel times impacted by traffic congestion, quantities of waste at generation points, and the locations of waste generation introduce significant fluctuation in resource planning within the context of DSS. Gasque and Munari (2022) asserted that web interface applications serve as highly effective tools for aiding decision-making processes related to pickup and delivery tasks and can also be utilized as a framework for different versions of the vehicle routing problem. Traditional vehicle routing models are unable to facilitate efficient and accurate decision-making processes due to their inherent limitations in responding to systemic changes on time.

Consequently, a new decision support system which is a web interface application tool has been introduced in this study to accommodate changes in various factors, including travel time, the volume of waste to be collected, and waste generation points, while dynamically presenting routes to the drivers (users) in the HHC sector for the first time

2 LITERATURE REVIEW

The VRP modelling research was first introduced in the literature in 1959, and since then, numerous studies have been published on various domains (Dantzig & Ramser, 1959). As of 1974, research efforts have been directed towards addressing the VRP specifically within the context of waste collection (Beltrami & Bodin, 1974). In more recent times, to guarantee the practicality of these research efforts, studies related to web interface application development have been undertaken (Nacakli, Guzel, & Zontul, 2022). These web frameworks initially designed to handle the dynamic demands and uncertainties of forward logistics, are now gradually being incorporated into reverse logistics, though in a more limited scope.

In the realm of logistics optimization, recent studies have demonstrated innovative applications of web-based tools combined with advanced algorithms. Moeini and Mees (2021) addressed the Kindergarten Tour Planning Problem (KTTP), an adaptation of the classic traveling salesman problem, using heuristic methods and a web application featuring FLASK, MySQL, Bootstrap, Leaflet, JavaScript, and jQuery, focusing on minimizing total distance with datasets of 10 to 100 children. Nacakli et al. (2022) developed a variant of the vehicle routing problem for a lift and escalator service using algorithms like MaxRects and Dijkstra's, and crafted a web interface with Flask, React.js, and Leaflet for route visualization. Both studies highlight the synergy between algorithmic problem-solving and practical, real-time web applications in addressing complex logistical challenges.

It emerges from the review of related literature that there is a scarcity of studies on innovative decision support systems for VRP, especially web-based interfaces, with most research centred on forward logistics. This study addresses this shortfall by offering a Flask-based web user interface for a sophisticated vehicle routing model dedicated to waste collection, known as SCVRPTW-TWL.

3 METHODOLOGY

To address the medical waste collection challenges within the HHC sector, this study introduces an innovative SCVRPTW-TWL model that embodies all aspects of sustainability: reducing travel time, lowering carbon emissions, and diminishing customer dissatisfaction. Uniquely, this study ventures beyond traditional VRP models in medical waste collection by incorporating customer satisfaction and travel time as new social and economic objectives, respectively. Moreover, leveraging Internet of Things (IoT) advancements, the TWL concept has been applied to monitor waste levels, enabling smarter routing by avoiding superfluous stops. Furthermore, a Google API distance tool for traffic congestion-based real travel time was integrated, allowing for the formulation of more precise and timely routing plans, benefiting from the integration of real data. In this section, an in-depth analysis of the SCVRPTW-TWL model is provided and detailed insights into the NSGA-II and SPEA-2 metaheuristic solution techniques are elucidated. Furthermore, a comprehensive overview of the web interface application is given.

3.1 Mathematical Model

The relevant notations used in our work are shown in Table 1-3.

Table 1: Sets and Descriptions.

Sets	Description
C	Set of collection centres C={1,2,3...c}
H	Set of customer house H={1,2,3...h}
N	Set of all collection points, including depot N = (C∪ H) ={1,2,3...n, n+1 depot={0}
A	Set of arcs, A={(i,j)| $i,j \in N$, $i \neq j$}
K	Set of vehicles, V={1,2...k}
T	Set of trips T={1,2...t}

Table 2: Parameters and Descriptions.

Parameters	*Unit*	*Description*
Q_k	kg	Vehicle capacity
Q_h	kg	Customer house capacity
Q_c	kg	Collection centre capacity
q_i	kg	The amount of waste at collection site $i \in N$
t_{ijk}	minutes	Travel time of vehicle k on arc $(i,j) \in A$
d_{ijk}	meter	Transportation distance of vehicle k on arc (i,j) ∈ A
LT_j	minutes	Latest service end time at collection points j ∈ N without causing penalty cost
s_{jk}	minutes	Service time at vertex j for vehicle k
s_{ik}	minutes	Service time at vertex i for vehicle k
D_k	minutes	The time limit that vehicle k can operate
e	$kg.CO_2/L$	emission coefficient
η_0	kg/L	Amount of fuel consumed per km when the car is fully empty
η	kg/L	Amount of fuel consumed per km when the car is fully loaded
P_{idle}	kg/L	Amount of fuel consumed per minutes when the car is running on idle
c_p		Penalty score
M		Sufficiently large number

Table 3: Decision Variables and Descriptions.

Decision Variables	*Description*
x_{ijk}^t	Binary variable with a value of 1 if arc (i,j) is traversed of vehicle k on trip t, 0 otherwise
z_k^t	Binary variable with a value of 1 if vehicle k performs trip t, 0 otherwise
st_{ik}	Arrival time of vehicle k at vertex i ∈ N
st_{jk}	Arrival time at the next vertex j for vehicle k
Q_{ijk}	the load on vehicle k after leaving node j
Q_{ik}	the load on vehicle k upon arrival at node i

The SCVRPTW-TWL model encompasses a network of nodes labelled N = {0,1,2,3...n, n+1}, spread across various locations. Central to the system are depot points at nodes 0 and n+1, with the intervening nodes representing collection points that accumulate medical waste. The developed VRP model introduces three objective functions designed to assess the waste collection issue from social, economic, and environmental viewpoints. The daily waste generation at each point triggers the collection service when it surpasses 70% of its capacity—a threshold informed by previous studies (Akhtar, Hannan, Begum, Basri, & Scavino, 2017; Facchini, Digiesi, & Vitti, 2021; Faccio, Persona, & Zanin, 2011; Hannan et al., 2018; Wu, Yang, & Tao, 2020).

3.1.1 Objective Function 1: Minimization Travel Time

Research commonly emphasizes reducing travel distance for its economic advantages, but in VRP scenarios, the least distance may not translate to the most efficient path due to varying traffic conditions. Addressing this, the present study shifts the focus toward minimizing the total travel time (outlined in Equation-1), which is a more accurate economic indicator for solving the SCVRPTW-TWL challenge. The Google Distance Matrix API is utilized for calculating travel times, allowing for adjustments based on current traffic patterns.

$$min\, Z_1 = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} x_{ijk}^t \cdot t_{ijk} \tag{1}$$

3.1.2 Objective Function 2: Minimization Total Emission

In the field of logistics, cutting down on carbon emissions is a key concern. The study's second objective function aims to lower total carbon emissions, which correlate with the distance that vehicles travel, and vary with the type of vehicle and the fuel it uses. The model also accounts for emissions generated during travelling (in Equation 2a), as well as when vehicles idle (Equation 2b) at collection points. For a comprehensive calculation of emissions, both during travel and idling, the formula provided by Xiao, Zhao, Kaku, and Xu (2012) (in Equation 2) is applied, an aspect that is often neglected in such analyses. The study ensures that emissions from idling at collection points are incorporated into the total emission figures for a more accurate assessment.

$$C_{fd} = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N}(\eta_0 \frac{\eta-\eta_0}{Q} Q_{ijk})d_{ijk}x_{ijk}^t e \tag{2a}$$

$$C_{fi} = \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ijk}^t\, s_j P_{idle}\, e \tag{2b}$$

$$\min Z_2 = C_{fd} + C_{fi} \tag{2}$$

3.1.3 Objective Function 3: Minimization Social Risk

Recent research indicates that from an economic perspective, it's advantageous to target only locations where waste levels exceed 70% in routing plans for waste collection. However, this approach might lead to customer dissatisfaction due to significant waste accumulation. To strike a balance between economic efficiency and social benefit, this study suggests using soft time windows to give priority to areas such as where waste levels surpass 90%, especially during the first hour of collections. If these time windows are missed, penalty scores are applied to reflect the heightened social risk, though these penalties are only incurred for late arrivals, not for arriving early. This strategy to mitigate customer dissatisfaction is defined as the third objective function in our model, detailed in Equation 3, where the penalty score is specifically outlined. The detailed equation description is shown in Equation 3a.

$$S_{penalty} = c_p \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i,j=1}^{N} x_{ijk}^t \max\{t_{ijk} - LT_j),0\} \quad (3a)$$

$$min\, Z_3 = S_{penalty} \quad (3)$$

3.1.4 Constraints

$$\sum_{t=1}^{T} \sum_{i=0}^{N} \sum_{k=1}^{K} x_{ijk}^t = 1 \quad if \;\; q_i \geq Q_h 70\% \quad j = 1,2,\dots,N \quad (4)$$

$$\sum_{t=1}^{T} \sum_{i=0}^{N} \sum_{k=1}^{K} x_{ijk}^t = 1 \quad if \;\; q_i \geq Q_c 70\% \quad j = 1,2,\dots,N \quad (5)$$

$$\sum_{i=0}^{N} x_{ijk}^t = \sum_{j=0}^{N} x_{ijk}^t \quad t = 1,2,\dots,T \quad k = 1,2,\dots,K \quad (6)$$

$$Q_{ijk} \geq Q_{ik} + q_j - \mathcal{M}(1 - \sum_{k=1}^{K} x_{ijk}^t) \quad j = 1,\dots,N \quad (7)$$

$$Q_{ijk} \leq Q_k \quad i,j = 0,\dots,N \quad k = 1,\dots K \quad t = 1,\dots,T \quad (8)$$

$$\sum_{t=1}^{T} \sum_{i,j=0}^{N} (t_{ijk} + s_{jk} x_{ijk}^t \leq D_k \quad (9)$$

$$\sum_{j=1}^{N} x_{0jk}^t = z_k^t \quad k = 1,\dots,\mathrm{K} \quad \mathrm{t} = 1,\dots,\mathrm{T} \quad (10)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} x_{ijk}^t \leq z_k^t \quad k = 1,\dots,K \quad \mathrm{t} = 1,\dots,\mathrm{T} \quad (11)$$

$$st_{ik} + t_{ijk} + s_{ik} - \mathcal{M}(1 - x_{ijk}) \leq st_{jk} \quad i,j = 1,\dots,N \; k = 1,\dots,K. \quad (12)$$

$$x_{ijk}^t = 0,1 \;\; and \;\; z_k^t = 0,1 \quad i,j = 0,\dots,N \quad k = 1,\dots,K \quad (13)$$

$$s_{ik} \geq 0 \quad i = 0,\dots,N \quad k = 1,\dots K \quad (14)$$

Constraints (4) and (5) provide that every point with waste over 70 % of its capacity must be visited and these visits must be made by only one vehicle. Constraint (6) is a flow balance constraint. In this way, a vehicle visiting a point can leave that point once the collection has been completed. Constraint (7) ensures that the vehicle capacity is calculated on the route. Constraint (8) provides that the load of the vehicle does not exceed its capacity on the route. Constraint (9) ensures that the sum of all travel and service times for each vehicle over its entire set of trips does not exceed the vehicle's allowable maximum duration of operation. Constraint (10) allows all vehicles to start the route from the depot. Constraint (11) ensures that only active vehicles are allowed to make customer visits. Constraint (12) calculates the vehicle arrival time in each collection point. Constraint (13) defines the binary decision variable. Constraint (14) defines the characteristics of continuous variable.

3.2 Solution Algorithm

This study employed NSGA-II and SPEA-2 algorithms for multi-objective optimization. NSGA-II, developed by Deb, Pratap, Agarwal, and Meyarivan (2002) involves steps like initializing a random solution population, ranking solutions based on performance, using crowding distance for even Pareto solution distribution, generating new solutions through mutation and crossover, and selecting the best solutions iteratively until a set number of iterations is reached. SPEA-2, introduced by Zitzler, Laumanns, and Thiele (2001), follows a similar process starting with an initial population, evaluating fitness, updating an external set with non-dominated solutions, using binary tournament selection, applying genetic operations for new populations, and iterating until a termination condition, such as reaching a maximum number of generations, is met. The algorithms were evaluated using both small and medium-sized datasets. It was concluded that NSGA-II offers a quicker response for web-based applications and is, therefore, better suited for practical research applications.

3.3 Web Interface

This web interface application as a decision support system designed for route optimization in waste collection uses metaheuristic algorithms, NSGA-II, and SPEA-2, to provide decision-makers with optimized paths. These algorithms, particularly NSGA-II for its swift responses in the web application, are selected for practical efficacy. With an emphasis on scalability, the system permits the integration of further algorithms and supports different vehicle fleets. The interface operates on real-time data through JSON files and has been rigorously tested with varying data sizes to ensure robustness. The web application architecture is comprised of three layers (can be seen in Figure 1): the Interface Layer for user interaction, the Technical Layer for data processing, and the Data Resources Layer for data storage. This structure ensures a seamless flow from user input to the display of actionable outputs.

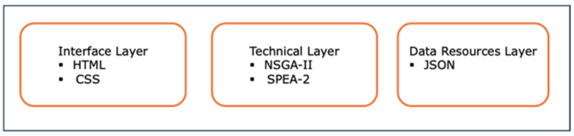

Figure 1: Web Application Layer.

The Flask framework underpins the web application, offering a flexible and efficient methodology for addressing VRP. The application structure accommodates both GET and POST requests, handling input data and leveraging algorithms to find near-optimal routes, balancing multiple objectives. Visualization of results is achieved through Google Maps and Folium, with interactive maps that depict the optimized routes, aiding in the practical evaluation of routes. This user-friendly interface (can be seen in Figure 2) simplifies complex optimization, democratizing access to advanced routing tools for sustainable and efficient logistics.

Figure 2: Overview of web application user interface.

In terms of design, the front-end utilizes HTML for structure, CSS for styling, and JavaScript for dynamic functionality. The "/vehicle-routing-result" route is a core feature, presenting mapped results and performance metrics. This system marks a leap in making practical VRP solutions integrated with metaheuristic optimization.

4 COMPUTATIONAL RESULTS

The model was evaluated using datasets of varying sizes, including small datasets consisting of 20 nodes and medium datasets consisting of 50 nodes. The initial focus is on the results obtained from the small dataset. The routing plan included 14 out of the 20 nodes dataset because they met the necessary thresholds. The problem of routing, which was approached from the perspectives of social, economic, and environmental factors, was successfully solved within a short time by employing NSGA-II and SPEA-2. The information in Table 4 suggests that completing the routes within the working hour needs one vehicle.

Table 4: Small dataset route information.

Vehicle id	Route id	Nodes	Trip route time	CPU
Vehicle 1	Route 1	0-6-1-7-8-0	106.93 minutes	2.52 second
	Route 2	0-3-19-16-15-2-0	147.22 minutes	
	Route 3	0-17-18-11-14-20-0	141.42 minutes	

The real map presented in Figure 3 illustrates the three necessary trips to visit the points in the small dataset, with each of the black, green, and blue lines representing the respective route for each trip.

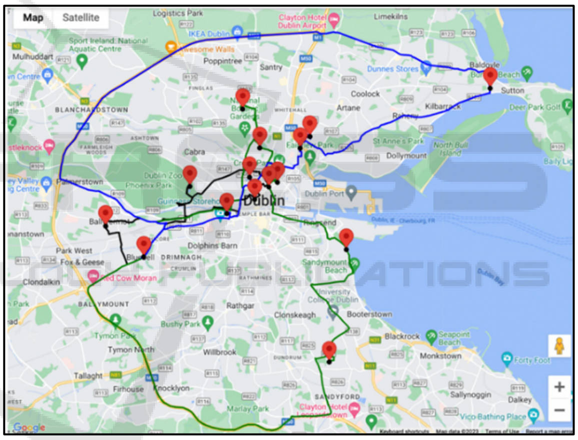

Figure 3: Small dataset route demonstration on the real map.

There are 50 data points in the medium dataset indicating various amounts of waste. Out of these, 35 points have exceeded the 70% threshold and are considered for the routing plan. The model has determined that 6 optimal routes are needed to effectively manage waste based on social, economic, and environmental factors, and has indicated that 2 vehicles are necessary to carry out these routes. Table 5 presents detailed information regarding the specifics and travel times for each of the proposed routes.

Table 5: Medium dataset route information.

Vehicle id	Route id	Nodes	Trip route time	CPU
Vehicle 1	Route 1	0-45-9-43-17-2-31-0	98.25 minutes	3.42 second
	Route 2	0-12-42-16-4-28-8-0	144.18 minutes	
	Route 3	0-39-1-25-50-5-0	237.27 minutes	
Vehicle 2	Route 1	0-7-21-40-32-24-0	166.28 minutes	
	Route 2	0-22-20-38-36-44-48-34-0	193.73 minutes	
	Route 3	0-14-6-23-15-47-30-0	92.08 minutes	

The actual routes for each vehicle are depicted in Figure 4, with the routes in red, olive, and blue representing the first vehicle, and the routes in maroon, teal and black representing the second vehicle.

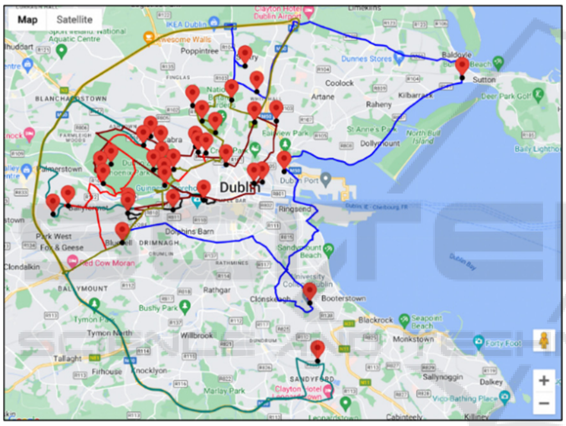

Figure 4: Medium dataset route demonstration on the real map.

4.1 Theoretical and Managerial Implications

This practical study introduces an innovative method for addressing the waste collection routing issue by integrating live data, including waste collection frequencies, traffic updates, and customer positions through a web interface application. This developed interface helps establish robust coordination between those making decisions and the system parameters. Also, it enhances efficiency by minimizing manual intervention, saving both time and money, while also reducing the likelihood of human errors. The results are presented with easy-to-understand map visuals and the ultimate figures of the objective function, highlighting a shift towards more automated processes. While the system is built to operate in real-time based on user inputs, its efficiency was evaluated using two distinct-size datasets. Across all datasets, the outcome, including the routing map and objective function details, was generated, and displayed within a timeframe of under 30 seconds. While this web-based application is tailored to the waste collection needs of the HHC sector, its adaptable design allows it to cater to the waste collection challenges of various other sectors with slight adjustments.

The developed web interface features one of the most comprehensive mathematical models developed for waste collection routing. This model incorporates a range of constraints and parameters such as waste threshold levels, real-time travel duration, integration of all sustainability concerns, and multiple vehicle and trip options, offering solutions for different vehicle fleets. The advancement of this web interface elevates its theoretical impact by offering an array of selectable parameters and leveraging cutting-edge solution algorithms, all built upon one of the most detailed mathematical models for waste collection routing. This interface streamlines the decision-making process, making it quicker and devoid of errors with minimal human input. Moreover, it offers a cost-benefit, enhances the quality of service, and improves the ability to adapt to changing variables.

5 CONCLUSION

In this research, the medical waste collection routing problem was addressed by integrating it with the SCVRPTW-TWL mathematical model for HHC context. NSGA-II and SPEA-2 metaheuristics solution algorithms were employed to examine the problem from environmental, social, and economic perspectives. Also, a web interface application-based decision support system that was developed using Flask was proposed for problem-solving. This application aims to transcend a purely theoretical framework, offering practical implications as well. The dynamism introduced by variables like solution algorithm, number of vehicles, and vehicle capacity has enhanced the study's alignment with real-world scenarios. Furthermore, by integrating travel time parameters—sourced from the Google API distance matrix and adjusted for traffic conditions—into the model, a closer approximation to real-world conditions was achieved.

Future research could involve augmenting current metaheuristic solution algorithms or incorporating innovative algorithms into the interface as additional options. The inclusion of diverse or hybrid vehicle fleets is also feasible. Given its adaptable architecture, the system can easily be tailored to meet various waste collection challenges with minor adjustments. Additionally, for future work, the potential to add new objective functions will be explored. Time windows could evolve from fixed parameters to dynamic factors through a customer-user interface, creating a more flexible and responsive model.

ACKNOWLEDGEMENTS

This work is supported by The Ministry of Education of Turkish Republic in the content of 1416 Higher Education Law under grant ID: ZYPN5T3990HWQ7Z.

REFERENCES

Akhtar, M., Hannan, M. A., Begum, R. A., Basri, H., & Scavino, E. (2017). Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization. *Waste Management, 61*, 117-128. doi:10.1016/j.wasman.2017.01.022

Applegate, D. L. (2006). *The traveling salesman problem: a computational study* (Vol. 17): Princeton university press.

Babaee Tirkolaee, E., & Aydın, N. S. (2021). A sustainable medical waste collection and transportation model for pandemics. *Waste Management and Research, 39*(1_suppl), 34-44. doi:10.1177/0734242X211000437

Beltrami, E. J., & Bodin, L. D. (1974). Networks and vehicle routing for municipal waste collection. *Networks, 4*(1), 65-94.

Burton Watson, R., & John Ryan, P. (2021). *Visualization and Waste Collection Route Heuristics of Smart Bins Data using Python Big Data Analytics.* Paper presented at the 2021 The 4th International Conference on Software Engineering and Information Management.

Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science, 6*(1), 80-91.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*(2), 182-197.

Facchini, F., Digiesi, S., & Vitti, M. (2021). *Waste collection with smart bins and residual capacity forecasting: The case of an Apulia Town.* Paper presented at the 2021 29th Mediterranean Conference on Control and Automation, MED 2021.

Faccio, M., Persona, A., & Zanin, G. (2011). Waste collection multi objective model with real time traceability data. *Waste Management, 31*(12), 2391-2405. doi:10.1016/j.wasman.2011.07.005

Gasque, D., & Munari, P. (2022). Metaheuristic, models and software for the heterogeneous fleet pickup and delivery problem with split loads. *Journal of Computational Science, 59*. doi:10.1016/j.jocs.2021.101549

Ghannadpour, S. F., Zandieh, F., & Esmaeili, F. (2021). Optimizing triple bottom-line objectives for sustainable health-care waste collection and routing by a self-adaptive evolutionary algorithm: A case study from tehran province in Iran. *Journal of Cleaner Production, 287*. doi:10.1016/j.jclepro.2020.125010

Govindan, K., Nasr, A. K., Mostafazadeh, P., & Mina, H. (2021). Medical waste management during coronavirus disease 2019 (COVID-19) outbreak: A mathematical programming model. *Computers and Industrial Engineering, 162*. doi:10.1016/j.cie.2021.107668

Hannan, M. A., Akhtar, M., Begum, R. A., Basri, H., Hussain, A., & Scavino, E. (2018). Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm. *Waste Management, 71*, 31-41. doi:10.1016/j.wasman.2017.10.019

Hoffman, K. L., Padberg, M., & Rinaldi, G. (2013). Traveling salesman problem. *Encyclopedia of Operations research and Management science, 1*, 1573-1578.

Moeini, M., & Mees, L. (2021). *Automated Tour Planning for Driving Service of Children with Disabilities: A Web-Based Platform and a Case Study.* Paper presented at the Computational Logistics: 12th International Conference, ICCL 2021, Enschede, The Netherlands, September 27–29, 2021, Proceedings 12.

Nacakli, I., Guzel, S., & Zontul, M. (2022). *Web Service-Based Two-Dimensional Vehicle Pallet Loading with Routing for a Real-World Problem.* Paper presented at the 2022 International Conference on Theoretical and Applied Computer Science and Engineering (ICTASCE).

Sar, K., & Ghadimi, P. (2023, 19-22 June 2023). *A bi-objective Smart Capacitated Vehicle Routing Problem with Threshold Waste Level for the Home Health Care.* Paper presented at the 2023 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC).

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

Vitorino de Souza Melaré, A., Montenegro González, S., Faceli, K., & Casadei, V. (2017). Technologies and decision support systems to aid solid-waste management: a systematic review. *Waste Management, 59*, 567-584. doi: https://doi.org/10.1016/j.wasman.2016.10.045

Wu, H., Yang, B., & Tao, F. (2020). Optimization of vehicle routing for waste collection and transportation. *International Journal of Environmental Research and Public Health, 17*(14), 1-26. doi:10.3390/ijerph17144963

Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. *Computers & Operations Research, 39*(7), 1419-1431.

Zitzler, E., Laumanns, M., & Thiele, L. (2001). SPEA2: Improving the strenth Pareto evolutionary algorithm. *TIK report, 103*.