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# Modeling and Solving a Logistics Problem with Smart Bins and Dynamic Travel Cost for Vehicles Using the NSGA-II Algorithm

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**Abstract**

This research addresses the design and solution of a waste collection supply chain optimization problem using smart bins based on the Internet of Things (IoT). In this model, each waste generation center is equipped with bins that automatically send collection alerts to the transportation fleet once they are full. These alerts assist in determining the optimal routing and scheduling of vehicles, thereby enabling precise and timely service. The proposed mathematical model is formulated as a multi-objective model, with objectives including minimizing deviation from soft time constraints and reducing the total supply chain cost. In addition to the traveled distance, system costs are affected by factors such as vehicle type, fuel consumption, and load weight. A set of constraints, including bin and vehicle capacities, delivery times, and allocation to refineries, ensures the optimal performance of the system. For small-sized instances, the model was solved using GAMS; however, for larger instances, in order to manage computational complexity while maintaining accuracy, a hybrid metaheuristic algorithm based on NSGA-II was employed. The results indicate that integrating smart bins with the NSGA-II algorithm not only optimizes routes and reduces costs, but also provides diverse, reliable, and efficient solutions across different scales of the supply chain. This approach offers a suitable platform for optimal decision-making in waste collection management and improving logistical efficiency.

Keywords: Vehicle routing problem (VRP), NSGA-II, time constraints, capacity, heterogeneity, load amount
2022 MSC: O20, O10

## Introduction

One of the key challenges in supply chain management is the vehicle routing problem, as the optimal allocation of vehicles to different routes has a significant impact on reducing operational costs. This problem, as one of the most well-known optimization problems and a central concept in the field of operations research, involves planning the routes of a set of vehicles dispatched from one or more depots to provide services to customers with specified demands. The main objective in this field is to use mathematical models and optimization methods to minimize the total traveled distance, total travel time, number of vehicles used, delay penalties, and transportation costs, while maximizing customer satisfaction [2]. With the growth of urbanization, cities are facing problems such as population congestion, traffic jams, transportation inefficiency, environmental issues, and waste management. The use of smart networks and Internet of Things technologies, especially in waste collection, makes it possible to automatically send alerts when bins reach full capacity and helps optimize collection routes and reduce costs. Accordingly, integrating information and communication technologies with urban management provides an effective tool for improving service quality and reducing operational costs in smart cities [3].

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A smart city is defined as a city that, with a forward-looking approach and optimal performance, integrates key components such as smart mobility, smart environment, smart people, smart economy, and smart waste management into its structure. By leveraging information and communication technologies, these cities facilitate effective interaction between citizens and technology, thereby enhancing quality of life and urban sustainability. One of the key tools in this context is the sensors installed on IoT-based smart bins, which provide real-time information on the fill level of the bins. This data enables the optimal management of waste collection routes and resource allocation. By using the Internet of Things, the waste management system can monitor the status of each bin in real time and, through the analysis of collected data, significantly improve operational efficiency and workforce productivity. Such a system, in addition to reducing operational costs, also has considerable positive environmental and social effects. However, many municipalities still rely on traditional methods for collecting solid waste, in which containers are emptied uniformly and along fixed routes, a practice that reduces the efficiency and productivity of the system [13]. The integration of Internet of Things technology with smart bins enables precise monitoring, data analysis, and optimal decision-making in urban waste management, and as one of the key components of a smart city, it plays an important role in reducing costs, saving resources, and improving the quality of urban services. In this study, IoT-enabled smart bins are used; these bins are capable of automatically sending alerts when their capacity is full, and based on these alerts, vehicles are dispatched along predetermined routes for collection and service operations. In previous studies, the main focus has usually been on reducing the total system cost, one important component of which is vehicle travel cost. Most of these studies have considered travel cost solely as a function of the traveled distance; however, in the present study, travel cost is affected not only by distance but also by vehicle type, fuel consumption coefficient, and the amount of load carried. To solve the problem and obtain optimal solutions, the NSGA-II evolutionary algorithm is employed, as it is capable of multi-objective optimization and handling complex, large-scale problems. Various studies have been conducted on vehicle routing logistics for waste, but fewer studies have focused on food waste.

## Literature Review

In the article by Kim et al [6] a real-world vehicle routing problem for waste collection with time windows was addressed, considering multiple trips and drivers' lunch breaks. The objective was to minimize the number of vehicles and the total travel time. In the study by Kim et al [5], the reduction of the total travel distance required for reverse logistics was evaluated based on the total weight of food waste in each collection area. The research was formulated as a capacitated vehicle routing problem and incorporated daily total food waste weight information from each collection area in order to determine optimal routes for reverse logistics. In the paper by Liu and Wang [10], a two-echelon vehicle routing problem for waste collection was investigated with respect to cooperation and profit distribution among participants in the collection network. An optimization model was developed for the two-echelon waste collection vehicle routing problem with the aim of minimizing total costs and carbon emissions. Subsequently, a three-stage solution approach was proposed to solve the model. Finally, an improved value model was constructed to determine costs, emission reduction levels, and the best coalition sequence for each participant.In the research by Mahmoud Awad et al [2], a systematic review of the recent literature related to food distribution was presented, and possible areas for expanding research in modeling and decision-making were identified. This paper analyzed the content of 65 recent articles related to perishable food. The review showed that dynamic vehicle routing models considering product quality and environmental impacts remain an open area for research. There is still no consensus among researchers regarding the quality-decline models used to assess the freshness of transported cold food. Therefore, examining critical parameters and quality modeling is essential. Due to the complexity of the problem, there is a need to develop heuristic and metaheuristic approaches for solving such models.The study by Krishnan et al [11], proposed an integrated robust multi-objective optimization model for network design, considering all three dimensions of sustainability economic, social, and environmental while simultaneously accounting for perishability, food waste valorization, and supply uncertainty. This study demonstrated the impact of focusing on only one sustainability dimension on the others, as well as the trade-offs among sustainability dimensions, helping the decision-maker select a suitable non-dominated solution aligned with organizational sustainability goals.In the study by Mousavi et al [14], a new routing model for perishable products with uncertain demand was presented. The objective was to minimize production, inventory, routing, wasted-product, and non-freshness penalty costs. This model is particularly applicable to perishable products with limited and discrete shelf life and high freshness value. A five-phase mathematical algorithm was proposed to solve the stochastic mathematical model. Computational experiments showed that the proposed mathematical model can significantly reduce wasted products, especially when consumer purchasing patterns change due to events such as a pandemic. Moreover, numerical analysis for small, medium, and large instances confirmed the validity and efficiency of the proposed algorithm compared with an exact solver.The paper by Moazzeni et al [13], proposed a dynamic location-arc routing optimization model for electric waste collection vehicles. The proposed

model suggested an optimal routing plan for waste collection vehicles and determined the optimal locations of charging stations, dynamic charging arcs, and waste collection centers. A genetic algorithm and a grey wolf optimizer were used to solve the stochastic large-scale NP-hard location-arc routing problem. A case study for the city of Edmonton, Canada, was presented, showing that the grey wolf optimizer outperformed the genetic algorithm. The study also identified the required number of waste collection centers, charging stations, and dynamic charging arcs needed to ensure the minimum service level for electric vehicles in the entire Edmonton waste collection system.The objective of Pratap et al [16], was to develop an integrated production-inventory-routing problem for perishable food products considering capacity, time windows, and carbon emission reduction. The impact of model parameters on the response value was examined through sensitivity analysis, and computational experiments discussed comparative results obtained from both algorithms for various case scenarios. The results of the two algorithms were evaluated for ten instances, and the cuckoo search algorithm consistently outperformed the flower pollination algorithm.In the study by Kabadurmus et al [4], a circular food supply chain network model was designed to reduce food waste generated in municipal circular food supply chain systems. A mixed-integer linear programming model was then developed to represent the proposed circular food supply chain network. Due to the bi-objective nature of the proposed mathematical model, an enhanced improved epsilon-constraint method was implemented to solve the problem optimally. To demonstrate the applicability and effectiveness of the proposed model, two real case studies were conducted in Izmir, the third-largest city in Turkey. The computational results showed that the proposed model is beneficial for both small and large municipalities, as it provides a Pareto-optimal set in which the total distributed food waste is maximized and the total cost is minimized.The article by Prajapati et al [15], introduced an integrated first-mile pickup and last-mile delivery logistics problem, where agricultural food grainswere available at various farmer locations and were demanded by businesses such as e-retailers, supermarkets, grocery stores, restaurants, hotels, and others.In the article by Akkerman et al [1], a review of the key supply chain challenges in food bank supply chains was presented. The results showed that important challenges related to the management of highly perishable products and limited information technology infrastructure have received little attention in the literature. Moreover, the interdependence among supply-, demand-, and supply-demand-matching-related challenges requires greater interaction with different research fields. In the study by Reusken et al[17], a capacitated vehicle routing problem with travel time constraints and stochastic demand, service times, and waiting times was introduced, in which the uncertainties are interdependent. The objective of this problem is to determine the minimum number of vehicles and schedule cost-effective routes for these vehicles such that each route violates the vehicle capacity and travel time constraints only with a very low probability.Masmoudi et al [12], introduced a new version of the multi-compartment waste collection problem with bin washing capability. The aim of this study was to examine the performance of a fleet of vehicles equipped with multiple compartments and bin-washing functions. The proposed model was formulated as a mixed-integer linear programming model, and for large-scale instances, a hybrid metaheuristic algorithm based on hybrid variable neighborhood search (HVNS) was developed. The results showed that the proposed algorithm was able to provide higher-quality solutions in less computational time, and that compaction and bin-washing operations improved efficiency and reduced fleet trips. Li et al [8], provided a comprehensive review of the state of sustainable waste collection and the waste collection vehicle routing problem. The study examined waste types, model characteristics, objective functions, solution methods, and case studies, and showed that existing research has mainly focused on municipal waste, while other types such as medical waste have been less explored. It also highlighted the need for the development of efficient and sustainable methods due to the lack of multi-objective models, hybrid algorithms, and attention to uncertainty.Kim et al [7], investigated the clustered vehicle routing problem for waste collection in smart cities from the perspective of intelligent operational management. The study focused on IoT-enabled smart bins, and to manage uncertainty in bin fill levels, a combination of ant colony optimization and k-means clustering was proposed. The results showed that integrating IoT with optimization algorithms improves prediction accuracy, reduces travel time and operational costs, and increases the efficiency of the waste collection system. Xu et al [18], examined the optimization of the vehicle routing problem for medical waste collection in stochastic transportation networks with time constraints. The aim of this study was to increase travel time reliability (TTR) and reduce transportation costs and penalties arising from time window violations. Due to the NP-hard nature of the problem, the researchers used a genetic algorithm enhanced with an improved harmony search algorithm. The evaluation results for the model and algorithm in a city in northern China showed that travel time reliability plays a critical role in optimizing medical waste collection operations, and that the proposed algorithm outperformed traditional methods in reducing costs and improving operational reliability. Sensitivity analysis of the key parameters also confirmed the robustness and validity of the model and emphasized the importance of considering additional costs associated with travel time variation in decision-making. Lin et al [9], proposed a two-echelon vehicle routing problem for medical waste collection in an urban reverse logistics network. This model included time synchronization of vehicles at meeting points so that waste transfer from inner-city areas by low-capacity vehicles to high-capacity vehicles responsible for transporting waste to recycling centers outside the city could be performed optimally. The innovative feature of the study was the integration of time synchronization,

vehicle waiting times, and meeting-point time-capacity constraints, which increased the practical realism of the model. Advanced and hybrid metaheuristic algorithms were used to solve the problem, and the analyses showed that adding time-capacity constraints improved the accuracy and efficiency of collection routes. This study demonstrates the importance of using multi-objective and hybrid algorithms in complex logistics problems and in the sustainable operation of medical waste collection with electric vehicles.

Table 1: Research gap

| Row | Article Title | Year | Author(s) | Solution Method | Smart Bins | Load-Dependent Travel Cost | Time Window Constraint | Route-Type Constraint | Objective Function |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Waste Collection Vehicle Routing Problem with Time Windows | 2006 | Byung-In Kim et al. | Metaheuristic algorithm | | | * | | Number of vehicles and total travel time |
| 2 | Vehicle Routing with Stochastic Demand, Service and Waiting Times — The Case of Food Bank Collection Problems | 2024 | Meike Reusken et al. | Heuristic method | | | * | | Minimum number of vehicles; cost |
| 3 | Pollution Routing Problem to Reverse Logistics of Disposed Food Waste | 2016 | Kim, Wonsob et al. | Exact method | | | | | Cost |
| 4 | An Application of Capacitated Vehicle Routing Problem to Reverse Logistics of Disposed Food Waste | 2014 | Hyunsoo Kim et al. | Exact method | | | | | Travel distance |
| 5 | A Dynamic Approach for the Multi-Compartment Vehicle Routing Problem in Waste Management | 2023 | Mostafa Mohammadi et al. | Hybrid Particle Swarm Optimization and Genetic Algorithm | | | * | | Genetic algorithm and particle swarm optimization |
| 6 | Sustainable Vehicle Routing of Agro-Food Grains in the E-Commerce Industry | 2022 | Prajapati et al. | Four nature-inspired algorithms | | | | | Environmental sustainability aspects; cost |
| 7 | Stochastic Optimization Approach for Green Routing and Planning in Perishable Food Production | 2022 | Saurabh Pratap et al. | Flower Pollination Algorithm and Cuckoo Search Algorithm | | | | | Cost; greenhouse gas emissions |
| 8 | A Circular Food Supply Chain Network Model to Reduce Food Waste | 2022 | Ozgur Kabadurmus et al. | Enhanced Improved Epsilon-Constraint Method | | | | | Cost; waste |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 9 | Optimization and Profit Distribution in a Two-Echelon Collaborative Waste Collection Routing Problem from Economic and Environmental Perspective | 2021 | Lin Liu, Wenzhu Liao | ALNS algorithm | | | | | Costs and reduction in carbon emissions |
| 10 | An Optimization Model for Fresh-Food Electronic Commerce Supply Chain with Carbon Emissions and Food Waste | 2023 | Darma Wangsa et al. | Heuristic method | | | | | Cost; greenhouse gas emissions |
| 11 | Robust Optimization of Sustainable Food Supply Chain Network Considering Food Waste Valorization and Supply Uncertainty | 2022 | Ramesh Krishnan et al. | Heuristic method | | | * | | Sustainability dimensions |
| 12 | Stochastic Production Routing Problem for Perishable Products: Modeling and a Solution Algorithm | 2022 | Razieh Mousavi et al. | Exact method | | | | | Cost |
| 14 | A Dynamic Location-Arc Routing Optimization Model for Electric Waste Collection Vehicles | 2022 | Sahar Moazzeni et al. | Genetic algorithm | | | | | Distance; time |
| 15 | Multi-Compartment Waste Collection Vehicle Routing Problem with Bin Washer | 2024 | Masmoudi, Baldacci, Mancini, & Kuo | Mixed-Integer Linear Programming + HVNS algorithm | - | * | - | - | Reduction in costs and total travel time |
| 16 | Clustered Vehicle Routing Problem for Waste Collection with Smart Operational Management Approaches | 2025 | Kim, Manna, Roy, & Moon | Hybrid Ant Colony Optimization + k-means | * | - | - | - | Route optimization and reduction in collection time and cost |
| 17 | Optimization of Reliable Vehicle Routing Problem for Medical Waste Collection with Time Windows in Stochastic Transportation Networks | 2025 | Xu, Wu, Wang, et al. | Enhanced Genetic Algorithm with IHSGA | - | - | * | - | Increased travel time reliability and reduced transport cost |
| 18 | Adaptive Multi-Objective Algorithm for the Sustainable Electric Vehicle Routing Problem in Medical Waste Management | 2024 | Lin, Musa, & Yap | Multi-objective metaheuristic and hybrid algorithms | - | - | * | * | Reduction in waiting time, temporal synchronization, and route optimization |
| 19 | Clustered Vehicle Routing Problem for Waste Collection with Smart Operational Management Approaches | 2025 | Kim, Manna, Roy, & Moon | Hybrid Ant Colony Optimization + k-means | * | - | - | - | Route optimization and reduction in collection time and cost |
| Current Study | | | | NSGA-II | * | * | * | - | * |

## Mathematical Model

In this study, the supply chain associated with waste collection and transportation is designed and analyzed. At the first level, the waste generation centers include bakeries, confectioneries, restaurants, fast-food outlets, and retail stores, each equipped with smart Internet of Things (IoT)-based bins. Once the waste stored in these bins reaches a predefined capacity threshold, the bins automatically send a fill-level alert to the collection centers, and the emptying and collection process begins immediately.Waste is transported from the generation centers to the collection centers by a heterogeneous fleet of vehicles, which differ in terms of payload capacity, speed, and operating cost. The routes of this fleet are planned in such a way that, while satisfying the problem constraints, the total system cost is minimized. After collection, the waste is transferred to biorefineries, where heavier vehicles are responsible for the transportation task.A key feature of the proposed model is that, in each service period, only those centers whose smart bins have issued an alert are visited. This approach prevents unnecessary visits and improves fleet efficiency. In addition, capacity constraints are considered for both the collection centers and the biorefineries. Furthermore, time constraints are defined in two forms: hard and soft. Under the hard time-window constraint, waste must be delivered exactly at the prescribed time, with no delay allowed. In contrast, under the soft time-window constraint, delay is permitted; however, each unit of delay reduces the value of the waste, such as bread waste. This highlights the importance of time management in the waste supply chain.Moreover, not all vehicles are allowed to travel on all routes; in other words,

vehicle movement is only permitted on routes for which the required technical conditions and permits are available. On the other hand, an increase in cargo weight along the route has a direct impact on transportation cost, meaning that as the load increases, the transportation cost also rises.The mathematical model developed in this research is based on two objective functions that incorporate these considerations.

The first objective function aims to minimize deviation from the soft time window, thereby improving delivery accuracy and efficiency within the desired time frame. The second objective function focuses on minimizing the total system cost. The considered costs in the model include fixed costs of collection centers, vehicle rental costs, transportation costs from generation centers to collection centers, transfer costs from collection centers to biorefineries, and the additional cost associated with vehicle load.In addition to these two objective functions, a set of constraints is included in the model to capture the different aspects of the system and ensure its realism. The first group of constraints relates to the mandatory servicing of smart bins; specifically, each filled bin must be emptied within a specified time window to prevent overflow and sanitary problems.

The second group concerns fleet and collection-center capacity constraints; that is, vehicles cannot carry loads beyond their allowable capacity, and collection centers also have limited storage and acceptance capacities.Finally, the third group of constraints focuses on the proper allocation of waste to biorefineries so that transportation and recycling can be carried out more efficiently. In this section, the model is designed in such a way that each collection center is assigned to a biorefinery that is optimal in terms of capacity, cost, and time. Such appropriate allocation plays a key role in reducing total costs and improving the efficiency of the supply chain. In addition, delivery time control is one of the essential constraints of the model, since delays can reduce the value of the waste and, under the hard time-window condition, may even be unacceptable. Therefore, the model must ensure that vehicles strictly adhere to the delivery schedule.Overall, this set of objectives and constraints makes the proposed model more than a theoretical framework; it serves as an operational decision-support tool capable of balancing operational efficiency, cost reduction, and compliance with time and capacity limitations.

- **Sets**
  - $C$: set of waste generation centers
  - $D$: set of collection centers
  - $W$: set of all first-level nodes, including waste generation centers and collection centers
  - $S$: set of biorefineries
  - $T$: set of time periods
  - $P$: set of waste types
  - $K$: set of vehicles used to collect waste from generation centers
  - $K'$: set of vehicles used to transport waste from collection centers to biorefineries
- **Parameters**
  - $M$: a sufficiently large positive number
  - $Fix_d$: fixed cost of opening collection center $(d)$
  - $cost_k$: vehicle rental cost for vehicle $(k)$
  - $tr_{dsk}$: transportation cost of vehicle $(k)$ from collection center $(d)$ to biorefinery $(s)$
  - $ct_{ijk}$: transportation cost of vehicle $(k)$ from node $(i)$ to node $(j)$
  - $A_{ijk}$: binary parameter; equals 1 if vehicle $(k)$ is allowed to travel from node $(i)$ to node $(j)$, and 0 otherwise
  - $dx_{ij}$: distance between node $(i)$ and node $(j)$
  - $cost_k$: travel cost of vehicle $(k)$ per unit distance and unit weight
  - $cp_j$: capacity of the smart bin located at customer node $(j)$
  - $q_p$: weight of one unit of waste type $(p)$
  - $cpd_d$: capacity of collection center $(d)$
  - $d_{jtp}$: amount of waste type $(p)$ generated by location $(j)$ in time period $(t)$
- **DecisionVariabl**

- $X_{ijdkt}$: binary variable; equals 1 if vehicle ($k$) assigned to collection center ($d$) travels from node ($i$) to node ($j$) in time period ($t$), and 0 otherwise
- $Y_{dstk}$: binary variable; equals 1 if vehicle ($k$) travels from collection center ($d$) to biorefinery ($s$) in time period ($t$), and 0 otherwise
- $ND_{dtk}$: number of vehicles ($k$) assigned to transport waste from collection center ($d$) to the biorefinery in time period ($t$)
- $hst_{jt}$: unmet service time for serving waste generation location ($j$) in time period ($t$) under the soft time
- window constraint - $F_d$: binary variable; equals 1 if collection center ($d$) is $\frac{\text{opened}}{\text{used}}$, and 0 otherwise
- $\theta_{jt}$: additional cost resulting from the load amount for reaching waste generation location ($j$) from the previous node
- $L_{jt}$: load on the vehicle after leaving waste generation location ($j$) in time period ($t$)
- $de_{jt}$: amount of waste contained in the smart bin at collection point ($j$) in time period ($t$)
- $LO_{kdt}$: amount of load transported by vehicle ($k$) assigned to collection center ($d$) in time period ($t$)
- $dc_{dt}$: amount of waste sent to collection center ($d$) in time period ($t$)
- $Et_{jt}$: time required to transport waste from location ($j$) to the collection center in time period ($t$)

- **Objective Function**

$$\min \ z_1 = \sum_{j\in c}\sum_{t\in T} hst_{jt}$$

$$\min \ z_2 = \sum_{d\in D} F_d \times Fix_d + \sum_{j\in c}\sum_{t\in T}\sum_{k\in K}\sum_{d\in D} X_{djdtk}\times cost_k + \sum_{s\in S}\sum_{t\in T}\sum_{k\in K}\sum_{d\in D} Y_{dstk}\times dc_{dt}\times tr_{dsk}$$
$$+\sum_{j\in w}\sum_{i\in w}\sum_{t\in T}\sum_{k\in K}\sum_{d\in D} x_{ijkdt}\times ct_{ijk} + \sum_{j\in c}\sum_{t\in T}\theta_{jt}$$

The first objective function focuses on time management and aims to minimize the deviation from the soft time windows. In other words, this function is designed to ensure the timely delivery of waste so as to prevent any reduction in its value and quality. This issue is particularly important for waste items such as bread, which rapidly lose value over time. Delays in the collection and delivery of waste not only reduce its quality and usefulness, but also affect the overall efficiency of the system. Therefore, this objective function ensures that the waste collection and transportation process is carried out with high temporal accuracy and the minimum possible delay. The second objective function of the model seeks to optimize the overall economic performance of the waste collection and transportation system. It aims to minimize all costs associated with the establishment and operation of the system. These costs include the fixed costs of collection centers, which are required for opening and operating each center; vehicle rental costs, which vary depending on the heterogeneous capacity and characteristics of each vehicle; transportation costs from waste generation centers to collection centers, which are affected by distance, travel time, fuel consumption, and route conditions; transfer costs from collection centers to biorefineries; and finally, additional load-dependent costs, since heavier vehicle loads lead to higher fuel consumption and transportation expenses. By considering all cost components, this objective function provides an integrated framework for economic resource optimization and operational cost reduction. In interaction with the first objective function, the model enables a balance between cost minimization and compliance with time and capacity constraints, thereby playing a key role in improving the efficiency and productivity of the waste supply chain.

- **Constraints**

$\forall j \in c, t \in T \sum_{k\in K}\sum_{i\in w}\sum_{d\in D} x_{ijkdt} = B_{jt}$

$\forall j \in c, t \in T B_{jt} \times M \geq de_{jt} - cp_j$

$\forall j \in c, t \in T de_{jt} \geq \sum_{p\in P} d_{jtp} \times q_p$

$\forall j \in c, t \in T de_{jt} \geq de_{j(t-1)} + \sum_{p\in P} d_{jtp} - MB_{jt}$

$\forall j \in c, t \in T, k \in K, d \in D \sum_{i\in w} x_{ijkdt} = \sum_{i\in w} x_{jikdt}$

$\forall t \in T, k \in K, d \in D \sum_{j\in c} x_{djkdt} = \sum_{j\in c} x_{jdkdt}$

$\forall t \in T, k \in K, d \in D LO_{kdt} = \sum_{j\in c}\sum_{i\in w} x_{ijkdt} \times de_{jt}$

$$\forall t \in T, k \in K, d \in DLO_{kdt} \leq cap_k$$
$$\forall t \in T, d \in Ddc_{dt} = \sum_{k \in K} Lo_{kdt}$$
$$\forall t \in T, d \in Ddc_{dt} \leq cap_d$$
$$\forall t \in T, d \in D \sum_{s \in S} \sum_{k \in k'} Y_{dstk} = 1$$
$$\forall t \in T, s \in S \sum_{d \in D} \sum_{k \in k'} Y_{dstk} \times dc_{dt} \leq cps_s$$
$$\forall t \in T, k \in K, d \in D, i \in w, j \in cEt_{jt} \geq Et_{it} + st_{it} + \frac{dx_{ij}}{v_k} - M\,(1 - x_{jikdt})$$
$$\forall t \in T, j \in cEt_{jt} \leq timea$$
$$\forall t \in T, j \in chst_{jt} \geq Et_{jt} - timeb$$
$$\forall t \in T, k \in K, d \in D, j \in cL_{jt} \geq Lo_{kdt} - de_{jt} - M\,(1 - x_{jdkdt})$$
$$\forall t \in T, k \in K, d \in D, i \in w, j \in cL_{jt} \geq L_{it} - de_{jt} - M\,(1 - x_{jikdt})$$
$$\forall t \in T, k \in K, d \in D, i, j \in wx_{ijkdt} \leq A_{ijk}$$
$$\theta_{jt} \geq Lo_{kdt} \times dx_{dj} \times cost_k - M\,(1 - x_{jdkdt})$$
$$\theta_{jt} \geq L_{it} \times dx_{ij} \times cost_k - M\,(1 - x_{jikdt})$$
$$\forall t \in T, k \in k^{'}, s \in S, d \in DND_{dtk} \geq Y_{dstk} \times dc_{dt}$$
$$\forall t \in T, k \in K, d \in D, j \in cF_d \times M \geq x_{djkdt}$$
$$B_{jt}, x_{ijkdt}, Y_{dstk}, F_d = 0 \text{ or } 1$$
$$de_{jt}, Lo_{kdt}, L_j, dc_{dt}, Et_{jt}, hst_{jt}, \theta_{jt}, ND_{dtk} \geq 0$$

In the proposed model, a set of constraints is defined to cover the various aspects of waste collection and transportation operations and to ensure the system's operational performance. The first constraint guarantees that once a smart bin reaches its full capacity, a dedicated vehicle is assigned to service and empty that bin. The second constraint determines which bins require service in a given time period based on the alert messages sent by the smart bins. The third and fourth constraints are related to the weight of the waste stored in the bins and specify the cumulative load of each bin. The fifth constraint ensures that any vehicle entering a location must leave that same location after completing service. The sixth constraint guarantees that each vehicle returns to the same collection center after departing from it. Finally, the seventh and eighth constraints concern vehicle capacity: the seventh determines the maximum load that each vehicle can carry along the route, and the eighth ensures that the overall capacity of each vehicle is respected. These constraints allow the model to reflect the real behavior of the system, fleet efficiency, and operational and capacity limitations simultaneously, thereby providing a reliable framework for optimizing the waste supply chain.The ninth and tenth constraints focus on the waste flow into the collection centers: the ninth determines the amount of waste sent to each collection center, and the tenth ensures that the capacity of each center is not exceeded. The eleventh and twelfth constraints relate to the allocation of waste to biorefineries, such that each collection center is assigned to a biorefinery and the amount of waste sent to each biorefinery remains within its capacity.The thirteenth to seventeenth constraints focus on waste delivery scheduling. The thirteenth specifies the delivery time of waste from each generation center to the collection centers; the fourteenth enforces the hard time-window restrictions; and the fifteenth determines the amount of soft time-window violation. The sixteenth and seventeenth constraints specify the delivery times for the last and the other producers along the route, respectively. The eighteenth constraint ensures that each vehicle travels only on routes for which it is permitted or capable. The nineteenth and twentieth constraints calculate the additional costs arising from the amount of load carried by the vehicle. The twenty-first constraint determines the number of vehicles required to transport waste from the collection centers to the biorefineries, and the twenty-second specifies from which collection center each transfer is made. Finally, the twenty-third and twenty-fourth constraints define the decision-variable types of the model and specify which variables are binary and which are continuous.

## NSGA-II

AlgorithmThe NSGA-II metaheuristic algorithm is considered one of the powerful and widely used methods for solving multi-objective optimization problems, and its effectiveness has been demonstrated in various applications. In multi-objective problems, there is usually a conflict among different objectives; that is, the best solution for one objective may be incompatible with the optimal solution for another objective. In such cases, a set of solutions is known as the Pareto Front, which includes the best solutions for each objective independently, while intermediate

solutions exist among them that perform better than other solutions in each objective, although they do not provide full simultaneous optimization for all objectives.

In implementing the NSGA-II algorithm for the present problem, the initialization phase is first performed, in which the algorithm parameters, including the mutation rate, initial population size, and number of iterations, are specified. Then, the problem data and parameters, including the specifications of IoT-based smart bins, capacity constraints, delivery time, and vehicle characteristics, are entered into the software; usually, this information is prepared in Excel files so that the algorithm can compute the optimal routes and vehicle assignments while satisfying all constraints. After data entry, the algorithm generates a new population of solutions using selection, crossover, and mutation mechanisms, and the multi-objective optimization process continues iteratively until convergence is achieved. This approach makes it possible to identify a set of optimal solutions from which decision-makers can choose the best combination of routes and vehicle assignments for urban waste management and collection according to their operational and economic priorities.In the NSGA-II algorithm, the generation of the initial solution or chromosome structure is designed in such a way that each proposed solution to the problem is represented as a chromosome. This chromosome consists of three parts: the first and second parts include ordered numbers that usually represent the sequence of customer visits or the assignment of routes to vehicles, while the third part consists of random numbers between zero and one.

The first chromosome includes $n+k-1$ cells $(n)$: number of waste generation locations, $(k)$: number of vehicles), and the second chromosome includes $d+k-1$ cells $(d)$: number of collection centers. In the first chromosome, the numbers from 1 to $(n)$ indicate the waste generation locations, and the numbers greater than $(n)$ represent the vehicles; specifically, cell $n+1$ represents the first vehicle and cell $n+i$ represents the $(i)$-th vehicle. In this case, the numbers placed before cell $n+i$ are the waste generation locations served by the $(i)$-th vehicle, and their order indicates the service sequence. All waste generation locations whose numbers appear after the last cell greater than $(n)$ are assigned to the last vehicle. The second chromosome consists of $d+k-1$ cells, where the numbers from 1 to $(k)$ represent the vehicles and the number $k+i$ represents the $(i)$-th collection center. The vehicles appearing before number $k+i$ are assigned to the $(i)$-th collection center, and the vehicle after the last number greater than $(k)$ is served by the last collection center. If there is no waste generation location number before $n+i$, it means that that vehicle is not used. Similarly, in the second chromosome, if there is no vehicle number before $k+i$, it means that that warehouse is not used.If, along the route, the bin of a given location has not been projected for service, then that location is removed from the route. Figures 1 and 2 present a hypothetical initial solution (eight locations, three vehicles, and two collection centers).

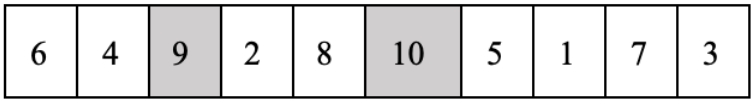



Figure 1: Representation of the Initial Solution for the Hypothetical Example of the First Chromosome




Figure 2: Representation of the Initial Solution for the Hypothetical Example of the Second Chromosome

Based on the two figures above, the initial solution is interpreted as follows.

Table 2: Interpretation of the Solution

| Vehicle | Collection Center | Route |
|---|---|---|
| 1 | 1 | 6-4 |
| 2 | 1 | 2-8 |
| 3 | 2 | 5-1-7-3 |

In the third chromosome, each collection center and each biorefinery is assigned a value in the interval $[0,1]$, which determines the share of each collection center allocated to each biorefinery. In this study, the initial population is generated randomly, such that each initial solution consists of three consecutive chromosomes. This procedure ensures

sufficient diversity in the initial population and enables effective coverage of the search space. For each chromosome, the evaluation function is applied to compute the values of the three objective functions. If a solution violates the problem constraints, its objective value is multiplied by a constant, thereby reducing its probability of being selected in subsequent stages; in this way, infeasible chromosomes are eliminated.After evaluating the population, the parent selection stage begins. In this stage, the algorithm randomly selects two chromosomes, and the solution with the better fitness value is chosen as the parent. For more appropriate selection, the algorithm gives priority to the chromosome located in a lower-ranked front. If two chromosomes belong to the same front, the one with the larger crowding distance is selected as the parent. In the next stage, the elitism mechanism is employed to preserve the quality of the population in subsequent generations. In each generation, to produce the next population consisting of $(N)$ members, $(M)$ solutions are selected through the best solutions of the previous generation, and the remaining $NM$ solutions are generated through the crossover operator. This process allows the best features of the previous population to be transferred to the next generation while maintaining the diversity required for optimal search.In the next stage of the NSGA-II algorithm, the generation of offspring is performed. For the first and second chromosomes, which represent the sequence of visits to generation centers and the assignment of routes to vehicles, a two-point crossover operator is used. In this method, two points are randomly selected, and the genes of the first parent between these two points are copied, while the remaining genes are transferred from the second parent to the offspring in order. For the third chromosome, which specifies the share of each collection center assigned to each biorefinery, one point is randomly selected, and the genes from the first gene to that point are copied from the first parent, while the remaining genes are copied from the second parent to form the final offspring. This process ensures that the characteristics of both parents are preserved in the next generation and that the population diversity necessary for optimal search in the solution space is maintained.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 5 | 9 | 3 | 7 | 8 | 6 | 2 | 4 | The first parent |
| 8 | 4 | 6 | 2 | 9 | 7 | 1 | 5 | 3 | The Second parent |
| 4 | 2 | 9 | 3 | 7 | 8 | 6 | 1 | 5 | offspring |

After the offspring are generated, the mutation operator is applied. In this stage, a random number is generated, and if it is smaller than the specified mutation rate, mutation occurs. Then, two points are randomly selected on the chromosome, and their values are swapped to increase population diversity. Next, the feasibility of the solutions is examined; specifically, any chromosome that violates one of the problem constraints has its objective value multiplied by a specified coefficient and is gradually removed from the population, so that only feasible and valid chromosomes remain. The stopping criterion of the algorithm is activated when, after a specified number of iterations or a given time period, no significant improvement is observed in the solutions and the Pareto front remains unchanged. At this point, the algorithm terminates and the final results are presented. Accordingly, the main stages of the NSGA-II algorithm include generating the initial population, evaluating the objective function, selecting parents, applying crossover and mutation operators, checking solution feasibility, and finally terminating the algorithm under the specified conditions.

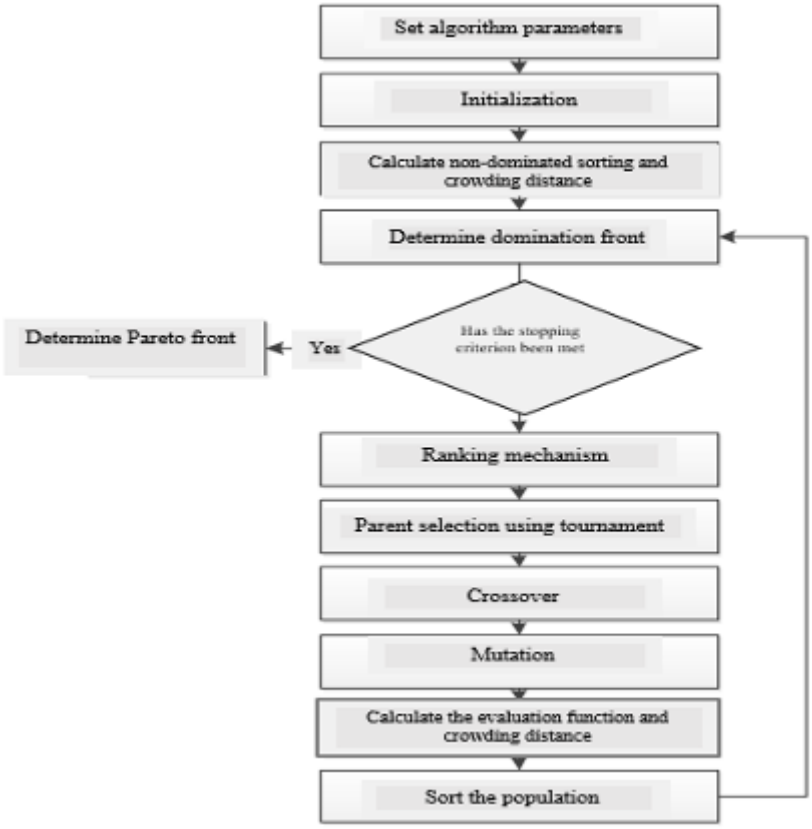



Figure 3: Designed NSGA-II Algorithm

## Results and Discussion

In this section, the performance of the NSGA-II metaheuristic algorithm in solving the vehicle routing problem for smart waste collection is examined. First, the algorithm was implemented on small-sized instances to enable a comparison of the results with those obtained from the GAMS software. Table 4 presents the results of this comparison and includes the deviation from the soft time-window constraint, the best solution obtained by the NSGA-II algorithm, the solution obtained by GAMS, the deviation in the cost objective function, and the number of waste generation centers, collection centers, and biorefineries.As can be seen in the table, the difference between the results of the NSGA-II algorithm and GAMS is very small for both objective functions and is generally less than 3%. This indicates the high accuracy of the algorithm in generating solutions that are nearly identical to the exact mathematical solution of the problem. In addition, the computational time required to solve the small instances using the NSGA-II algorithm was compared with that of GAMS. As shown in the figure, the execution time of the algorithm is significantly lower than the time required by GAMS. This highlights the advantage of using metaheuristic algorithms in real-world problems with time limitations and high computational complexity.

Table 3: Performance Evaluation of the NSGA-II Algorithm in Small-Scale Instances

| Example No. | Waste Generation Centers | Collection Centers | Biorefineries | Cost Objective (GAMS) | Cost Objective (NSGA-II) | Cost Deviation | Time Objective (GAMS) | Time Objective (NSGA-II) | Time |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 6 | 3 | 2 | 180.2 | 180.7 | 0.28% | 38.2 | 38.3 | 0.26% |
| 2 | 8 | 4 | 2 | 198.7 | 200.5 | 0.91% | 46.7 | 47.1 | 0.86% |
| 3 | 10 | 5 | 3 | 236.4 | 240.6 | 1.78% | 68.7 | 69.5 | 1.16% |
| 4 | 12 | 6 | 3 | 310.1 | 316 | 1.90% | 96.4 | 97.9 | 1.56% |
| 5 | 14 | 7 | 4 | 410.3 | 419.5 | 2.24% | 102.3 | 104.7 | 2.35% |

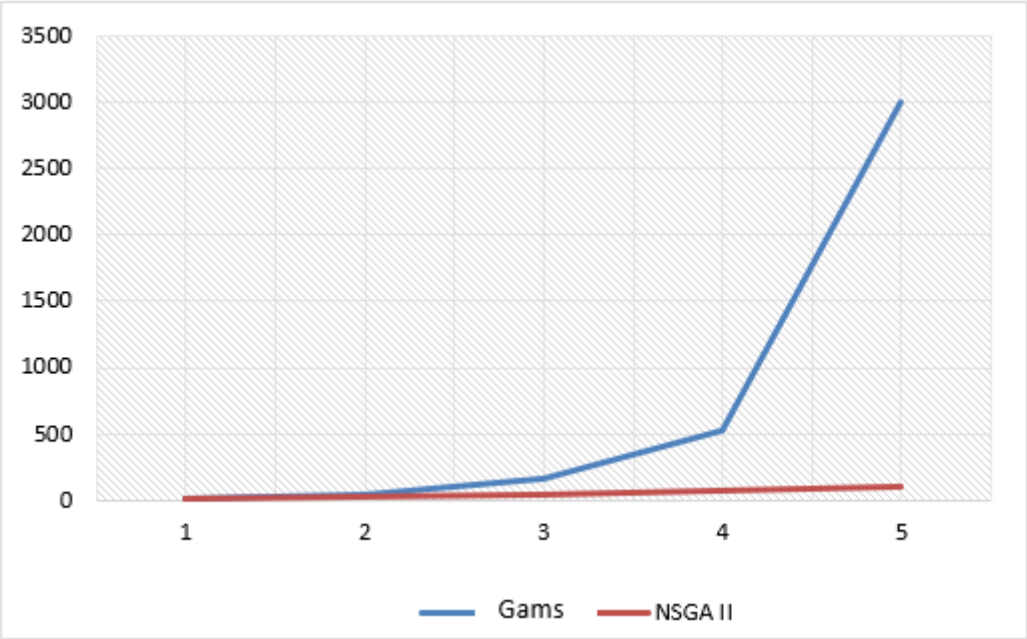



Figure 4: Comparison of Solution Time Using the NSGA-II Algorithm

In the next stage, in order to evaluate the performance of the NSGA-II algorithm in larger-scale instances, several numerical examples were designed by increasing the number of waste generation centers, collection centers, and biorefineries, and the algorithm was then applied to solve these problems. The results obtained from running the algorithm are presented in Table 4. As can be seen, the deviations among the different solutions and the variances obtained from multiple runs of the algorithm are very small. This indicates the stability and convergence of the algorithm even at large scales and increases its reliability for solving real-world problems.

In addition, the results show that the NSGA-II algorithm is capable of simultaneously optimizing multiple objective functions and can establish an appropriate balance between minimizing economic costs and satisfying time constraints, vehicle capacity limits, and collection-center capacity limits. The algorithm's ability to handle multi-objective problems, especially in situations where there is conflict among objectives, makes it possible to generate a set of boundary solutions and a Pareto front. As a result, decision-makers can select the best option based on operational policies and constraints.

The results further indicate that, while significantly reducing computational time compared with exact mathematical methods, the NSGA-II algorithm is able to preserve the quality of the obtained solutions and can therefore be introduced as an efficient and reliable tool for practical applications in smart waste collection supply chains, particularly when using IoT-enabled bins.

Table 4: Performance Evaluation of the Algorithm in Large-Scale Instances for the Time Objective

| Example No. | Run 1 | Run 2 | Run 3 | Run 4 | Run 5 | Run 6 | Run 7 | Run 8 | Best Solution | Worst Solution | Mean Solution | Deviation Between Best and Worst | Deviation Between Mean and Worst | Variance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 151.2 | 151.2 | 151.6 | 151.2 | 151.8 | 151.5 | 151.7 | 151.2 | 151.2 | 151.8 | 151.43 | 0.40% | 0.15% | 0.065 |
| 2 | 165.3 | 165.3 | 166.7 | 165.5 | 165.3 | 165.7 | 165.9 | 165.3 | 165.3 | 166.7 | 165.63 | 0.85% | 0.20% | 0.239 |
| 3 | 184.3 | 184.3 | 186.2 | 184.7 | 184.3 | 185.2 | 185.4 | 184.3 | 184.3 | 186.2 | 184.84 | 1.03% | 0.29% | 0.497 |
| 4 | 196.7 | 196.7 | 199.8 | 199.3 | 196.7 | 196.9 | 196.7 | 197 | 196.7 | 199.8 | 197.48 | 1.58% | 0.39% | 1.671 |
| 5 | 211.3 | 212.3 | 211.3 | 213.6 | 211.3 | 213.4 | 213.5 | 211.5 | 211.3 | 213.6 | 212.28 | 1.09% | 0.46% | 1.139 |

Table 5: Performance Evaluation of the Algorithm in Large-Scale Instances for the Cost Objective

| Example No. | Run 1 | Run 2 | Run 3 | Run 4 | Run 5 | Run 6 | Run 7 | Run 8 | Best Solution | Worst Solution | Mean Solution | Deviation Between Best and Worst | Deviation Between Mean and Worst | Variance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 438.2 | 438.2 | 439.4 | 438.2 | 439.5 | 438.2 | 440.2 | 438.2 | 438.2 | 440.2 | 438.76 | 0.46% | 0.13% | 0.657 |
| 2 | 563.1 | 564.1 | 563.1 | 562.9 | 563.1 | 567.5 | 563.1 | 564.5 | 562.9 | 567.5 | 563.93 | 0.82% | 0.18% | 2.416 |
| 3 | 639.7 | 640.3 | 643.2 | 639.7 | 639.7 | 640.9 | 642.3 | 643.4 | 639.7 | 643.4 | 641.15 | 0.58% | 0.23% | 2.526 |
| 4 | 438.2 | 438.2 | 439.4 | 438.2 | 439.5 | 438.2 | 440.2 | 438.2 | 438.2 | 440.2 | 438.76 | 0.46% | 0.13% | 0.657 |
| 5 | 563.1 | 564.1 | 563.1 | 562.9 | 563.1 | 567.5 | 563.1 | 564.5 | 562.9 | 567.5 | 563.93 | 0.82% | 0.18% | 2.416 |

## Conclusion

In this research, the waste collection problem was modeled and analyzed through a vehicle routing perspective. To provide a comprehensive framework, a three-level supply chain was designed, consisting of waste generation centers, collection centers, and biorefineries. Each waste generation center was equipped with IoT-based smart bins that send a collection alert to the control center when the waste level reaches a predefined threshold. This feature enables real-time monitoring of waste status and more efficient fleet management, thereby reducing service time and improving operational efficiency.

To solve this complex problem, the NSGA-II metaheuristic algorithm was employed as one of the most effective methods for multi-objective optimization. In this algorithm, an initial population of chromosomes was generated, followed by evaluation, parent selection, crossover, and mutation to create subsequent generations. During the solution process, the feasibility of each solution was checked according to the problem constraints, and chromosomes violating the constraints were penalized or removed. This enabled the algorithm to converge toward a set of Pareto-optimal solutions while preserving solution quality.

The performance of the algorithm was evaluated through several small- and large-scale numerical examples. The results showed that the algorithm could produce accurate and stable solutions with significantly lower computational time than classical exact solvers such as GAMS. From an operational standpoint, the use of IoT-enabled smart bins allows real-time data collection and intelligent service policies. This capability can reduce operating costs, optimize routes, lower fuel consumption, and reduce environmental impacts. In addition, real-time IoT data support long-term planning and fleet-demand forecasting, leading to more accurate decision-making in supply chain management.

Overall, this study shows that integrating mathematical modeling, multi-objective metaheuristic algorithms, and IoT technology can lead to efficient, economical, and sustainable waste collection management systems. This framework also provides a suitable basis for future research and the development of smart urban systems. Using IoT-enabled smart bins in bread waste collection can reduce operational costs, optimize fleet routes, and mitigate environmental impacts. Municipalities and companies involved in waste collection and recycling can use this system to ensure timely and optimal service provision and improve the quality of urban services. Moreover, analyzing real-time data from the bins enables long-term planning and better fleet forecasting, thereby supporting more accurate supply chain decisions. Future studies may incorporate uncertainty and fuzziness in waste demand, and hybrid metaheuristic or machine-learning-based algorithms could be used to improve solution quality and reduce computational time. In addition, examining the effects of environmental factors such as traffic conditions, road restrictions, and coordination with other urban waste management sectors can increase the applicability and comprehensiveness of the proposed model.

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