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Developing a Decision Support System to Improve the Waste Transportation Process

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Abstract

Background: The increasing volume of waste and stricter environmental regulations necessitate efficient waste transportation. Optimizing the specialized vehicle fleet remains a challenge due to fragmented decision-making approaches. *Methods*: This study develops a Decision Support System (DSS) integrating a simulation model (developed in AnyLogic) with a vehicle competitiveness assessment module (developed in Python). The simulation reproduces waste generation, collection (schedule-based and event-based), and transport logistics. An optimization experiment was conducted to minimize total logistics costs by varying fleet composition. *Results*: The findings indicate that the optimal fleet configuration reduced total logistics costs by 40.64% compared to the baseline; this reduction was statistically significant. *Conclusions*: The proposed DSS enables integrated optimization of fleet composition, demonstrating substantial potential for improving both economic and environmental performance of waste transportation systems. The modular architecture supports adaptation to diverse operational contexts.

Keywords: waste management logistics; decision support system; simulation modeling; garbage trucks; environmental efficiency

1. Introduction

The increasing volume of waste generated by industrial and municipal activities, combined with stricter environmental regulations, places increasing demands on waste management systems. A critical element of these systems is the transport and logistics component, which accounts for a substantial share of total costs and environmental impact [1,2]. Inefficient fleet utilization, mismatched vehicle capacities, and suboptimal routing not only increase operational expenses but also contribute to unnecessary emissions and congestion [3]. Improving the efficiency of waste transportation, therefore, represents a high-leverage opportunity to enhance both the economic and environmental performance of the waste management sector.

In Russia, despite ongoing reforms and the adoption of regulatory acts aimed at modernizing the waste management industry, significant challenges remain [4]. A large portion of waste is still landfilled, recycling rates are low, and transport logistics are often based on outdated practices that do not account for the diversity of waste types or the variability of generation patterns. Operators face difficulties in selecting the appropriate fleet composition, balancing capacity with demand, and responding to dynamic changes in waste volumes. These difficulties are exacerbated by the lack of integrated decision support tools tailored to the Russian context.

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The central question addressed in this study is as follows: how can the waste transportation process be improved through the development of a Decision Support System that integrates a vehicle competitiveness assessment tool (to determine the qualitative composition of the vehicle fleet) with a simulation model for determining the required number of garbage trucks?

Existing research has explored various aspects of waste transport logistics, including route optimization [5], facility location [6], and vehicle selection [7]. The motivation for this research stems from the fragmentation of existing approaches: most studies address these elements in isolation. Moreover, the assessment of vehicle competitiveness is rarely linked to operational simulation, and few approaches incorporate the specific technical and operational characteristics of specialized waste transport vehicles. As a result, decision-makers often lack a holistic tool that can simultaneously optimize the quantitative and qualitative composition of the fleet while accounting for economic and environmental criteria.

This study addresses this gap. The aim of this research is to develop a Decision Support System (DSS) that integrates a simulation model as its intellectual core with a module for assessing the competitiveness of specialized waste transport vehicles. The DSS enables the optimization of fleet composition—both the number and types of garbage trucks—based on a minimization of total logistics costs, including direct transport costs, idle time penalties, and the conditional cost of environmental damage.

The main contributions of this study are threefold. First, it proposes an integrative framework that combines vehicle competitiveness assessment with simulation-based fleet optimization, addressing the fragmentation identified in the literature. Second, it develops a practical DSS with a modular architecture that can be adapted to different operational contexts by modifying input data and parameters. Third, it provides quantitative evidence—through a simulation experiment—that optimizing fleet composition can reduce total logistics costs.

The remainder of this paper is structured as follows: Section 2 reviews related literature and identifies the research gap. Section 3 describes the architecture of the proposed DSS, the mathematical model for vehicle competitiveness assessment, and the simulation model. Section 4 presents the results of the optimization experiment. Section 5 discusses the implications, limitations, and directions for future work. Section 6 concludes the paper.

2. Approaches to Improving the Waste Management Logistics System

The transport and logistics component is a central, system-forming element of the waste management chain. It ensures the physical movement of waste material flows between generation sources, collection points, sorting stations, processing facilities, and disposal sites, thereby determining the speed, cost, environmental impact, and overall effectiveness of the system. This section reviews existing research according to four thematic areas: (1) logistics network design and reverse logistics, (2) fleet composition and vehicle selection, (3) simulation and Decision Support Systems, and (4) the integration of sustainability criteria. The review concludes by identifying the research gap that motivates the present study.

2.1. Logistics Network Design and Reverse Logistics

Historically, waste management followed a linear "take-make-dispose" model with a primary focus on transporting waste to disposal sites [8]. The modern paradigm shifts toward differentiated waste collection and circular economy principles, which fundamentally change the requirements for transport logistics. Instead of mere removal, the system must manage material flows to maximize recycling and recovery. Reverse logistics—the process

of planning and controlling the flow of materials from consumption back to the point of recovery or proper disposal—has become a key element.

Several studies have addressed the optimal location of waste management facilities as a means to minimize transport distances and costs. In the study [6], a model was proposed that determines optimal locations for sorting and processing facilities based on waste generation volumes, vehicle capacity, and transport distances, using a transport-logistics function to minimize overall haulage. Similarly, the role of centralized logistics hubs in reducing carbon footprint and improving efficiency of waste collection networks has been emphasized [9].

The transition from linear to circular models faces multiple barriers. In the work [10], the authors identified several obstacles: insufficient leadership commitment, elevated implementation costs, limited policy effectiveness, inadequate software infrastructure, and uncertain consumer demand for recycled products. These findings underscore the need for practical, integrable decision support tools, particularly in evolving regulatory environments.

The Russian waste management system is characterized by specific regional and regulatory features. In the study [4], the drivers and barriers for waste management development in Russia were analyzed, highlighting the gap between legislative reforms and practical implementation. Similarly, the authors of [11] assessed the potential for greenhouse gas emission reductions through improved waste management practices, noting that despite ongoing reforms, the system remains characterized by underdeveloped sorting infrastructure, a predominance of landfilling, and fragmented institutional responsibilities. These factors create a context where standard logistics models developed for other regions cannot be directly applied without substantial adaptation, reinforcing the need for tailored decision support tools.

Beyond technical and economic factors, governance structures also play a critical role. In the study [12], the concept of polycentric collaborative governance was examined in the context of urban waste systems, demonstrating how public value can be co-created through CSR-community partnerships. While that study focused on institutional arrangements rather than transport logistics per se, its findings highlight the importance of aligning operational tools—such as the proposed DSS—with the broader governance context. This aspect should be considered during implementation.

2.2. Fleet Composition and Vehicle Selection

The material basis of waste transport is specialized rolling stock. The efficiency of the entire system depends not only on routing but also on the quantitative and qualitative composition of the fleet. As shown in the study [13], mismatches between vehicle capacity and waste volumes, as well as the use of unsuitable vehicle types for specific waste fractions, lead to increased costs and environmental impacts.

Further advancing the consideration of heterogeneous fleets, the study [14] investigated the vehicle routing problem for classified municipal solid waste collection using multiple vehicle types and multi-compartment vehicles. The proposed approach combines single-carriage and multi-carriage vehicles within a mixed fleet, optimizing both loading and routing through an adaptive large neighborhood search algorithm. The results demonstrate that heterogeneous fleet configurations can significantly reduce transportation costs compared to homogeneous or single-type fleets, highlighting the importance of matching vehicle characteristics to waste type diversity.

In parallel, research on vehicle competitiveness has gained attention. In the study [7], a total cost of ownership approach was used to compare electric and conventional vehicles, finding that battery electric vehicles achieved the lowest total cost of ownership in certain segments. A competitiveness assessment based on consumer quality and price fairness was

proposed in [15], while the role of R & D and environmental innovations in determining competitiveness was emphasized in [16]. However, these assessments are often generic and do not account for the specific operational conditions of waste transport, such as frequent stops, high load factors, and the need for specialized bodywork.

Beyond route assignment, the operational efficiency of garbage trucks under real-world conditions has been examined in [17], where a mathematical model was developed to evaluate route efficiency based on fuel consumption. The authors recommended reassigning routes or altering collection sequences when fuel consumption exceeded thresholds. Together with the findings of [3], this work underscores the need for tools that link vehicle characteristics with operational performance—a principle that underpins the competitiveness module developed in the present study.

2.3. Simulation Models and Decision Support Systems

Simulation modeling has been widely recognized as a powerful tool for analyzing complex logistics systems. Its application in waste management allows decision-makers to test scenarios without disrupting real operations. In the study [18], a system dynamics model for municipal solid waste management was developed that integrates financial planning and capacity expansion scenarios, providing a comprehensive view of costs and resource flows to support strategic decisions.

The use of simulation as the intellectual core of a Decision Support System (DSS) for logistics operations was demonstrated in [19], showing significant efficiency gains through parameter optimization. In [20], a fleet management system was implemented that predicts garbage truck arrival times with high accuracy, improving transparency and operational planning.

Simulation modeling has also been applied to understand behavioral and systemic dynamics in waste management. In the study [21], a system dynamics model was developed to evaluate interventions promoting appropriate waste disposal behaviors in low-income urban areas. Their approach demonstrated how simulation can capture the complex interactions between policy interventions, community behavior, and waste management outcomes.

The integration of multiple simulation paradigms within a single DSS was explored in [22], where a bi-objective decision support tool combining system dynamics and discrete event simulation in AnyLogic 8.9.8 was developed for a sustainable supply chain. The proposed approach enables simultaneous optimization of cost and CO_2 emissions, demonstrating that combining different simulation methods yields a more comprehensive analysis of complex logistics systems. This aligns with the methodological choice of the present study, which uses AnyLogic to integrate agent-based, discrete-event, and system dynamics approaches.

Several studies have incorporated intelligent monitoring and IoT technologies. In [23], a real-time monitoring system was presented using distance sensors to measure container fill levels, enabling dynamic route adjustments. An IoT-based management and evaluation framework for municipal waste was proposed in [24]. These approaches show the potential of integrating real-time data into decision support, but they often focus on monitoring rather than optimization of fleet composition and vehicle characteristics.

2.4. Sustainability and Multi-Criteria Considerations

Increasingly, research incorporates environmental and social criteria alongside economic objectives. In the systematic literature review [25], green and sustainable logistics were examined, noting a trend toward multi-criteria optimization. In [26], the concept of

sustainable reverse logistics service quality was introduced, using the triple bottom line approach and considering operational risk as a mediating variable.

A broader perspective on waste management improvement is offered in [27], where the authors proposed a framework to develop and improve waste management through collaboration among organizations, governments, and academia. Their framework emphasizes the need for integrated approaches that combine technical, organizational, and policy dimensions—an insight that reinforces the value of a DSS that can support decision-making across different stakeholders.

In the work [5], route optimization models were developed for dry and wet waste that minimize total costs, carbon footprint, and secondary pollution. In [28], machine learning methods—including regression, random forest, and support vector machines—were applied to forecast waste generation and optimize management strategies, achieving high predictive accuracy. These works underscore the value of predictive analytics and multi-objective approaches, but they rarely combine fleet composition optimization with real-time simulation and vehicle competitiveness assessment in a unified DSS.

2.5. Synthesis and Research Gap

The reviewed literature reveals significant advances in individual areas of waste transport logistics. However, three main gaps remain.

First, fragmentation: most studies address either routing, facility location, or fleet composition in isolation. There is a lack of integrated frameworks that combine these elements into a single decision support tool.

Second, lack of vehicle-specific optimization: competitiveness assessments are often generic and do not account for the unique operational constraints of waste transport, such as compatibility with different waste types, container lift mechanisms, or urban versus rural operating conditions.

Third, limited applicability to the Russian context: institutional, regulatory, and infrastructural specificities of waste management in the Russian Federation are rarely considered in existing models, which are often developed for other geographic or regulatory settings.

These gaps justify the development of a DSS that combines a simulation-based optimization core with a module for assessing the competitiveness of specialized waste transport vehicles, tailored to the operational realities of the Russian waste management sector. The present research addresses this need.

3. Materials and Methods

Empirical studies and operational reports indicate that existing waste transport logistics in many regions, including Russia, suffer from several systemic inefficiencies. For instance, route planning is often performed manually or based on static schedules, leading to unnecessary mileage and fuel consumption [3,5]. Fleet composition frequently does not match the actual distribution of waste types and generation rates, resulting in underutilization of some vehicles and overflow of containers in others [13]. These problems are compounded by the lack of real-time adaptation to fluctuations in waste volumes [20,23]. Consequently, logistics costs are inflated, and environmental impacts—such as CO_2 emissions and noise—are higher than necessary [25]. Addressing these shortcomings requires an integrated approach that combines fleet optimization, scenario analysis, and decision support.

To this end, we propose a Decision Support System (DSS) based on a simulation model that serves as its intellectual core (Figure 1). The AnyLogic 8.9.8 software platform was chosen for model development, as it supports the combination of discrete-event, agent-based,

and system dynamics approaches. The DSS is designed to optimize both the quantitative and qualitative composition of the specialized vehicle fleet used for waste transport.

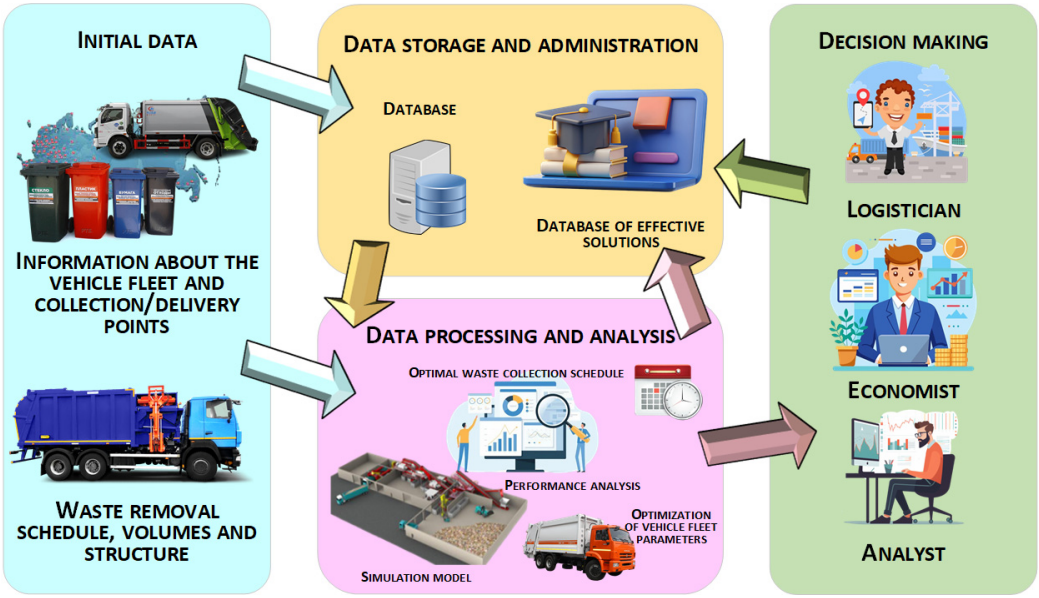


Figure 1. Conceptual model of the Decision Support System.

The data collection and integration module aggregates information on waste and its sources, the vehicle fleet used for waste transport, and infrastructure (landfill locations, sorting stations, processing plants, throughput capacity).

The intellectual core (simulation model) implements the logic of waste generation processes, the waste management system, transport ordering, loading-unloading, and route movement. The optimization module, based on data generated by the model and specified criteria, finds optimal system parameters. Optimized fleet parameter values are fed into the model from the "Assessment of Competitiveness of Specialized Waste Transport Vehicles" module.

The DSS database serves as a repository for storing optimal solutions to various problems. Its use significantly reduces the time for developing and adopting necessary measures. In recurring situations, the system ensures rapid selection of the optimal action algorithm. If a situation has significant differences, adjustments are made to the database, ensuring its continuous development and relevance. Based on system recommendations (effective solutions provided by the DSS), authorized personnel make optimal decisions.

The system is built on a modular architecture, implying its structuring as a set of loosely coupled, functionally independent components (modules). Each such module is responsible for a specific task, possesses its own logic, and has a standardized interface for integration with other system parts. This approach ensures maintenance flexibility: the system can be easily modified, and its functionality expanded by adding new modules.

3.1. Optimization Module for Specialized Waste Transport Vehicles

Given the specificity of the research object, a software product was developed in Python 3.11 using open-source libraries to assess the competitiveness of existing or manufacturer-developed waste transport vehicles. The program can be used by vehicle manufacturers or operators of special equipment. Functional capabilities include creating directories of vehicles, assessing and comparing vehicle parameters, operating conditions, calculating relative competitiveness value, approximate calculation of vehicle ownership cost, and vehicle parameter optimization.

The program's algorithm formalizes the process of comparing competitor special equipment using a hierarchical criteria system. A core was developed for calculating the integral indicator and conducting scenario analysis; its mathematical model automates input data processing and variation in criteria weight coefficients depending on specific customer requirements or operating conditions. For each vehicle, a set of n parameters is evaluated. Each parameter has a defined direction of preference: either maximization (e.g., payload capacity, fuel efficiency) or minimization (e.g., acquisition cost, maintenance cost):

$$I = \left(\sum_{i=1}^{n} \frac{I_i}{a_i}\right) \cdot 10 \cdot (I_{max} - I_{min}) \cdot 100\%$$

—vehicle competitiveness value, where

$$I_i = \begin{cases} \left(\frac{x_i - z_i}{z_i - y_i}\right) \cdot \frac{a_i}{10} & | x_i \to max \cap x_i < z_i \\ \frac{a_i}{10} & | (x_i \to max \cap x_i \geq z_i) \cup (x_i \to min \cap x_i < z_i) \\ \left(\frac{y_i - x_i}{y_i - z_i}\right) \cdot \frac{a_i}{10} & | x_i \to min \cap x_i \geq z_i \end{cases}$$

—competitiveness value of the i-th parameter; a_i—significance of the i-th parameter, $a_i \in [1, 10]$; n—number of parameters.

For each i-th parameter, three reference values are defined:

y_i—the actual value of the parameter for the vehicle being assessed;

z_i —the ideal (target) value, representing the best achievable performance;

x_i—the worst permissible value, representing the minimum acceptable performance.

The significance values a_i for each parameter are assigned based on expert judgment, reflecting the relative importance of different vehicle characteristics for waste transport operations. In this study, the weights were determined through consultation with specialists from a regional environmental operator and a specialized vehicle manufacturer. The following criteria guided the weight assignment: (1) operational parameters affecting daily performance (e.g., body volume, waste weight) received higher weights; (2) economic parameters (e.g., price, fuel consumption) were prioritized based on total cost of ownership considerations; (3) parameters with marginal impact on operational efficiency (e.g., maximum speed, torque) received lower weights.

The module also supports parameter optimization, allowing the user to determine the optimal values of vehicle characteristics within feasible ranges. The optimization problem is formulated as:

$$I = \left(\sum_{i=1}^{n} \frac{I_i}{a_i}\right) \cdot 10 \cdot (I_{max} - I_{min}) \cdot 100\% \to I^*,$$

where I^*—optimal parameter value

$$\begin{cases} y_i \leq x_i \leq z_i \ | x_i \to max \\ z_i \leq x_i \leq y_i \ | x_i \to min \end{cases} \cup \begin{cases} y_i^* \leq x_i \leq z_i^* \ | x_i \to max \\ z_i^* \leq x_i \leq y_i^* \ | x_i \to min \end{cases}$$

$[\forall i \ : x_i \in \ Z_{\geq 0}]$—integerness of the variable x_i.

Where x_i now represents the optimized value of the parameter, constrained between the worst permissible (y_i) and ideal (z_i) values. The objective is to maximize the integral competitiveness index by selecting optimal parameter values, subject to integer constraints for parameters such as capacity, number of compartments, etc.

3.2. Simulation Model of Waste Transportation

The simulation model serves as the intellectual core of the Decision Support System. It reproduces the key processes of waste generation, collection, and transportation, allowing

evaluation of different fleet configurations under various operational strategies. The model was developed in AnyLogic, which supports a hybrid approach combining discrete-event, agent-based, and system dynamics paradigms. This section describes its structure, entities, parameters, decision rules, and optimization setup.

The model simulates the transportation of industrial waste from two generation sources to a sorting station, and subsequently from the sorting station to processing facilities (for recyclable waste) and to a landfill (for non-recyclable waste). The following assumptions are made:

1. Waste flows were set deterministically (by schedule) and stochastically (based on empirical distributions).
2. Waste is separated into recyclable and non-recyclable fractions at the generation sources.
3. The sorting station has limited throughput capacity; waiting times may occur if multiple vehicles arrive simultaneously.
4. Processing plants and landfills are assumed to have sufficient capacity; no queuing occurs at these facilities.
5. Travel times and distances are modeled using a network of links with specified distances and speeds; congestion is not considered in the current version.
6. All vehicles start from a central depot and return to the depot after completing their assigned tasks.

The model includes the following main entity types (Table 1).

Table 1. The main entity types.

Entity Type	Description	Key Attributes
Waste generation source	Two sources (e.g., production lines or workshops) that produce waste	Location (coordinates), waste generation rate (kg/hour), fraction (recyclable/non-recyclable), container capacity (m^3), fill level (dynamic), removal trigger (schedule or critical fill level)
Container	Intermediate storage at each source	Capacity, current fill level, waste type
Vehicle	Specialized garbage trucks	Type ID, capacity (m^3), waste type compatibility, operating cost (€/km), fixed cost (€/trip), speed (km/h), fuel consumption (L/km), loading/unloading time (min)
Sorting station	Facility where waste is separated	Location, throughput capacity (vehicles/h), processing time per vehicle (min)
Processing plant	Facility for recyclable waste	Location, no capacity limit (assumed)
Landfill	Facility for non-recyclable waste	Location, no capacity limit (assumed)
Depot	Vehicle home base	Location

Waste generation at each source is modeled as a continuous accumulation process. Two collection strategies are implemented, selectable by the decision-maker:

- Schedule-based collection: vehicles are dispatched according to a fixed timetable (e.g., every 8 h, every 12 h). The schedule can be specified independently for each source;
- Event-based collection: a vehicle is dispatched when the container fill level reaches a predefined critical threshold (e.g., 80% of capacity). This mimics the "just-in-time" approach often used for industrial waste with variable generation.

When a collection event is triggered, the system selects a suitable vehicle from the available fleet based on:

- Compatibility with the waste type (recyclable/non-recyclable);
- Capacity sufficient to accommodate the current container content;
- Proximity to the source (if multiple vehicles are available, the nearest is chosen).

A discrete-event approach was used in developing the model. The model simulates the flow of requests (waste, containers, garbage trucks) through a network consisting of processing units and directed links connecting the units. The structural diagram of the model is shown in Figure 2.

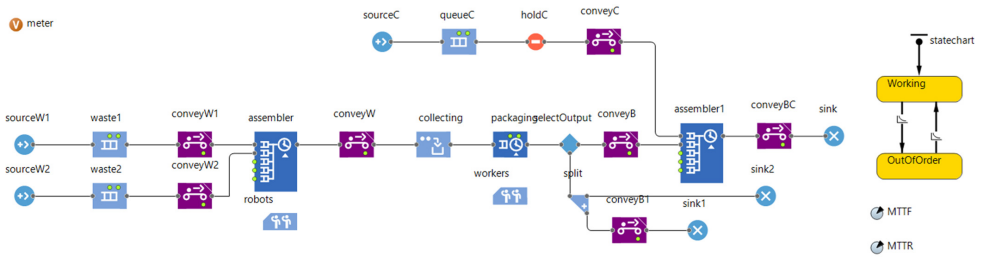


Figure 2. Structure of the simulation model.

The operational cycle for a vehicle dispatched to a source is:

1. Travel from depot to source;
2. Load waste (loading time depends on vehicle type and waste volume);
3. Travel to sorting station;
4. Unload at sorting station (unloading time);
5. After unloading, the vehicle either:
    - Returns to depot (if no further tasks), or
    - If recyclable waste is present at the sorting station and a processing plant is available, the vehicle may be assigned to transport recyclables from the sorting station to the processing plant (in a subsequent trip).

Non-recyclable waste is transported from the sorting station to the landfill by the same or other vehicles, depending on fleet availability.

The model uses a combination of fixed parameters and variable inputs. Table 2 summarizes the key parameters used in the simulation experiments.

Table 2. Simulation model parameters.

Parameter	Value/Range	Description
Number of waste sources	2	Fixed in current experiments
Source 1 generation rate	500–1500 kg/day	Stochastic
Source 2 generation rate	300–800 kg/day	Stochastic
Recyclable fraction	40%	Fixed proportion
Container capacity per source	8 m^3	Same for both sources
Critical fill level (event-based)	80%	Trigger for collection
Collection schedule	Schedule-based	For some of the waste
Vehicle types	4	Different capacity, cost, compatibility
Vehicle capacities	8 m^3, 12 m^3, 16 m^3, 21 m^3	
Loading time	10–20 min	Proportional to load volume
Unloading time	5–15 min	Fixed per vehicle type
Sorting station throughput	4 vehicles/h	
Simulation duration	30 days	

4. Results

This section presents the results of the experiment to determine the optimal quantitative and qualitative composition of the specialized vehicle fleet for waste transportation, minimizing total logistics costs. The results are organized as follows: first, the vehicle

competitiveness assessment is briefly summarized; second, the baseline fleet configuration is described; third, the optimization results are presented, including convergence behavior and comparison of scenarios; finally, a statistical analysis of the results is provided.

4.1. Vehicle Competitiveness Assessment

This module was used to evaluate the competitiveness of various garbage truck models. Table 3 lists the key parameters of the vehicles being evaluated and their significance. The decision maker can modify this list of parameters.

Table 3. Characteristics of evaluated vehicle types.

Parameter	Significance Value	Parameter Value (KAMAZ KO-440V)	Parameter Value (MAZ MKM-3403)
Engine power	5	301	280
Waste Weight	9	6695	7000
Body Volume	9	21	16
Waste Compaction Ratio	5	6	8
Fuel Consumption	8	25	26
Maximum Speed	3	60	60
Price	9	6,500,000	5,000,000
Torque	4	1087	1160
Warranty Period	5	1	1
Loader crane	5	0	1
Fuel Tank Capacity	6	60	60
Service Quality	8	7	4

The weight set used in this study is provided as an example; the DSS allows decision-makers to modify these weights and their values according to their specific operational priorities.

The results of calculating the competitiveness of the considered models of garbage trucks are presented in the form of petal diagrams in the software interface (Figure 3).

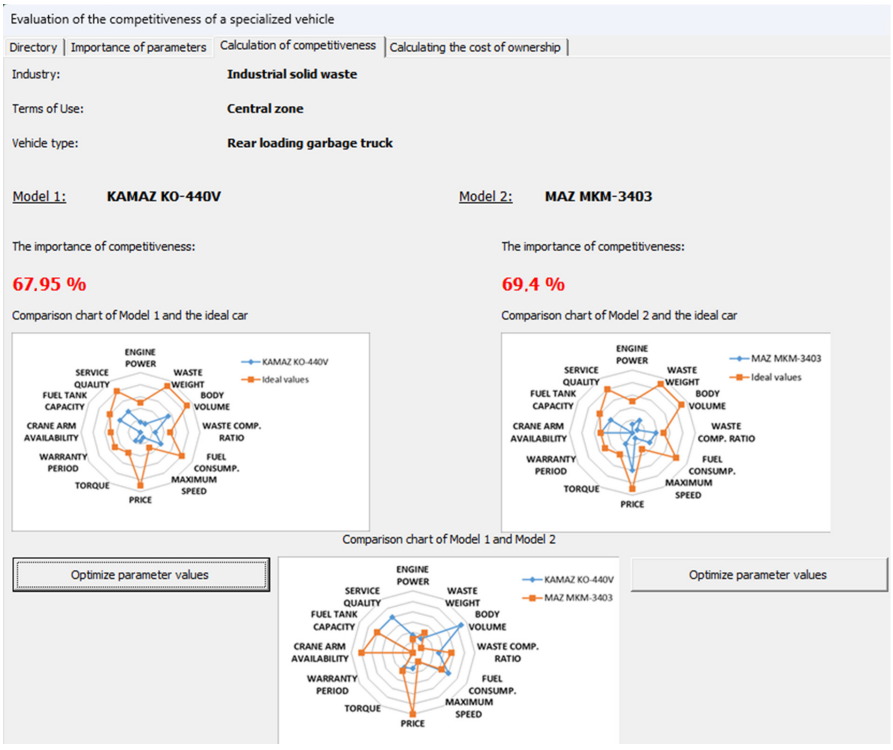


Figure 3. Results of garbage truck competitiveness assessment.

The competitiveness index, calculated using weighting factors, shows that the MAZ MKM-3403 garbage truck is slightly more competitive (69.4%) than the KAMAZ KO-440V

garbage truck (67.95%). The latter model has better key performance parameters, but the former truck is significantly less expensive, which is an important factor for specialized vehicles. However, the optimal fleet composition is not determined solely by individual vehicle competitiveness; it also depends on the interaction of multiple vehicles operating within the logistics network—a factor captured by the simulation model.

4.2. Conducting an Optimization Experiment

The optimization experiment was conducted using the OptQuest engine integrated with AnyLogic, applying the following settings:

- Number of iterations: 500;
- Stopping criterion: no improvement in objective function for 50 consecutive iterations;
- Search strategy: scatter search with adaptive memory;
- Number of replications per candidate: 10 (for rapid screening), with top candidates re-evaluated over 30 replications for final selection.

For each fleet configuration, the simulation was run for 30 independent replications using different random seeds for stochastic waste generation. The average total cost and 95% confidence intervals were calculated using Student's t-distribution. The significance of differences between scenarios was assessed using a paired *t*-test with $\alpha = 0.05$.

The optimization experiment varied the number of vehicles of each type within the following ranges:

- Vehicles of Type A (8 m^3)—minimum 0, maximum 5;
- Vehicles of Type B (12 m^3)—minimum 0, maximum 5;
- Vehicles of Type C (16 m^3)—minimum 0, maximum 5;
- Vehicle of Type D (21 m^3)—minimum 0, maximum 5.

Figure 4 shows the convergence of the optimization process. The objective function value (total logistics cost) decreased rapidly during the first 7 iterations, with gradual improvement thereafter, stabilizing after 16 iterations.

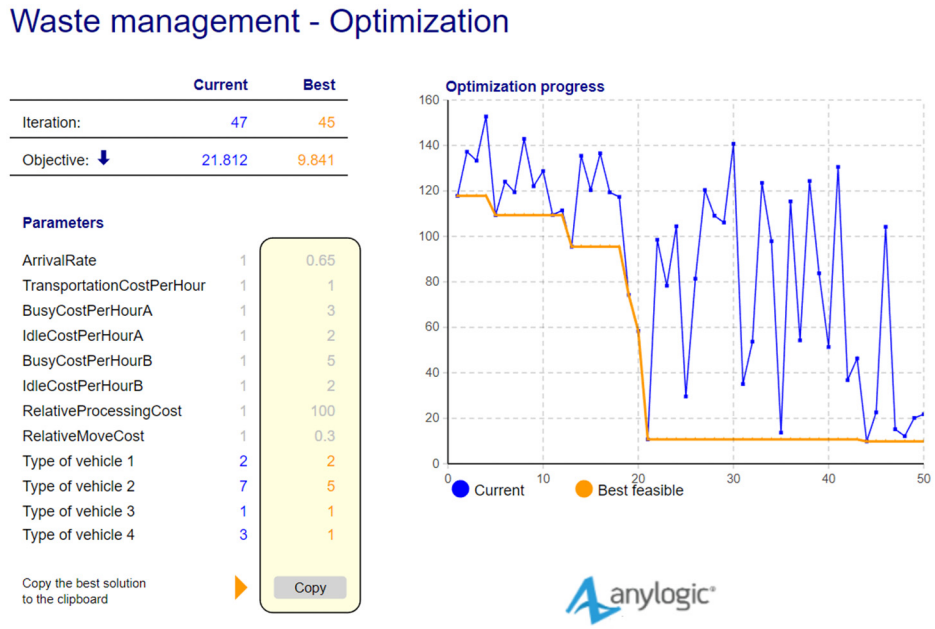


Figure 4. Results of the optimization experiment on the model developed in AnyLogic 8.9.8.

The results of the optimization experiment show the following optimal values for the variables:

- Number of vehicles of Type A—2;

- Number of vehicles of Type B—1;
- Number of vehicles of Type C—1;
- Number of vehicles of Type D—1.
- The objective function (logistics costs) decreased by 40.64% (from 12,000,000 RUB to 7,120,000 RUB) compared to the baseline.

4.3. Simulation Experiment Results

To analyze the model in more detail and visualize the waste management system, a simulation experiment was conducted (Figure 5).

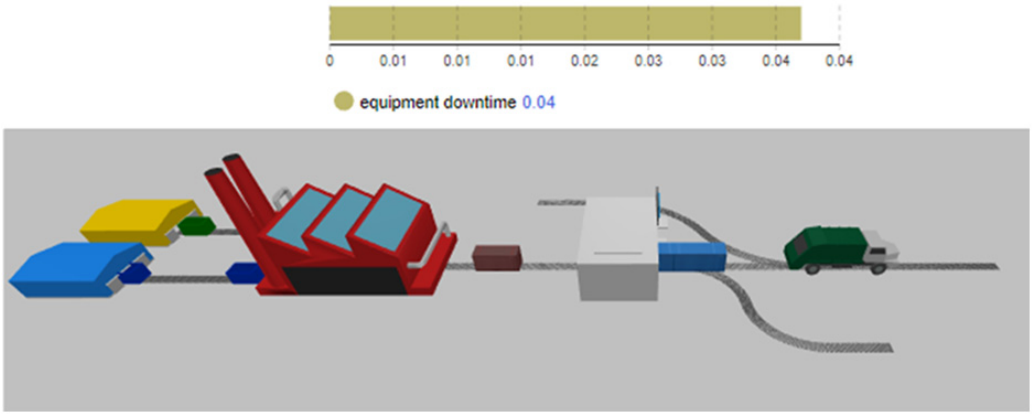


Figure 5. Simulation experiment on the model.

To assess the robustness of the results, a paired *t*-test was conducted comparing total logistics costs across the 30 replications for the baseline and optimal configurations. The test yielded a t-statistic of -12.4 ($p < 0.001$), confirming that the observed cost reduction is statistically significant at the 95% confidence level. A preliminary sensitivity analysis was conducted to examine the impact of key input parameters on the optimal solution. Varying fuel price by $\pm 20\%$ changed the optimal fleet composition only marginally (one Type B replaced by Type C in the high-fuel-price scenario), indicating that the solution is relatively robust to moderate changes in operating costs. However, changes in waste generation volume ($\pm 15\%$) led to adjustments in total fleet size (from 9 to 12 vehicles), suggesting that the model is sensitive to waste volume variability—an aspect that will be addressed in future work through dynamic re-optimization.

5. Discussion

The optimization results confirm the initial hypothesis: the quantitative and qualitative composition of the specialized vehicle fleet, when optimized through simulation modeling, has a decisive impact on both the economic and environmental efficiency of waste management systems. The developed DSS, with its integrated a module for assessing vehicle competitiveness and simulation core, enables the identification of an optimal fleet structure that minimizes total logistics costs. In the studied scenario, this approach yielded a potential waste transportation cost reduction of 40.64% compared to the baseline configuration, demonstrating the substantial practical value of the proposed methodology.

The results obtained in this study are consistent with and extend several recent findings in the field of waste transport optimization. In particular, the study [29] developed a three-level waste management model incorporating multi-compartment vehicles and employed a genetic algorithm to solve the resulting NP-hard routing problem. Their numerical experiments demonstrated that high-quality solutions for waste collection and transport could be achieved through appropriate algorithmic approaches.

The methodological approach of combining simulation modeling with multi-criteria evaluation finds resonance in work [30], which employed a multi-agent modelling method in AnyLogic to evaluate medical waste transportation modes in Beijing. Their study identified key speed thresholds that influence transportation efficiency, demonstrating the utility of AnyLogic for waste logistics problems.

Collectively, these comparisons demonstrate that the results of our study—particularly the substantial cost reductions achievable through integrated fleet optimization—are consistent with findings from both academic research and industrial practice. Moreover, our DSS extends existing approaches by combining vehicle competitiveness assessment, simulation-based fleet optimization, and flexible collection strategies within a single, modular framework.

The results should also be interpreted in the broader context of sustainable development and circular economy principles. Reducing logistics costs directly improves the economic viability of waste management operators, which can translate into lower tariffs and increased reinvestment capacity in recycling infrastructure. Moreover, an optimized fleet reduces unnecessary mileage, fuel consumption, and associated greenhouse gas emissions, thereby contributing to environmental sustainability. The proposed DSS offers a concrete solution to support decision-makers in implementing circular waste flows.

From a practical perspective, the modular architecture of the DSS makes it adaptable to different contexts—whether used by municipal environmental operators for fleet planning or by vehicle manufacturers during the design phase to assess the competitiveness of new models against operational requirements. The ability to conduct scenario analyses (e.g., varying waste volumes, collection schedules, or vehicle parameters) provides a flexible tool for strategic and tactical decisions.

Nevertheless, this research has several limitations that should be acknowledged. First, the simulation model assumes relatively stable input data, including waste generation rates and travel conditions. In reality, waste volumes may exhibit seasonal fluctuations, and unforeseen events such as vehicle breakdowns, road closures, or traffic congestion can disrupt operations. Incorporating stochastic elements and real-time adaptation mechanisms would increase the model's robustness. Second, the analysis focused on logistics costs as the sole optimization criterion; environmental impacts (e.g., CO_2 emissions, noise) were not directly included in the objective function, although they are indirectly affected by mileage reductions. A multi-objective formulation could provide a more comprehensive sustainability assessment. Third, the costs associated with implementing and maintaining the DSS itself—such as software development, data integration, and staff training—were not quantified; a full cost–benefit analysis is necessary to validate the economic feasibility for potential users. Fourth, the model was tested on a simplified, abstract network with two waste sources and a single sorting station. The distances, travel times, vehicle parameters, and cost structures used were representative but not derived from a specific real-world case study. This limits the generalizability of the quantitative results; the absolute cost figures should be interpreted as illustrative rather than universally applicable. Validation against real-world data—including actual coordinates of waste sources, infrastructure facilities, and operational costs—is a necessary next step to confirm the practical applicability of the proposed DSS. In its current form, the study serves as a proof of concept, demonstrating the methodology and the potential magnitude of improvements achievable through integrated fleet optimization.

Future research directions naturally emerge from these limitations. One promising avenue is the integration of real-time data streams from IoT sensors (e.g., container fill levels, GPS tracking of vehicles) to enable dynamic re-optimization of fleet operations. Machine learning techniques for waste generation forecasting could be incorporated to

predict short-term variations and adjust fleet deployment proactively. Another extension is the development of a multi-objective optimization module that balances economic and environmental criteria, such as minimizing total costs while constraining carbon emissions. Additionally, the current model could be expanded to simultaneously optimize vehicle routes and fleet composition, moving beyond the current focus on fleet sizing. The territorial placement of waste processing and disposal facilities represents a longer-term strategic problem that could be tackled with a location-allocation model integrated into the DSS. Finally, comparative studies applying the framework to different types of waste (e.g., municipal solid waste, construction debris, hazardous materials) and in various geographic settings would test its versatility and help identify context-specific adjustments. By addressing these directions, the DSS can evolve into an even more powerful tool for supporting the transition toward efficient, sustainable waste management systems.

6. Conclusions

This research addressed how the waste transportation process can be improved through the development of a Decision Support System that integrates a vehicle competitiveness assessment tool (to determine the qualitative composition of the vehicle fleet) and a simulation model for determining the number of garbage trucks. The study was motivated by the fragmentation of existing approaches, which typically address routing, vehicle selection, or facility location in isolation, and by the lack of tailored tools for the Russian context.

To answer this question, a modular DSS was developed, comprising a vehicle competitiveness assessment module (implemented in Python 3.11) and a simulation model (implemented in AnyLogic 8.9.8). The competitiveness module evaluates specialized waste transport vehicles based on a hierarchical criteria system, using a piecewise normalization function and weighted aggregation to produce an integral competitiveness index. The simulation model reproduces waste generation, collection (by schedule or by event), and transport logistics, allowing the evaluation of different fleet configurations under stochastic conditions.

An optimization experiment was conducted to determine the optimal quantitative and qualitative fleet composition. Compared to a baseline configuration, the optimal fleet reduced total logistics costs by 40.64%.

The study has several limitations, including the use of abstract input data (distances, travel times) and the absence of validation against a real-world case study. Future work will focus on integrating real-time IoT data, incorporating machine learning for waste generation forecasting, extending the optimization to multi-objective criteria, and validating the DSS on real-world data from municipal or industrial waste management systems.

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