TRANSPORT PROBLEMS 2025 Volume 20 Issue 4
PROBLEMY TRANSPORTU DOI: 10.20858/tp.2025.20.4.12

Keywords: FLP; facility location; logistics facilities; decision-making support

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DECISION-MAKING SUPPORT FOR LOCATING LOGISTICS FACILITIES IN TRANSPORT NETWORKS

Summary. This paper addresses the problem of locating logistics facilities within transport networks, with a particular focus on logistics hubs. A systematic literature review highlights key trends and gaps in facility location theory. Building on these findings, the authors propose a comprehensive decision-support method that combines a genetic algorithm with multi-criteria decision-making (MCDM). A genetic algorithm is used to explore a vast solution space, representing the transport network's structure through a matrix-based chromosome and enabling the simultaneous selection of hub locations and cargo flow allocation. The MCDM stage supports the evaluation and ranking of alternative network scenarios based on economic, operational, environmental, and social criteria. The approach was validated in a case study that demonstrated its effectiveness in identifying cost-efficient, strategically valuable facilities. The method supports strategic infrastructure planning and operational decision-making while remaining adaptable to future logistics challenges.

1. INTRODUCTION

The spatial allocation of logistics facilities constitutes a critical determinant of the efficiency of transport and logistics systems. The appropriate siting of distribution centers, transshipment terminals, or logistics hubs affects operational costs and service quality, energy consumption, emissions, delivery performance, and the overall competitiveness of supply chains. Contemporary processes of globalization, urbanization, and the rapid expansion of e-commerce, combined with the imperative of mitigating the environmental impact of transport, have intensified scholarly interest in this field [1]. Current research increasingly addresses sustainable development, the resilience of logistics systems, intermodal transport integration, network optimization, and the deployment of advanced decision-support methodologies [2].

In the literature, the location of logistics facilities is examined within the framework of classical facility location theory [3] as well as the advanced network location problems (NLPs), for which location decisions are integrated with transport infrastructure design and operation [4]. Increasing attention has been devoted to optimization models, heuristic and metaheuristic algorithms, multi-criteria decision-making (MCDM), and spatial analysis supported by geographic information systems (GISs) [5].

This paper proposes an integrated approach to locating logistics facilities within transport networks, considering both organizational structures and cargo flow intensity. The resulting decision-making framework is illustrated in Fig. 1. The paper includes a case study on the location of a logistics hub for a selected company. The results demonstrate that the proposed method identifies optimal terminal

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configurations that reduce transportation costs while allowing flexible adaptation to changing cargo volume forecasts. Thus, it can serve as a universal decision-support tool for planners and operators.

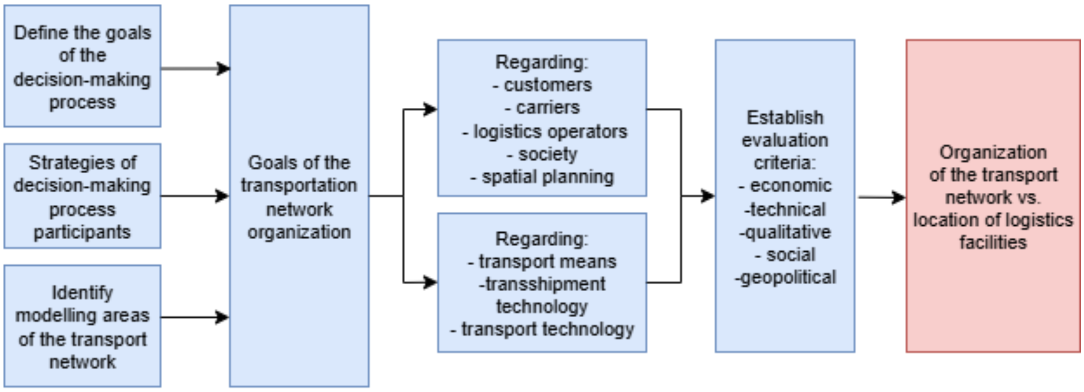

Fig. 1. Decision-making flowchart for facility location in transport networks. Source: own study

This article is structured into four sections. The first outlines the significance and challenges associated with location decisions in logistics and transportation systems. The second reviews selected literature on NLPs, methods, and evaluation criteria. The third presents a comprehensive method for determining logistics facility locations in transport networks, including the procedure and solution algorithm, illustrated by a case study of hub network development for a logistics operator. The concluding section summarizes the main findings and highlights key challenges and future research directions.

2. LITERATURE REVIEW

2.1. Selected theoretical aspects of NLPs in the literature

Facility location theory provides the foundation for strategic decisions on the spatial placement of logistics and transport infrastructure. The field has evolved from simple geometric formulations to advanced models that integrate multiple criteria, uncertainty, and dynamic system behavior. While early approaches emphasized minimizing costs (particularly transportation expenses), contemporary research also addresses robustness, adaptability, and resilience in the face of fluctuating demand, competition, and infrastructural constraints [3]. Classical models remain central to this field. The P-Median Problem minimizes the total distance between demand points and assigned facilities, supporting compact and cost-efficient service zones [6-8]. The P-Center Problem, by contrast, minimizes the maximum distance from demand points to facilities, ensuring equitable service access in contexts such as emergency or public infrastructure [9]. The uncapacitated facility location problem (UFLP**)** accounts for facility establishment costs under unlimited capacity assumptions [10], while continuous location problems, such as the Fermat-Weber model, optimize siting in continuous space with extensions for service ranges and coverage thresholds [11].

Building on these foundations, network-based models explicitly incorporate infrastructure structure and flow characteristics, using shortest-path and vertex-exchange algorithms to capture connectivity effects [12]. More advanced facility location and network design models jointly optimize siting and network configuration, supporting long-term planning of transport corridors, multimodal hubs, and intermodal terminals [13]. Given their computational complexity, these problems are typically solved with metaheuristic methods such as genetic algorithms or hybrid heuristics [14]. Further developments include competitive models, which integrate game-theoretic interactions to capture market dynamics [15], and dynamic and robust models, which account for temporal variability and uncertainty [16].

NLPs extend facility location theory by incorporating network topologies, link costs, and flow constraints, offering a more realistic representation of logistics infrastructure. Key formulations include source location problems, which optimize production or distribution siting under flow and capacity constraints [17]; hub location problems (HLPs), where hubs serve as consolidation nodes, solved via heuristics and metaheuristics [18]; and intermodal transport location problems (ITLPs), extending HLPs to multimodal freight systems [19, 20]. Further variants include fuzzy NLPs, which address uncertainty with fuzzy logic [21], location-routing problems (LRPs) integrating facility siting and vehicle routing [4], and capacitated facility location problems (CFLPs), solved with matheuristics and multi-objective frameworks to balance cost, service, and sustainability [22].

NLPs represent a specialized subset of facility location theory that integrates network structure, link costs, and flow constraints into decision-making. Unlike classical models, NLPs explicitly capture routing dynamics and operational interdependencies, offering a realistic basis for analyzing logistics infrastructure in dense or multimodal environments.

NLPs are inherently more complex than classical models due to multiple decision layers and network constraints, but they more accurately reflect modern infrastructure systems. Their typology includes source location problems, which optimize the siting of production or distribution centers under flow and capacity criteria [23]. Hub location problems (HLPs) designate subsets of nodes as redistribution hubs, with models considering congestion, capacity, and scale effects [24]. Heuristic and metaheuristic methods remain essential for large-scale HLPs, including urban and intermodal contexts [25]. Recent contributions include approximation algorithms for multi-allocation hubs [26] and continuous formulations such as the p-HLP [27], later enriched with stochastic and fuzzy logic approaches [28]. Location-routing problems (LRPs) jointly optimize facility siting and vehicle routing, reflecting the real-world interdependencies between these two aspects. Literature reviews [16] emphasize their growing integration of sustainability and resilience objectives. Similarly, research on capacitated facility location problems (CFLPs) highlights the use of metaheuristics and multi-objective frameworks to balance cost-efficiency with environmental performance [29]. Collectively, NLP developments reflect advances in transport technology, data availability, and sustainability imperatives, establishing them as critical decision-support tools for logistics infrastructure design.

Selecting logistics center locations remains a complex, multi-criteria task that shapes efficiency, sustainability, and competitiveness. Economic and operational factors dominate, including investment, construction, labor, and particularly transport costs, which strongly influence supply chain performance [30, 31]. Labor market conditions and flexibility in adapting facilities to future demand further affect feasibility. Operational synergies may arise in logistics clusters, fostering economies of scale and cooperation [32]. Connectivity resilience (e.g., exposure to flooding or congestion) is also crucial, while multimodal accessibility provides buffers against disruptions [33].

Facility location theory provides the foundation for strategic decisions regarding the placement of logistics and transportation infrastructure. Its evolution from simple geometric models to advanced approaches today encompasses the integration of multiple criteria, uncertainty, and dynamic system behavior. Classical problems, such as the P-Median, P-Center, or UFLP, focus mainly on minimizing costs and distances. In contrast, newer network-based models (e.g., facility location and network design, NLP) incorporate infrastructure structure, cargo flows, and complex operational interdependencies. Among these are source location problems (SLPs), hub location problems (HLPs), including intermodal variants (ITLPs), as well as problems integrated with vehicle routing (LRPs) or capacity constraints (CFLPs). Their solutions rely on heuristic and metaheuristic algorithms, often within multi-criteria frameworks emphasizing resilience and sustainability [34]. The selection of logistics centers remains a multidimensional task, where transport costs, economic and social factors, infrastructure resilience, and multimodal accessibility play a crucial role.

2.2. Optimization and multi-criteria decision support methods for the selection of logistics facility locations

Strategic decisions also depend on demand distribution, competitive landscape, and trade-offs between suburban sites (lower costs, expansion capacity) and central sites (proximity to dense markets) [35]. Environmental and social considerations increasingly influence decisions, with terrain, climate, and ecosystem sensitivity shaping construction and operations. A holistic evaluation must integrate economic feasibility, infrastructure access, market dynamics, environmental constraints, and regulatory frameworks to ensure a comprehensive assessment. Given these interdependencies, simulation, scenario planning, and participatory approaches are crucial for ensuring resilient, sustainable, and future-oriented logistics networks.

The analysis of the literature review reveals a wide range of factors or criteria for selecting methods to determine the location of logistics facilities. Fig. 2 presents a classification of optimization methods used for locating logistics facilities. The classification of methods for locating logistics facilities reflects the complexity of decision-making and encompasses multiple dimensions, including the transport system structure, cargo type, and time factor.

This classification highlights the multidimensional nature of logistics facility location problems. It emphasizes the need to tailor methodological choices to the specific characteristics of the distribution system, data availability, and decision-making context.

As indicated above, selecting the optimum site location is a complex decision-making problem that requires consideration of multiple, often conflicting criteria, uncertainty and expert knowledge. A range of decision support methodologies has been developed, encompassing both qualitative and quantitative approaches, to address these challenges. These methods aim to improve transparency, objectivity, and robustness in location decisions. Their diversity reflects the interdisciplinary nature of logistics planning, where operational research, artificial intelligence, spatial analysis, and stakeholder collaboration must converge to support strategic choices.

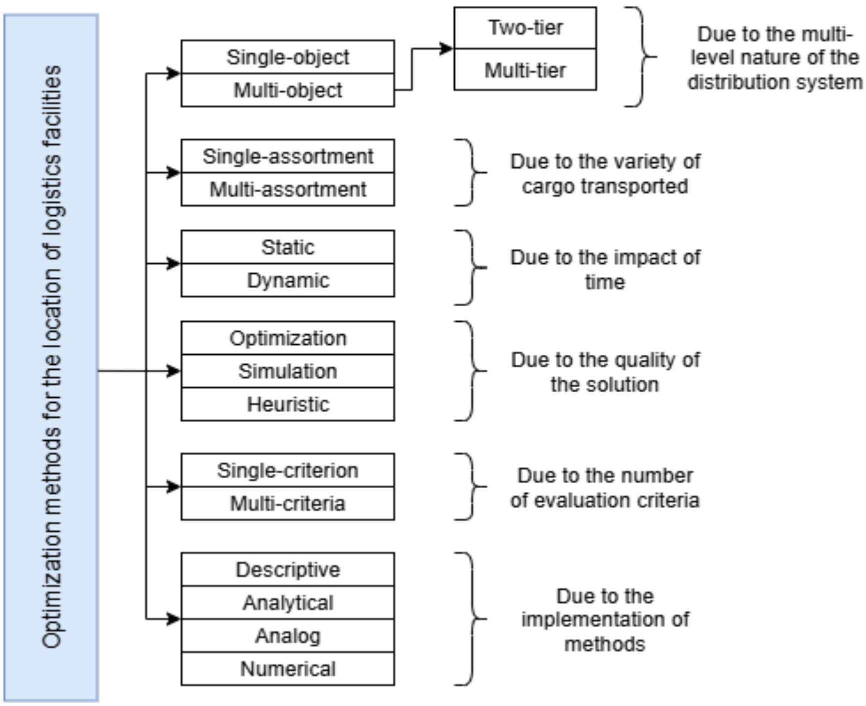

Fig. 2. Classification of optimization methods for the location of logistic facilities. Source: own elaboration based on [36]

Among the available MCDM methods, the analytic hierarchy process (AHP) is one of the most widely used techniques in location problems. It decomposes the problem into a hierarchy of criteria and sub-criteria, allowing decision-makers to assign pairwise comparisons and calculate weights accordingly [37]. Another widely adopted MCDM technique is the technique for order preference by similarity to ideal solution (TOPSIS), which evaluates alternatives based on their geometric distance from an ideal solution [38]. It ranks location options by identifying which alternative is closest to the "positive ideal" and farthest from the "negative ideal".

ELECTRE I is an outranking method that compares alternatives pairwise, considering both concordance (agreement) and discordance (disagreement) indices. It is particularly useful in multi-actor environments where various stakeholders bring in diverse preferences and evaluation criteria [30].

In many real-world problems, criteria and preferences are not crisp or precisely known. Fuzzy MCDM techniques, often employing triangular fuzzy numbers, allow decision-makers to express judgments under uncertainty [39]. Combined with the fuzzy Delphi method, expert knowledge can be systematically synthesized to assign more accurate weights to criteria in uncertain environments. The fuzzy Delphi approach helps converge toward more stable and reliable location recommendations by iteratively aggregating expert opinions. Models based on interval-valued intuitionistic fuzzy (IVIF) sets allow for even more nuanced expression of uncertainty by capturing hesitation and partial knowledge through interval-based membership and non-membership functions.

With advances in computational tools and the increasing availability of spatial data, data-driven methods are playing a growing role in location analysis. Geographic information system (GIS) tools offer powerful capabilities for collecting, visualizing, and analyzing spatial data [5]. In location problems, GIS tools enable assessments of proximity, accessibility, land use, and environmental constraints.

Taking the above into account, the authors propose the integration of multi-criteria decision-making methods with heuristic algorithms, which enables consideration of numerous economic, operational, environmental, and social aspects, as well as uncertainty and dynamic changes in transport systems. This approach enables more flexible and realistic modeling of the logistics facility location problem, combining the advantages of classical MCDM methods (AHP, TOPSIS, ELECTRE I) with the capabilities of heuristic techniques that support decision-making under ambiguous data and conflicting criteria.

3. METHOD FOR DETERMINING THE LOCATIONS OF LOGISTICS FACILITIES IN A TRANSPORT NETWORK

3.1. General framework

Based on the above discussion, the process of determining the location of logistics facilities within transport networks should be based on a multi-stage decision-making procedure that considers both formal and practical aspects. This procedure should begin with the identification of the decision problem, which involves recognizing the decision context, defining key stakeholders, and gathering requirements from individual clients regarding the types of cargo handled, delivery frequency, technological constraints, and available resources. This stage formed the foundation for further analyses and enabled the definition of the framework for the designed solutions, considering the specifics of the target market. In the next step, a mathematical model was developed, which constituted a formal representation of the real decision-making problem. This model was constructed based on previously adopted design assumptions and includes the identification of decision variables, the formulation of constraints, and the definition of the objective function. At this stage, defining the optimization criteria was particularly important. These criteria may be quantitative (e.g., minimizing transport costs, maximizing accessibility) or qualitative (e.g., compliance with sustainable development policies, level of customer service).

After the model was formulated, the next step was to select optimization methods and algorithms that would be used to solve it. This selection depended on the type of objective function, the computational complexity of the problem, the available computational resources, and the expected solution accuracy. At this stage, the selected algorithms were also initially configured, including the determination of control parameters such as the number of iterations or the weights assigned to specific sub-criteria.

Subsequently, a computer implementation of the model was developed to create a decision support tool that could enable simulation and computational experiments. During this phase, the correctness of the algorithm was verified, and, if necessary, modifications to the source code or parameters were made to improve the solution's quality or stability. The effectiveness of the implementation was evaluated based on tests conducted using synthetic or real-world logistics data.

The final step of the procedure involved verifying the method using real data and conducting a detailed analysis of the results. The objective of this stage was to assess the practical applicability of the developed model and the effectiveness of the proposed method under actual decision-making conditions. The results were analyzed in terms of solution quality, stability, and robustness to changes in input parameters. The conclusions drawn from this stage may be used for further model validation, refinement, or adaptation to new operational conditions.

A general framework for determining the location of logistics facilities in a transport network is presented in Fig. 3. It is worth noting that the diagram includes the verification of the selected solution method in terms of both optimization criteria and available input data. An essential element of the proposed method is that it can evaluate whether the defined criteria are sufficient in relation to the applied solution method. If not, it is necessary to either change the selected method or adjust the optimization criteria accordingly. A similar verification is then performed regarding the input data. If these data are insufficient to solve the problem using the selected method, a new solution method must be chosen.

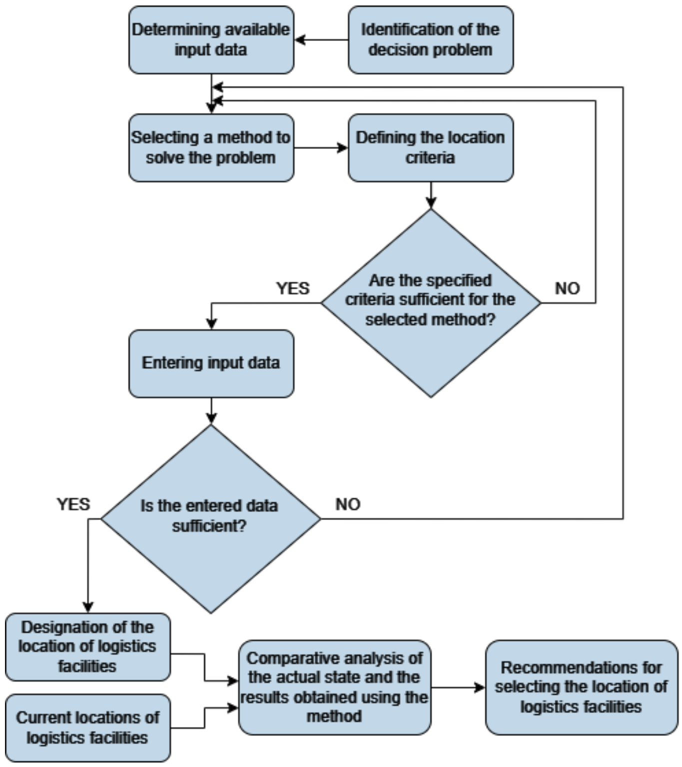

Fig. 3. Procedure for determining the location of logistics facilities in a transport network – general framework. Source: own elaboration

If the data are complete, it is possible to determine the locations of logistics facilities and compare them with the current infrastructure layout. The final step was a comparative analysis of the obtained results, which was done to evaluate the quality and effectiveness of the proposed solutions. This analysis led to the development of recommendations regarding the location of logistics facilities, which can serve as a basis for investment or organizational decision-making.

3.2. Model of transport network organization

The construction of a transport network organization model involved considering only those features of the transport system that are relevant from the perspective of the modeling objective. It was assumed that the developed model should both accurately reflect the real-world system and be user-friendly. Therefore, during the modeling process, it was necessary to adopt certain assumptions that define the scope of applicability of the model. The main assumptions of the transport network organization model were as follows:

- the execution of the transport task, which involves delivering a specified volume of goods from senders to receivers, is the primary objective and determines the structure of the system;
- goods must be transported from senders to receivers using a logistics facility (e.g., a warehouse or hub);
- the transport mode changes at the logistics facility during the handling process;
- the model allows for the inclusion of both existing logistics facilities and potential facilities (with proposed locations predefined);
- operating a logistics facility generates both fixed and variable costs (the latter dependent on the number of handling operations performed);
- all cargo volumes are expressed in the same units.

Assuming that the structure of the transport network is denoted by *G*, the set of transport mode types by *P*, the set of network element characteristics by *C*, the size of transport tasks carried out within the system by *Z*, and the organization of the transport network, understood as the allocation of resources to transport tasks, by *O*, the model of the transport network organization can be represented as:

$$MST = \langle G, P, C, Z, O \rangle \tag{1}$$

It is assumed that i denotes the index of the sender, where $i \in I$, while I is the set of all senders; j denotes the index of the receiver, where $j \in J$, while J is the set of all receivers. Similarly, h denotes the index of the hub, where $h \in H$, while H is the set of hubs. The sets I, H, and J are mutually disjoint. Geographically, the locations of senders and receivers may overlap; however, they differ in the roles they play within the transport network, and thus, they are considered distinct.

Due to the nature of the problem, it was essential to account for several key parameters that could have influenced the functioning of the logistics system. In particular, technical and economic parameters that characterize hubs—such as the storage capacity of individual facilities and their associated operating costs—were considered. Equally important were the economic parameters related to the transport network connections, primarily the unit costs of transporting goods between different elements of the network. Additionally, parameters describing the characteristics of transport tasks had to be considered, especially the volume of shipments, which is typically expressed in terms of mass, volume, or number of packages to be transported between senders and receivers within a specified time period.

Accordingly, q_{ij} denotes the volume of goods to be transported between sender i and receiver j. At the same time, zc_h represents the maximum capacity of hub h, and zm_h indicates the minimum number of handled cargo units required for the operation of a hub to be economically viable at a given location.

Cost indicators were also defined to describe the different components of the transport network. The symbol $k1_{ih}$ refers to the unit cost of transporting goods from sender i to hub h; $k2_{hh'}$ refers to the unit cost of transportation between two hubs; and $k3_{hj}$ represents the unit cost of delivering goods from hub h to receiver j. Additionally, fixed operational costs ke_h were defined for each hub h; these were independent of the number of handled units, as well as variable operational costs kp_h, which depended on the volume of processed goods.

Formulating the optimization problem for determining the optimal organization of the transport network required defining the decision variables. Accordingly, the following decision variables were formulated in the optimization task: $x1_{ih}$, $x2_{hh'}$, and $x3_{hj}$. These represent, respectively, the number of goods transported from sender to hub, between hubs, and from hub to receiver. A binary decision variable $x4_h$ was also defined, which indicated whether a given hub should have been activated at a specific location.

The objective was to determine the values of the decision variables for which the objective function, as described in the following equation:

$$\begin{aligned} F(X1, X2, X3, X4) = \Big(\big(& \textstyle\sum_{i \in I} \sum_{h \in H} x1_{ih} \cdot k1_{ih} + \sum_{h \in H} \sum_{h' \in H} x2_{hh'} \cdot k2_{hh'} + \\ & + \textstyle\sum_{h \in H} \sum_{j \in J} x3_{hj} \cdot k3_{hj} \big) + \sum_{h \in H} kp_h \cdot \big(\sum_{i \in I} x1_{ih} + \sum_{j \in J} x3_{hj} \big) + \sum_{h \in H} ke_h \cdot x4_h \Big). \end{aligned} \tag{2}$$

The objective function reaches a minimum when the following constraints are met:

- the number of goods transported in all relations must be non-negative;
- the number of goods delivered to hub *h* must be equal to the number of goods dispatched from hub *h*;
- the total number of goods dispatched from sender *i* must match the outbound demand for that sender;
- the total number of goods delivered to receiver *j* must match the inbound demand for that receiver;
- the total volume of goods passing through hub *h* must not exceed its maximum storage capacity;
- the total volume of goods passing through hub *h* must not be lower than the minimum threshold required for the operation of that warehouse to be economically viable.

3.3. Method for determining the location of logistics facilities in the transport network

The proposed method for determining the location of logistics facilities in a transport network is a comprehensive, multi-stage decision-support framework that integrates mathematical optimization with MCDM. Its main objective is to support the selection of optimal hub locations and the design of efficient cargo flow structures, while simultaneously considering economic, operational, environmental, and social aspects. The overall procedure is presented in Fig. 4, while Fig. 5 illustrates the structure of the optimization algorithm.

The method begins by defining the input data necessary for modeling. This includes the size and structure of traffic flows, the geographical distribution of demand and supply points, the set of potential hub locations, and the technical and operational characteristics of the transport network. At this stage, it is also crucial to define relevant constraints, including facility capacity limits, regulatory requirements, and spatial and environmental restrictions. Based on these data, modeling objectives are formulated, focusing on minimizing total system costs and optimizing network performance.

The optimization stage, which is the most computationally intensive component, is based on a genetic algorithm. Each chromosome represents a complete configuration of the network, including activated hub locations and the allocation of cargo flows between them. The algorithm starts with the generation of an initial population of randomly generated solutions. It then iteratively applies selection, crossover, and mutation operations to evolve solutions toward optimality. Each solution is evaluated using a fitness function that considers transportation costs but may also include additional constraints or penalties related to capacity usage or service quality. Through multiple iterations, the algorithm generates a set of alternative solutions (scenarios), which represent different feasible network configurations.

The evaluation criteria can be divided into several main groups, as illustrated in the figure, where examples of typical indicators are presented. However, depending on the specific objectives of the analysis, decision-making context, and stakeholder preferences, additional criteria may also be considered. Other types of criteria, such as regulatory, technological, or strategic alignment indicators, may also be incorporated to provide a more comprehensive assessment.

The final stage of the procedure involves a multi-criteria analysis based on the MCDM method, which evaluates all scenarios and ranks them according to their aggregated performance. This enables the identification of the most balanced solution that meets strategic, operational, and sustainability requirements simultaneously. The final output of the method comprises the designation of optimal hub locations, the definition of an optimized transportation plan, and a comprehensive assessment of the network's cost and performance.

By combining advanced optimization techniques with multi-criteria evaluation, the proposed method provides a powerful decision-support tool capable of solving complex location problems. It supports strategic decisions (e.g., infrastructure planning, investment prioritization) and operational decisions (e.g., daily flow management, capacity allocation). Additionally, its modular structure allows future extensions, such as incorporating machine learning methods to improve scalability, handle larger problem instances, and capture complex, nonlinear dependencies in demand forecasting or service quality prediction.

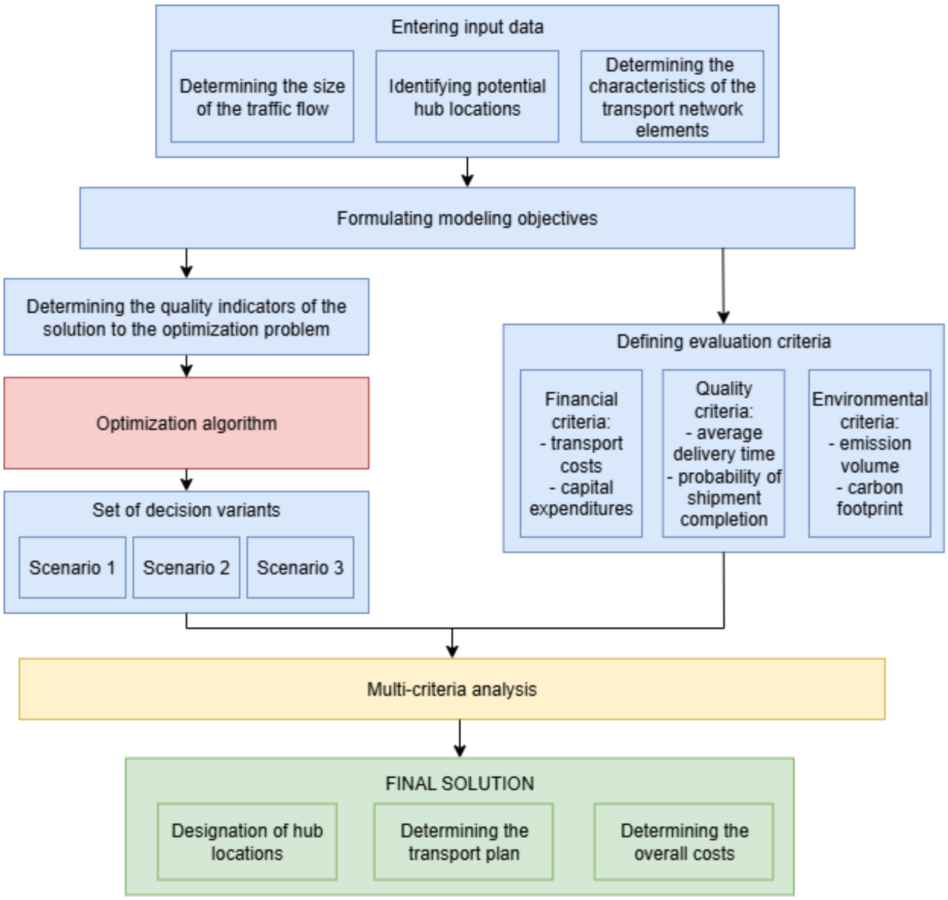

Fig. 4. Diagram of the method for determining the location of logistics facilities in a transport network. Source: own elaboration

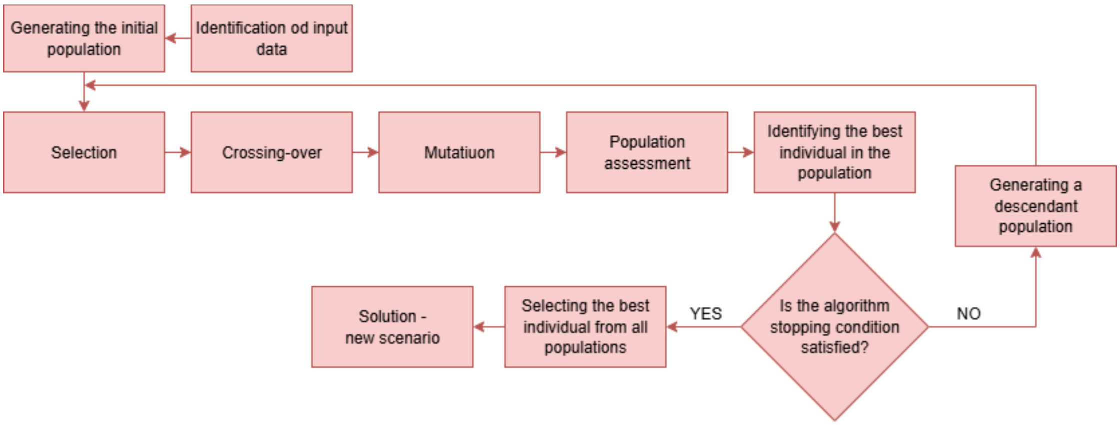

Fig. 5. Optimization algorithm. Source: own elaboration

4. CASE STUDY

For the case study, the transport network of a selected company was analyzed. It consists of 60 shipment/receiving points, between which cargo units are to be transported. The expected number of palletized cargo units to be delivered was given, based on historical demand data reported by customers. It was assumed that the cargo could be transported using six hubs. Transshipment operations and short-term storage may take place at the hubs.

It was assumed that transport may only occur through the following route: sender – origin hub – destination hub – receiver. The example does not account for direct shipments between senders and receivers (such cases may occur when the sender and receiver are in the same warehouse region). Also, the main objective of the analysis was to determine the location of hubs; therefore, the input data included only those cargo flows that required the involvement of a hub.

Transport costs for each relation were determined based on unit transport rates (which varied depending on the type of route) and the distance matrix. The following unit transport costs were adopted:

- transport between hubs: PLN 2.30/km,
- transport from sender to hub and from hub to receiver: PLN 4.50/km.

The potential locations of the hubs and locations of shipment/receiving points are shown in Fig. 6, and the hub distance matrix is provided in Table 1.

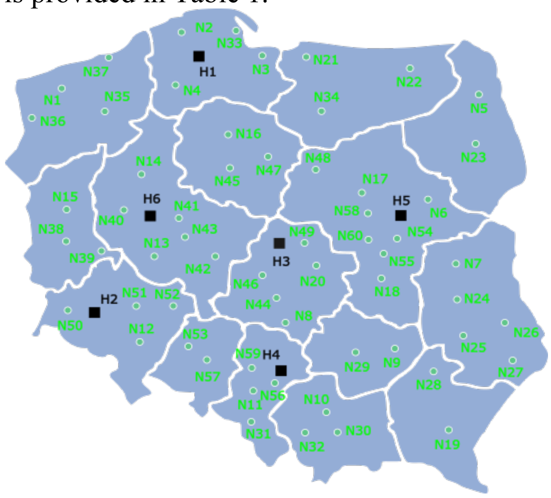

Fig. 6. Locations of shipment/receiving points (green circles) and potential locations of hubs (black squares). Source: own elaboration

Table 1

Distance matrix for hubs

Distance [km]	H1	H2	H3	H4	H5	H6
H1	-	592	340	571	362	296
H2	592	-	333	276	451	265
H3	340	333	-	245	129	228
H4	571	276	245	-	343	398
H5	362	451	129	343	-	350
H6	296	265	228	398	350	-

Calculations were performed using the described method to determine the location of logistics facilities. A transport plan and hub locations were determined. The analysis indicates that, for the proposed case, operating hubs at locations H1, H2, H4, and H5 is economically viable. In contrast, hubs H3 and H6 should not be activated (Fig. 7a). An example transport plan for shipments originating from sender N1 is presented in Table 2 and illustrated in Fig. 7b.

5. CONCLUSIONS

The article presented a comprehensive approach to determining the location of logistics facilities within transport networks, with a particular emphasis on hubs. In the first part of the study, a systematic literature review was conducted on location problems and routing using electric vehicles. This review enabled the identification of the main research trends as well as gaps in the literature, particularly regarding the integration of location problems with comprehensive cargo flow planning and realistic representation of the technical, economic, and spatial conditions of logistics systems.

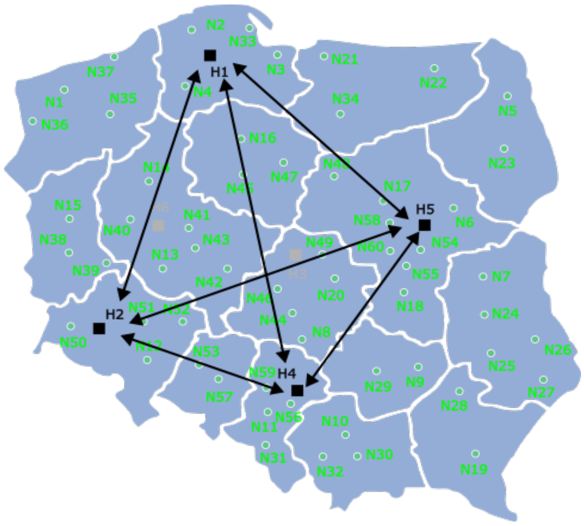

Fig. 7a. Hub locations determined using the presented method. Source: own elaboration

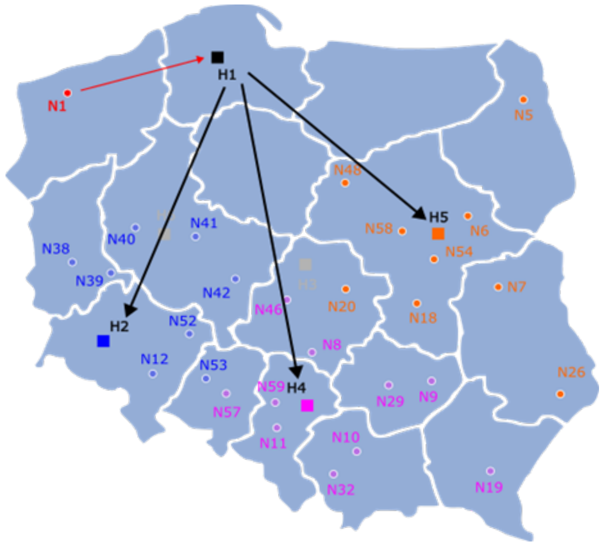

Fig. 7b. Designated transport plan - example for cargo shipped from sender N1. Source: own elaboration

Table 2

Designated transport plan – Example for cargo shipped from sender N1

Sender - Hub		
From	To	Cargo
N1	H1	81916

Hub - Hub		
From	To	Cargo
H1	H2	32992
	H4	24150
	H5	24774

Hub - Receiver		
From	To	Cargo
H2	N12	2824
	N38	7895
	N39	2736
	N40	740
	N41	8163
	N42	9784
	N52	501
	N53	349

Hub - Receiver		
H4	N8	1736
	N9	2895
	N10	7663
	N11	4479
	N19	627
	N29	1156
	N32	782
	N46	968
	N57	3226
	N59	618
H5	N5	449
	N6	494
	N7	7736
	N18	9784
	N20	4274
	N26	323
	N48	151
	N54	628
	N58	935

Based on the conducted analyses, a method for determining the location of logistics facilities was proposed using a genetic algorithm. A distinctive feature of this method is the use of a matrix-based chromosome representation, which naturally reflects the structure and organization of the transport network. The method enables the simultaneous determination of optimal hub locations, allocation of cargo volumes to specific routes, and selection of transport paths, all while considering transportation and operational costs. The algorithm also accounts for constraints related to facility capacity and minimum profitability thresholds for their operation.

The effectiveness of the method was confirmed through a case study analyzing a network consisting of 60 shipment and receiving points and six potential hub locations. The results demonstrate that the algorithm accurately identifies the logistics facilities that should be activated, while excluding those whose operation is not economically viable. Thus, the developed method supports decision-making processes at both the strategic level (when planning logistics infrastructure) and the operational level (related to the day-to-day organization of flows).

In light of the results, it can be concluded that the proposed solution effectively integrates location and transport aspects into a single, coherent optimization model. The analysis also confirms the high effectiveness of genetic algorithms in solving complex planning problems, particularly in cases where deterministic methods fail due to the problem's scale or complexity.

Future research should focus on several directions. First, the model could be extended with additional optimization criteria—such as environmental or quality factors—and implemented in a multi-criteria framework to reflect real-world decision-making conditions more accurately. Another important avenue is assessing network resilience to disruptions and integrating the model with predictive systems that support demand forecasting. Finally, a promising perspective is the application of methods based on machine learning and artificial intelligence, which offer the ability to handle larger and more complex decision-making problems, improve scalability, and incorporate new categories of criteria, including social and behavioral aspects of logistics. Such approaches could significantly enhance the adaptability and robustness of decision-support systems, ensuring that logistics networks are designed not only to minimize costs but also to meet the requirements of sustainability, resilience, and societal acceptance.

Acknowledgement

This paper was co-financed under the research grant of the Warsaw University of Technology, supporting scientific activity in the discipline of Civil Engineering, Geodesy, and Transport.

References

1. Sharma, A. & Jakhar, S.K. & Vlachos, I. & Kumar, S. Advances in hub location problems: a literature review and research agenda. *International Journal of Productivity and Performance Management*, 2025. Vol. 74(1). P. 24-55. DOI: 10.1108/IJPPM-09-2023-0514.
2. Zhang, J. & Li, H. & Han, W. & Li, Y. Research on optimization of multimodal hub-and-spoke transport network under uncertain demand. *Archives of Transport*. 2024. Vol. 70(2). P. 137-157. DOI: 10.61089/aot2024.1g17bx18.
3. Szczepański, E. & Jachimowski, R. & Izdebski, M., & Jacyna-Gołda, I. Warehouse location problem in supply chain designing: a simulation analysis. *Archives of Transport*. 2019. Vol. 50(2). P. 101-110. DOI: 10.5604/01.3001.0013.5752.
4. Lopes, M.C. & de Andrade, C.E. & de Queiroz, T.A. et al. Heuristics for a hub location-routing problem. Networks. 2016. Vol. 68. P. 54-90. DOI: 10.1002/net.21685.
5. Wazer, Z.B. & Moutaz. Location of freight warehouses facilities: A GIS-based multi-criteria decision analysis. *Journal of Physics: Conference Series.* 2021. Vol. 1973(1). P. 012193). DOI: 10.1088/1742-6596/1973/1/012193.
6. Rivera-Gonzalez, C. & Holguin-Veras, J. A facility location problem considering freight tours to support freight-efficient land use planning. *Transportation Research Part A: Policy and Practice*. 2025. Vol. 192. P. 104321. DOI: 10.1016/j.tra.2024.104321.
7. Zaferanieh, M. & Abareshi, M. & Fathali, J. The minimum information approach to the uncapacitated p-median facility location problem. *Transportation Letters*. 2022. Vol. 14(3). P. 307-316. DOI: 10.1080/19427867.2020.1864595.

8. Berrajaa, A. & Outmani, A.E. & Benaini, A. A GPU-based genetic algorithm for the multiple allocation p-hub median problem. *Journal of Computational Science.* 2023. Vol. 19. P. 629-640. DOI: 10.3844/jcssp.2023.629.640.
9. Brimberg, J. & Mladenović, N. & Todosijević, R. & Urošević, D. General variable neighborhood search for the uncapacitated single allocation p-hub center problem. *Optimization Letters.* 2017. Vol. 11(2). P. 377-388. DOI: 10.1007/s11590-016-1004-x.
10. Harris, I. & Mumford, C. & Naim M. The multi-objective uncapacitated facility location problem for green logistics. *2009 IEEE Congress on Evolutionary Computation*. 2009. P. 2732-2739. DOI: 10.1109/CEC.2009.4983285.
11. Rezner, Z. & Eiselt, H.A. Competitive location models: A review. *European Journal of Operational Research.* 2024. Vol. 316(1). P. 5-18. DOI: 10.1016/j.ejor.2023.10.030.
12. Daskin, M.S. *Network and Discrete Location: Models, Algorithms, and Applications*. 2013. Wiley.
13. Melkote, S. & Daskin M.S. Capacitated facility location/network design problems. *European Journal of Operational Research*. 2001. Vol. 129(3). P. 481-495. DOI: 10.1016/S0377-2217(99)00464-6.
14. Revelle, C.S. & Eiselt, H.A. & Daskin M.S. A bibliography for some fundamental problem categories in discrete location science. *European Journal of Operational Research*. 2008. Vol. 184(3). P. 817-848. DOI: 10.1016/j.ejor.2006.12.044.
15. Tsao, Y.-C. & Mangotra, D. & Lu, J.-C. & Dong M. A continuous approximation approach for the integrated facility-inventory allocation problem. *European Journal of Operational Research*. 2012. Vol. 222(2). P. 216-228. DOI: 10.1016/j.ejor.2012.04.033.
16. Khaleghi, A. & Eydi, A. Multi-period hub location problem: a review. *RAIRO-Operations Research.* 2022. Vol. 56(4). P. 2751-2765. DOI: 10.1051/ro/2022134.
17. Sakashita, M. & Makino, K. & Fujishige, S. Minimum cost source location problems with flow requirements. In: Correa, J.R. & Hevia, A. & Kiwi, M. (eds) *LATIN 2006. Theoretical Informatics.* 2006. Vol. 3887. P. 769-780. DOI: 10.1007/11682462_70.
18. Liu, Q. & Li, X. & Liu, H. & Guo, Z. Multi-objective metaheuristics for discrete optimization problems: A review of the state-of-the-art. *Applied Soft Computing*. 2020. Vol. 93. No. 106382. DOI: 10.1016/j.asoc.2020.106382.
19. Sorensen, K. & Vanovermeire, C. & Busschaert, S. Efficient metaheuristics to solve the intermodal terminal location problem. *Computers & Operations Research*. 2012. Vol. 39(9). P. 2079-2090. DOI: 10.1016/j.cor.2011.10.005.
20. Basallo-Triana, M.J. & Cordeau, J.-F. & Vidyarthi, N. Intermodal hub network design with probabilistic service-level constraints. *Transportation Science*. 2025. Vol. 59(3). P. 518-539. DOI: 10.1287/trsc.2024.0657.
21. Davari, S. & Zarandi, M.H.F. & Turksen I.B. The fuzzy reliable hub location problem. *Annual Meeting of the North American Fuzzy Information Processing Society*. 2010. P. 1-6, DOI: 10.1109/NAFIPS.2010.5548271.
22. Caserta, M.A. & Voss, S. A general corridor method-based approach for capacitated facility location. *International Journal of Production Research*. 2020. Vol. 58(13). P. 3855-3880. DOI: 10.1080/00207543.2019.1636320.
23. Dissanayake, I. & Gunathilake, M. A comprehensive survey of recent advances in facility location problems: Models, solution methods, and applications. *Journal of Sustainable Development of Transport and Logistics.* 2024. Vol. 9(2). P. 78-91. DOI: 10.14254/jsdtl.2024.9-2.6.
24. Ou, Q. & Gan, M. & An, M. & Wang, Y. Road-rail intermodal hubs site selection based on road freight demand mining: A case from Beijing–Tianjin–Hebei region. *Promet – Traffic & Transportation.* 2024. Vol. 36(3). P. 492-507. DOI: 10.7307/ptt.v36i3.462.
25. Liu, X. Hub network design problem with capacity, congestion and heterogeneous economies of scale. *arXiv preprint*. 2024. DOI: 10.48550/arXiv.2404.03521.

26. Chen, T.C. & Muda, I. & Salman, R. et al. Presenting a model for locating and allocating multi-period hubs and comparing it with a multi-objective imperialist competitive algorithm. *Foundations of Computing and Decision Sciences*. 2023. Vol. 48(3). P. 331-344. DOI: 10.2478/fcds-2023-0013.
27. Wu, Y. & Geunes, J. & Nie, X. Revisiting continuous p-hub location problems with the L_1 metric. *arXiv preprint*. 2025. DOI: 10.48550/arXiv.2501.08439.
28. Shavarani, S.M. & Mosallaeipour, S. & Golabi, M. & İzbirak, G. A congested capacitated multi-level fuzzy facility location problem: An efficient drone delivery system. *Computers & Operations Research*. 2019. Vol. 108. P. 57-68. DOI: 10.1016/j.cor.2019.04.001.
29. Dissanayake, I. & Gunathilake, M. A comprehensive survey of recent advances in facility location problems: Models, solution methods, and applications. *Journal of Sustainable Development of Transport and Logistics*. 2024. Vol. 9(2). P. 78-91. DOI: 10.14254/jsdtl.2024.9-2.6.
30. Lasota, M. & Zabielska, A. & Jacyna, M. et al. Method for delivery planning in urban areas with environmental aspects. *Sustainability*. 2024. Vol. 16(4). No. 1571. DOI: 10.3390/su16041571.
31. Agrebi, M. & Abed, M. Decision-making from multiple uncertain experts: case of distribution center location selection. *Soft Computing*. 2021. Vol. 25(6). P. 4525-4544, DOI:10.1007/s00500-020-05461-y.
32. Chen, J. & Lee, J. & Lee, H. A study on the site selection of urban logistics centers utilizing public infrastructure. *Sustainability*. 2025. Vol. 17(15). No. 6846. DOI: 10.3390/su17156846.
33. Tordecilla, R.D. & Juan, A.A. & Montoya-Torres, J.R. et al. Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review. 2021. *Simulation Modelling Practice and Theory*. Vol. 106. No. 102166. DOI: 10.1016/j.simpat.2020.102166.
34. Figueiredo, B. & Lopes, R.B. & Sousa, A. Location – routing problems with sustainability and resilience concerns: a systematic review. *Logistics*. 2025. Vol. 9(3). No. 81. DOI: 10.3390/logistics9030081.
35. Alvarez Gallo, S. & Maheut, J. Multi-criteria analysis for the evaluation of urban freight logistics solutions: a systematic literature review. *Mathematics*. 2023. Vol. 11(19). No. 4089. DOI: 10.3390/math11194089.
36. Wasiak, M. & Jacyna-Gołda, I. & Izdebski, M. Multi-criteria warehouses location problem in the logistics network. In: Sawik T. (eds). *ICIL 2016 Conference Proceedings*. P. 352-364.
37. Mijalkovski, S. & Stefanov, V. & Mirakovski, D. Application of the TOPSIS method for selecting the location of the main warehouse. *Transport & Logistics*. 2024. Vol. 24(56). P. 51-58. DOI:10.46544/TNL.v24n56.0.
38. Bennani, M. & Jawab, F. & Hani, Y. et al. A hybrid MCDM for the location of urban distribution centers under uncertainty: a case study of Casablanca, Morocco. *Sustainability*. 2022. Vol. 14(15). No. 9544. DOI: 10.3390/su14159544.
39. Basciftci, B. & Ahmed, S. & Shen, S. Distributionally robust facility location problem under decision-dependent stochastic demand. *European Journal of Operational Research*. 2021. Vol. 292(2). P. 548-561. DOI: 10.1016/j.ejor.2020.11.002.

Received 03.04.2024; accepted in revised form 07.11.2025