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Article

Effective problem solving in logistics with new framework for connecting problems and metaheuristics

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Abstract: Finding the right technique to optimize a complex problem is not an easy task. There are hundreds of methods, especially in the field of metaheuristics suitable for solving NP-hard problems. Most metaheuristic research is characterized by developing a new algorithm for a task, modifying or improving an existing technique. The overall rate of reuse of metaheuristics is small. Many problems in the field of logistics are complex and NP-hard, so metaheuristics can adequately solve them. The purpose of this paper is to promote more frequent reuse of algorithms in the field of logistics. For this, a framework is presented, where tasks are analyzed and categorized in a new way in terms of variables or based on the type of task. A lot of emphasis is placed on whether the nature of a task is discrete or continuous. Metaheuristics are also analyzed from a new approach: the focus of the study is that, based on literature, an algorithm has already effectively solved mostly discrete or continuous problems. An algorithm is not modified and adapted to a problem, but methods that provide a possible good solution for a task type are collected. A kind of reverse optimization is presented, which can help the reuse and industrial application of metaheuristics. The paper also contributes to providing proof of the difficulties in the applicability of metaheuristics. The revealed research difficulties can help improve the quality of the field and, by initiating many additional research questions, it can improve the real application of metaheuristic algorithms to specific problems. The paper helps with decision support in logistics in the selection of applied optimization methods. We tested the effectiveness of the selection method on a specific task, and it was proven that the functional structure can help the decision when choosing the appropriate algorithm.

Keywords: logistics; metaheuristics; optimization; decision support; framework; discrete; continuous; algorithm

1. Introduction

Many logistics problems are classified as NP-hard due to their complexity. In many cases, large data sets have to be handled, the tasks have large problem instances and the constraints are complex. Because of this, literature considers metaheuristics suitable for solving these problems (Sörensen and Glover, 2010), as they are able to provide an approximate optimal solution within an acceptable calculation time. Hundreds of thousands of articles are devoted to the efficient problem-solving ability of metaheuristics, and there are hundreds of different algorithms (Ma et al., 2023). The problem can be traced back to the multitude of scientific works and metaheuristics: it is not easy and clear to choose a metaheuristic to solve a problem. Even though countless metaheuristics have already been designed, there is still little reuse of these algorithms (Swan et al., 2022). Professionals in the industry need help to choose the right algorithm, which the scientific community can provide by identifying the parameters and data that can connect problems and metaheuristics along a defined principle.

We identified as a research gap that there is no selection, assignment structure or framework that connects logistics problems and metaheuristics: assigning metaheuristics to a problem that are most likely to solve the given problem properly based on general information and schemes, not in the case of specific, special tasks. Thus, metaheuristics and the grouping of problems based on their components and structural elements, which are responsible for basic optimization performances, are missing. This leads to the main research question: How can metaheuristic algorithms and logistics optimization problems be effectively connected, taking into account the characteristics of the problems and algorithms, as well as the real experiences of practical applications? It is therefore necessary to connect metaheuristic algorithms and logistic problems based on characteristics relevant to optimization, with particular regard to the nature of the decision variables, which can serve as the basis for a selection framework. It is also important to examine the actual areas of application of metaheuristics through the systematic analysis of previous research and practical results, because the definition of the real areas of application of the algorithms needs to be reconsidered and fine-tuned based not only on the original design goals, but also on the basis of practical experience.

Therefore, we classify problems and metaheuristic algorithms using a new kind of matching technique, which can be used to identify the appropriate solution method for type tasks. The common cluster is discrete and continuous: in the case of problems, the examination of variables, and in the case of metaheuristics the analysis of what kind of problems the given algorithm has mostly successfully solved based on literature. The goal is to create a simple assignment system to make an appropriate decision regarding the method used. The need to introduce a new type of classification structure is clearly shown in **Figure 1**: the presence of discrete and continuous tasks is not typical for the classification of metaheuristics, nor is the categorization of metaheuristics based on them.

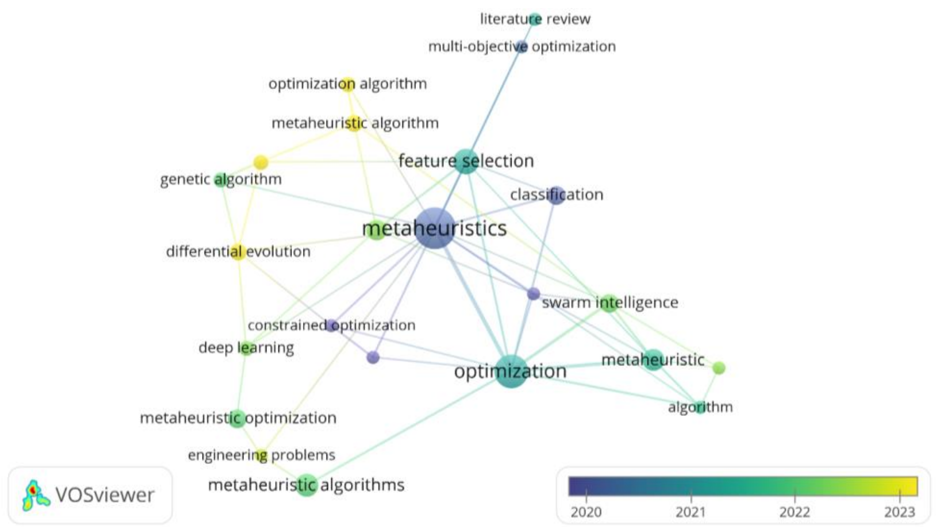

Figure 1. The connection of metaheuristics and classification (tool: VOSviewer; search term: Classification of metaheuristics; data retrieval: 09.10.2024; database: ScienceDirect.).

According to our further assumption, assigning the appropriate optimization procedure to a task also depends on how quickly we have to make a decision. It does not matter how much time is available to solve a task. Therefore, it is also important to determine whether a task belongs to the strategic, tactical or operational level. If more time is available to find the right solution, in that case it is worthwhile to try several metaheuristics and determine which algorithm gives the most favorable result. If there is not much time available, metaheuristics represent a suitable compromise between the quality of the solutions and the speed of the calculation time. In this case, it is advisable to select an algorithm from among the possible methods providing a good solution. According to our assumption, time is a factor during the choice that does not represent a particular limitation at the strategic and tactical level, but represents a bottleneck at the operational level.

The paper presents a selection structure, with the help of which metaheuristics that can efficiently solve a given logistics task can be determined with high probability, taking into account the level of the task (strategic, tactical or operational). With all this, the more frequent use of existing metaheuristic procedures can be promoted, and the reuse of procedures can be realized.

The paper is structured as follows: in Sections 2 and 3, the research difficulties and the literature related to the topic are reviewed. In Section 4, the strategic, tactical, operational levels and tasks in logistics are described. In Section 5 and 6 there is a presentation of the selection framework, and then in Section 7 the efficiency test. In Section 8, we examine the operation of the framework in an infrastructural context. Finally, in Section 9, we provide the conclusions of the paper and identify further research directions.

2. Research problem and literature statistics: Difficulties in assigning metaheuristics and logistic problems

Choosing the right metaheuristic and associating it with a specific logistics task is a difficult and complicated task due to many factors. On the one hand, it is not possible to clearly define which are the structural elements between the algorithms and tasks that can be connected in order for a given metaheuristic to be able to properly solve a given problem. On the other hand, it is very difficult to find a metaheuristic that provides a possible good solution for a given task, since there are hundreds of thousands of research materials related to the topic and their number shows an exponential increase. This huge number makes the work of research communities and practitioners extremely difficult, as it is not easy to find and select the work or works that can clearly help in choosing the optimization technique in such a large set.

Table 1 shows the most important terms of the topic, as well as some examples of metaheuristics and logistic tasks. (In this case, the specific examples are not of particular importance, they were only analyzed to provide a more comprehensive picture. There are hundreds of metaheuristics and countless logistical problems, so the analysis of all of them is an extremely time-consuming task and irrelevant from the point of view of the paper.) The literature statistics include—based on the search term given in **Table 1**—all search results found in the specified article type, as well as the number of research materials published in the last 5 years. Based on the numbers, it has been proven how difficult it is to get to a relevant publication. Based on the data obtained, it can be clearly stated that the number of scientific works is huge and it is really not easy to search among different types of materials. And this does not facilitate decision support for choosing the appropriate optimization technique.

Table 1. Literature statistics (retrieved: 03.11.2024, database: ScienceDirect).

Search term	Article type	All results	Results 2020–2024				
		−2024	2020	2021	2022	2023	2024
Optimization	Review articles	234,278	15,868	20,777	22,486	24,113	33,125
	Research articles	1,000,000+	166,313	192,958	215,805	233,849	293,981
	Encyclopedia	21,255	474	1024	1528	1081	2523
	Book chapters	173,367	9557	9380	11,369	10,830	11,165
Algorithm	Review articles	108,289	7081	8582	9204	10,035	12958
	Research articles	1,000,000+	105,031	121,919	133,612	142,682	167,028
	Encyclopedia	9562	343	406	525	623	1082
	Book chapters	103,225	4692	4831	5479	5214	5724
Metaheuristic	Review articles	1415	112	134	209	221	323
	Research articles	29,039	2119	2855	3608	3882	4721
	Encyclopedia	69	4	9	6	8	11
	Book chapters	1019	78	117	136	115	196
Genetic Algorithm	Review articles	8591	607	798	1022	1134	1503
	Research articles	149,845	9896	11,955	13,730	14,635	17,197
	Encyclopedia	702	38	43	26	35	87
	Book chapters	5454	355	459	527	465	538
Ant Colony Optimization	Review articles	1220	104	121	158	144	214
	Research articles	15,952	1232	1443	1655	1725	1874
	Encyclopedia	42	2	2	ND	2	11
	Book chapters	579	51	70	68	60	83
Firefly Algorithm	Review articles	477	46	52	71	81	91
	Research articles	5378	577	699	771	808	868
	Encyclopedia	8	ND	ND	ND	1	4
	Book chapters	239	23	35	28	21	49
Marine Predators Algorithm	Review articles	52	1	5	8	17	21
	Research articles	822	10	81	178	237	310
	Encyclopedia	ND	ND	ND	ND	ND	ND
	Book chapters	21	ND	ND	3	2	15
Sine Tree-seed Algorithm	All type	10	2	3	1	3	ND
Logistics	Review articles	38,487	2647	3249	3416	3802	4928
	Research articles	640,197	40,060	47,047	48,024	48,277	56,214
	Encyclopedia	3858	120	247	241	171	468
	Book chapters	27,491	1566	1413	1717	1677	1849

Table 1. (*Continued*).

Search term	Article type	All results	Results 2020–2024				
		−2024	**2020**	**2021**	**2022**	**2023**	**2024**
Traveling Salesman Problem	Review articles	421	30	34	33	39	54
	Research articles	11,415	533	597	691	718	815
	Encyclopedia	55	ND	3	ND	ND	6
	Book chapters	601	41	23	24	37	41
Vehicle Routing Problem	Review articles	324	29	35	36	35	46
	Research articles	9227	633	801	865	955	1019
	Encyclopedia	11	ND	5	ND	ND	1
	Book chapters	163	25	11	11	11	18
Knapsack Problem	Review articles	222	14	21	27	13	21
	Research articles	6086	324	356	371	349	390
	Encyclopedia	15	ND	ND	ND	2	1
	Book chapters	186	7	6	9	16	10
Warehouse location	Review articles	57	2	1	1	3	7
	Research articles	1240	75	60	71	84	110
	Encyclopedia	8	1	1	ND	ND	ND
	Book chapters	90	3	4	3	1	6
Inventory	Review articles	29,668	2025	2404	2560	2487	2938
	Research articles	347,530	17,541	19,914	19,619	19,755	22,276
	Encyclopedia	5165	183	235	278	202	449
	Book chapters	33,172	1376	1311	1393	1226	1226

Based on the results of **Table 1**, the question arises as to why this 5-5 specific example shows such a varied picture in terms of the number of hits. In the case of metaheuristics and problems, there are those that are more widely researched and more popular, on the one hand because of their practical applicability, and on the other hand, in terms of adaptability. Furthermore, in the case of algorithms, it doesn't matter when it was introduced, since the research of "a few years old" metaheuristics is not competitive with methods that have existed for 20–30 years.

Even in the case of simple expressions, there are plenty of results in the scientific databases, but it is an even more difficult task to find or assign the appropriate metaheuristic algorithm to a specific logistics problem. In **Table 2**, we examined five metaheuristics in terms of whether they have already been applied to a given logistics problem, whether there is research material on the given task. In the case of certain algorithms, there are thousands of works/articles for a given problem, however, we can also find application possibilities in the case of recently designed metaheuristics. And their number increases exponentially over the years, which makes it even more difficult to assign optimization techniques to a task.

Table 2. Literature statistics: "Name of metaheuristic" and "name of logistic problem" (retrieved: 21.11.2024, database: ScienceDirect).

AND	"Traveling Salesman Problem"	"Vehicle Routing Problem"	"Knapsack Problem"	"Warehouse location"	Inventory
"Genetic Algorithm"	5880	4753	2310	280	10,989
"Ant Colony Optimization"	2650	1872	767	52	1568
"Firefly Algorithm"	393	246	212	10	285
"Marine Predators Algorithm"	45	16	42	0	19
"Sine Tree-Seed Algorithm"	2	0	0	0	0

Based on the results, it can be concluded that there is a need to define a new type of assignment structure, a framework that can facilitate the assignment of algorithms to tasks using a unified, general scheme. There are approximately 700 different metaheuristics, so it can be clearly stated that finding the algorithm that provides the best solution for a given task is an almost impossible task based on the literature.

3. Literature review

In the field of logistics and supply chains, countless metaheuristic algorithms are used for optimization in both general and special tasks. Many metaheuristics have already been applied to the classic Traveling Salesman Problem (Many logistics problems, such as vehicle routing, distribution and network optimization, etc., can be transformed into Traveling Salesman Problem (TSP) (Wang and Han, 2021).), for example: African Buffalo Optimization, Ant Colony Optimization, Artificial Bee Colony Algorithm, Firefly Algorithm, Fish Swarm Algorithm, Genetic Algorithm (Ezugwu et al., 2021), Discrete Bacterial Memetic Evolutionary Algorithm (Kóczy et al., 2018), etc. RDS (reconfiguration of distribution systems (RDS) is a classical optimization problem that involves the planning and operation of the electrical distribution systems) is a more specialized field and the following metaheuristics have already been used to solve the problem (non-exhaustively): Simulated Annealing, Particle Swarm Optimization, Tabu Search, Ant Colony Search, Harmony Search Algorithm, Genetic Algorithm, Artificial Immune Algorithm, etc. (Silveira et al., 2021). Pérez et al. (2023) proposed a hybrid metaheuristic approach for tasks belonging to the inventory-route problem.

Simply, metaheuristic optimization can be described as a technique that can find the most suitable solution among the possible solutions of a given problem (Turkoglu et al., 2023). A metaheuristic searches for the optimal result among a large set of feasible solutions, which it can often involve less computational effort than the use of calculus-based methods (Gil-Rios et al., 2021). The formalization of the optimization model is usually linked to the nature or type of the decision variables of the system. Models with discrete variables are called discrete optimization problems, while models with continuous variables are called continuous optimization problems (Dagdia and Mirchev, 2020). In the case of discrete optimization, the feasible set is finite (Hladík, 2022), the variables are discrete, which can be binary (0 and 1) or integer values. Many real-world problems are modeled with discrete variables, since resources are usually indivisible. Discrete systems can be, for example, assignment problems, scheduling tasks, routes (Dagdia and Mirchev, 2020). During continuous optimization, the feasible set is uncountably infinite (Hladík, 2022), the decision variables are continuous by nature (Abdel-Basset et al., 2024), which can take an infinite number of possible values within a given range. This type of problem can be, for example, determining locations based on coordinates. It is characteristic of continuous type tasks that the data is mostly collected by measurement.

An optimization problem (OP) is the determination of the most favorable solution within a given feasible range. OPs generally fall into two categories: discrete and continuous (Abdel-Basset et al., 2024). However, real optimization problems (e.g. logistics, transportation, engineering design) contain both continuous and discrete variables. This is also why it is difficult to assign a suitable metaheuristic to a problem, since a metaheuristic algorithm cannot efficiently handle tasks containing mixed variables. One of the reasons for this is that standard metaheuristics are basically designed to solve either continuous (e.g., Differential Evolution, Evolutionary Strategies, Cuckoo Search, Firefly Algorithm) or discrete (Particle Swarm Optimization, Ant Colony Optimization, Simulated Annealing, Tabu Search) optimization problems (Talbi, 2024).

In the study of Badejo and Ierapetritou (2022), it was found that the sub-goals and sub-problems of supply chains are emphasized when defining most problems, even though it would be important to focus on cooperation and integration between different levels and elements of the supply chain. Many compromises can be reached between the global optimum and the decisions made at different levels of supply chains, if mutual benefits and dependencies are found and exploited (Badejo and Ierapetritou, 2022). An important factor in the framework presented in the paper is whether a problem belongs to a strategic, tactical or operational level.

Designing an algorithm is time-consuming and expensive, and the process itself is rarely documented (because of this, the thought process is often impossible to follow, and it is not clear what motivated certain design decisions) (Swan et al., 2022). The aim of the paper is to reduce the time, cost and resources needed to create a metaheuristic optimization procedure with the help of expert knowledge that can be obtained based on the literature. With all this, scientific work and practical application can be brought closer to each other. **Figure 2** shows the development of an algorithm in broad outline—of course, each part has many more components (Osaba et al., 2021)—highlighting which part the paper focuses on developing.

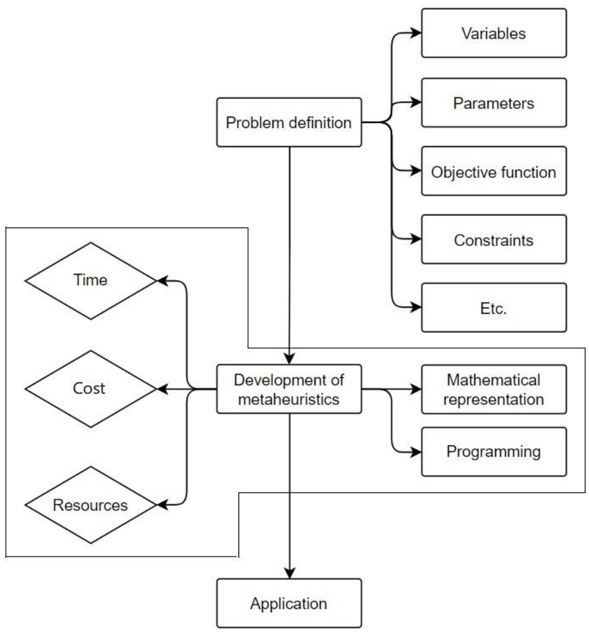

Figure 2. Broad development of metaheuristics.

4. Strategic, tactical and operational levels and tasks in logistics

Logistics decision-making can also be divided into 3 main levels, strategic, tactical and operational levels. Each level involves different goals, scopes and different time frames. From the point of view of a well-functioning logistics system, each level is equally important, and their proper coordination is necessary to ensure efficiency (Alvarez et al., 2020).

Strategic decisions are long-term, high-level planning decisions and serve a long-term goal. They are typically for a period of 5–10 years. They provide a framework for determining the direction and goals of an organization. In the field of logistics, this includes decisions related to the development of the network, for example, the definition of infrastructure needs, the location of distribution centers and warehouses, the selection of markets, the selection of suppliers, technological investments, and the selection of key partners. Extremely complex tasks, numerous data analyses, forecasts, and trends are required to be taken into account in order to make decisions (Badejo and Ierapetritou, 2022).

The primary role of tactical decisions is to support strategic goals. They are intended for medium-term planning, the duration of which is usually 1–3, possibly 5 years. The distribution of resources necessary for feasibility and the definition of planning methods take place at this level. Tasks belonging to this can be e.g. determination of delivery routes, determination of delivery frequency, development of stocking guidelines. An extremely high level of knowledge of logistics systems, guidelines and the resources required for implementation is required (Steadie Seifi, 2011).

Operational decisions include short-term, daily, weekly or monthly decisions and operations. Their goal is to effectively implement the goals defined on the basis of logistics plans and manage the allocation of resources and the necessary processes on a daily basis. Operational tasks can include, for example, scheduling deliveries, monitoring stock levels, allocating daily labor or handling customer inquiries. Fast and efficient decision-making and excellent problem-solving skills are required to deal with challenges at this level (SteadieSeifi, 2011). **Table 3** summarizes the most important aspects of each level.

Table 3. The main aspects of the strategic, tactical and operational decision levels.

Aspect	Strategic	Tactical	Operative
Time frame	5–10 years (long-term)	1–3 years (medium term)	1–30 days (short term)
Task focus	Broad, enterprise-wide goals	Optimization and resource use, allocation	Fulfillment and management of day-to-day tasks
Complexity	High	Medium	Low or medium
Main goals	Structural design, direction determination	Process optimization	Completing tasks and problem solving
Impact	Large (long-term)	Medium (medium term)	Immediate (short term)

In order to choose the right optimization method, it is necessary to organize the logistics tasks to which level they belong. An example of this can be seen in **Table 4** (Alvarez et al., 2020; Badejo and Ierapetritou, 2022; Gritsch, 2001; Steadie Seifi, 2011).

Table 4. Strategic, tactical and operational tasks in logistics.

Strategic tasks	Tactical tasks	Operational tasks
Determining the location of distribution centers	Development of inventory management policies	Organization and scheduling of daily shipments
Determining the location of warehouses	Choice of delivery method	Order picking
Definition of logistics functions that are outsourced to a third-party logistics service provider	Optimizing the layout of warehouses	Packaging of orders and preparation for delivery
Definition of logistics functions that are solved within the company	Supplier relationship management	Continuous monitoring of stock levels, intervention if necessary
Development of strategies to reduce the environmental impact of logistics operations (sustainability, green logistics)	Selection of Carriers	Allocation and planning of vehicles and routes
Determining the integration possibilities of new, advanced technologies	Route optimization	Real-time tracking of shipments
Developing emergency plans and strategies	Continuous monitoring and development of applied systems	Preparation of daily work schedules, shift planning
Investigating the possibilities of global expansion and new market entry	Negotiation with carriers to ensure competitive prices	Loading of goods
Development of long-term efficiency improvement strategies	Determining how the vehicles will be used (leasing or purchasing)	Quality control
Determination of optimization techniques for different subareas		Solving sudden problems
Building long-term partnerships		

5. Modeling a framework for choosing the right metaheuristic

The majority of logistical problems are extremely complex and complicated tasks. Optimization is crucial in countless areas: the proper allocation of resources, minimizing the time or distance traveled, choosing the right warehouse structure, and the proper placement of depots are just a few examples of the countless tasks to be solved. In many cases, these tasks can only be performed properly if the processes are coordinated and properly optimized. **Figure 3** shows the structure of the framework, which helps to assign a metaheuristic that provides a possible good solution to a task.

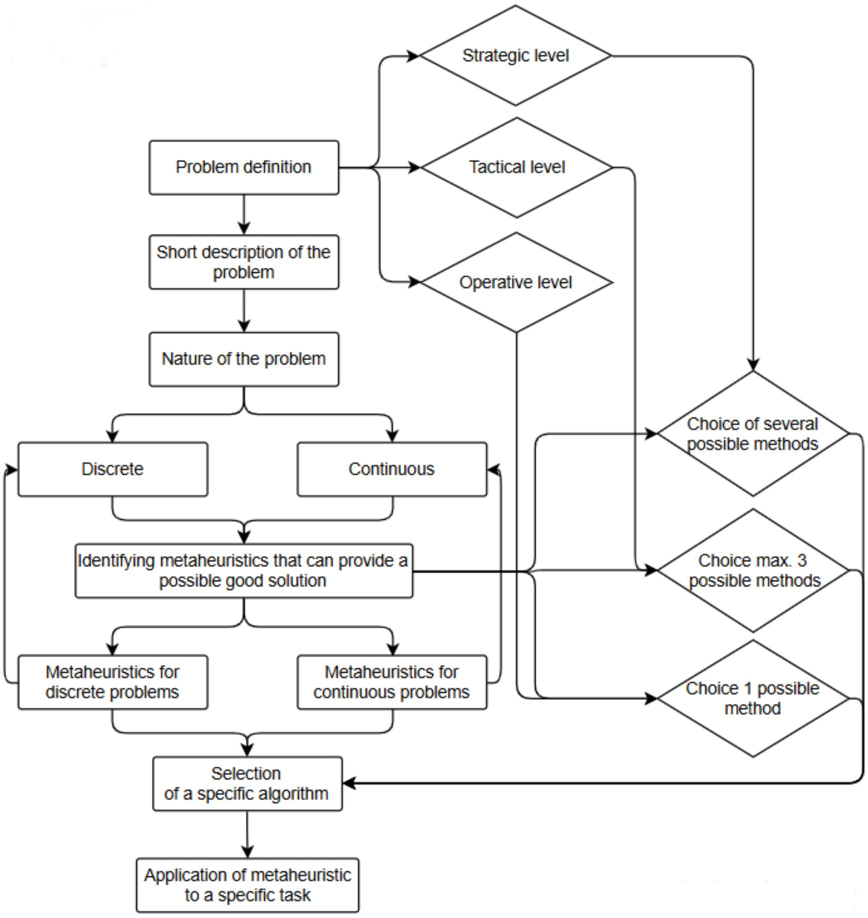

Figure 3. Selection framework model.

The framework consists of 2 main branches from the point of view of the problem:

1) Determination of the nature of the problem: discrete or continuous based on the variables.
2) Level classification of the problem: does it belong to strategic, tactical or operational decision levels.

The steps for branch 1 are:

After formulating and briefly describing the problem, it is necessary to determine the most important variables of the problem, based on which it can be classified as discrete or continuous tasks. After that, metaheuristics should be analyzed according to whether they are typically suitable for solving discrete or continuous problems. Once a specific task has been classified into discrete or continuous classes, and the groups of metaheuristics that are suitable for solving discrete or continuous tasks have been determined, tasks and metaheuristics of the same class can be connected and the specific algorithm with which we want to optimize a given task can be determined.

Steps for branch 2:

After formulating the problem, it is necessary to decide which decision level the given problem belongs to: strategic, tactical or operational. When choosing the algorithm, it does not matter how much time is available to perform the optimization task: as already mentioned, the time factor does not represent a particular limitation at the strategic and tactical level, but it represents a bottleneck at the operational level. As a result, we defined the following regarding the number of selectable metaheuristics:

Once the algorithms that provide a possible good solution have been determined, as well as the nature and level of the task, the required number of specific algorithm(s) can be selected from the appropriate sets (discrete or continuous) based on **Table 5** and the actual application can begin.

Table 5. The effect of level of problems on the choice of metaheuristics.

Level	Recommended number of metaheuristics to choose from	Explanation
Strategic	unlimited/no need to specify	In theory, it is possible to examine and test the application of any number of metaheuristics at this level. The number of algorithms chosen may depend on the company's policy, available time and resources.
Tactical	1, 2 or 3	The time factor is not a particular limitation at this level either, although there is less time available to find the right method than at the strategic level. At the tactical level, it can be a compromise between the quality of the solutions and the available time - which, depending on the task, can be a few years, a few months, or even weeks - if the company chooses and tests maximum 3 metaheuristics (if necessary).
Operative	1	The time available for optimization is a bottleneck at the operational level, and practice also shows that quick and efficient decisions must be made to deal with problems at this level. Therefore, it is only recommended to choose one metaheuristic here, because even a medium-quality solution is preferable to the absence of a complete solution.

Connection of branches 1 and 2:

The connection point of branches 1 and 2 is clearly represented by metaheuristics: after identifying and classifying the characteristics of the problems, it is possible to determine whether it is worth choosing an algorithm suitable for solving discrete or continuous tasks, and the number of metaheuristics that can be chosen from a defined set is influenced by which decision-making level a given problem belongs to. Overall, the 1st branch helps to specify the possible good optimization procedures, and the 2nd specifies the suggested number of selectable algorithms, how many algorithms it is advisable to try in order to reach the optimal solution before making the final decision.

The complexity of the framework promotes efficient algorithm selection for a specific task in such a way that it requires the fulfillment of 3 important boundary conditions for the final choice:

(1) Determination of the nature of the task: discrete or continuous (binary classification variable).
(2) Identification of metaheuristics, which have already been successfully applied to discrete or continuous tasks.
(3) The level affiliation of the task, which can be strategic, tactical or operational.

With the help of this formulation, it can be ensured that the framework systematically selects the appropriate algorithm based on the combination of the nature of the problems (discrete or continuous), the matching of metaheuristics (algorithms suitable for solving discrete or continuous problems) and the level situation of the problems (strategic, tactical or operational).

This is a new type of selection method, where the main hypothesis is that a logistics problem consisting of discrete or continuous variables can most likely be efficiently solved with metaheuristics that, based on literature, have been used successfully to solve mostly discrete or continuous tasks. Therefore, after assigning logistics tasks to strategic, tactical or operational levels, it is still necessary to determine whether the nature of the problem is discrete or continuous. It is advisable to identify the goal and the most important constraints. Examples of this can be seen in **Table 6**.

Table 6. Example: The nature of the tasks and their most important goals and constraints.

Problem	Level	Description	Type of the problem
Determining the location of distribution centers	Strategic	Optimizing network design by evaluating up to thousands of configurations and selecting the best one. Goal: minimizing total costs. Constraints: cost, distance, certain service level limits.	Continuous
Route optimization	Tactical	Determination of optimal route. Goal: minimize travel distance, time or cost. Constraints: travel distance, time or cost.	Discrete
Allocation and planning of vehicles and routes	Operative	Determination of optimal route and vehicles of transport. Goal: minimize travel distance, time or cost. Constraints: number and size of resources, time, cost.	Discrete

6. Metaheuristics for discrete or continuous tasks

Metaheuristic algorithms have already been classified in many different ways, but there is no structural aggregate analysis that would help to solve the logistical task given to select an algorithm. That is why it is necessary to introduce a new type of interconnection system. However, this requires knowledge of the classification methods presented so far.

Presenting a systematic classification of all metaheuristic algorithms available in the literature is an extremely difficult task and a great challenge (Ezugwu et al., 2021).

Since most algorithms imitate processes and patterns inspired by nature, this is the category that researchers in the field deal with the most. The majority of classification techniques classify these algorithms into different categories. Currently, one of the newest taxonomies with the most subcategories is represented by the work of Darvishpoor et al. (2023). The nature-based algorithms were classified according to the source of inspiration and can actually be interpreted as an extended version of the classification of Abdel-Basset et al. (2018). Nine main categories are distinguished: bio-based, ecosystem-based, social-based, physics-based, chemistry-based, music-based, sports-based, hybrid and math-based. The bio-based category is further divided into 10 subcategories: evolution-based, organ-based, behavior-based, disease-based, microorganism-based, insect-based, avian-based, aquatic-based, terrestrial animal-based, and plant-based (Darvishpoor et al., 2023). The classification categories shown in **Figure 4** according to Darvishpoor et al. (2023).

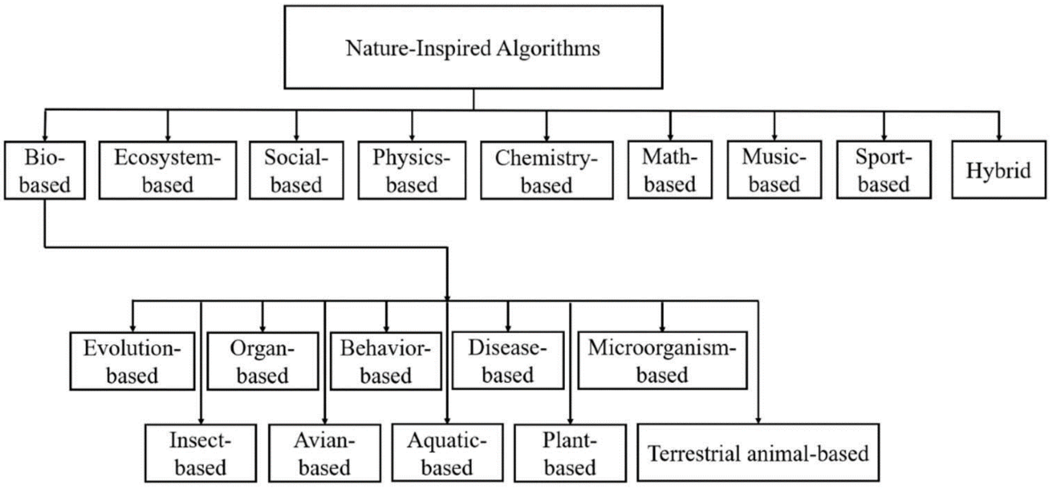

Figure 4. Classification of nature-inspired algorithms by Darvishpoor et al. (2023).

We selected the metaheuristics examined in the paper from these groups, one from each, and analyzed the algorithms according to whether they were successfully used to solve more discrete or more continuous problems, according to the literature (**Table 7**). (One selected reference was attached to the metaheuristics.)

Table 7. Metaheuristics for discrete or continuous problems.

Metaheuristic	Variable's type (Problem)	References
African Vultures Optimization Algorithm (AVOA)	continuous	Rajaguru and Annapoorani (2023)
Bacterial Colony Chemotaxis Optimization (BCCO)	continuous	Lu et al. (2013)
Flower Pollination Algorithm (FPA)	continuous	Lyu et al. (2023)
Gravitational Search Algorithm (GSA)	continuous	Jiang et al. (2020)
Grey Wolf Optimizer (GWO)	continuous	Zhang et al. (2024)
Selfish Herd Optimizer (SHO)	continuous	Zhao et al. (2020)
Swine Influenza Models-Based Optimization (SIMBO)	continuous	Sharma et al. (2016)
Whale Optimization Algorithm (WOA)	continuous	Xue et al. (2024)
Ant Colony Optimization (ACO)	discrete	Cui et al. (2024)
Artificial Immune System (AIS)	discrete	Schmidt et al. (2017)
Chemical Reaction Optimization (CRO)	discrete	Xiao et al. (2022)
Golden Ball Algorithm (GBA)	discrete	Worawattawechai et al. (2022)
Harmony Search (HS)	discrete	Makhmudov et al. (2024)
Hybrid Metaheuristic (HM)	discrete	Nohair et al. (2024)
Particle Swarm Optimization (PSO)	discrete	Afrasyabi et al. (2023)
Sine Cosine Algorithm (SCA)	discrete	Liu et al. (2023)
Water Cycle Algorithm (WCA)	discrete	Sadollah et al. (2015)
Genetic Algorithm (GA)	discrete-continuous	Esmaelian et al. (2018), Roghanian and Pazhoheshfar (2014)

Based on the results and the **Table 7**, it can be seen that in practice metaheuristics are applied to discrete tasks in a relatively large proportion, although a significant part of metaheuristics were found to be suitable for solving continuous optimization, and were originally designed for solving continuous tasks (Ezugwu et al., 2019; Mohammadi and Sheikholeslam, 2023). However, our research shows that in practice there is not a very big difference between solving discrete and continuous tasks. Based on this, the following conclusions can be made:

- It is important to examine what algorithm has already been used to solve a given type of problem in practice, and from this it is advisable to draw conclusions regarding the suitability of a metaheuristic, furthermore
- It has the right to exist as a new classification of metaheuristics according to the fact that mostly discrete or continuous tasks have already been solved effectively, since this study reflects well the actual fields of application of metaheuristics.

With the help of these data, we determined the metaheuristics that provide a possible good solution for a given task from among the 18 selected algorithms, which are summarized in **Table 8**.

Table 8. Possible metaheuristics providing good solutions for logistics tasks.

Problem	**Determining the location of distribution centers**	**Route optimization**	**Allocation and planning of vehicles and routes**
Nature of the problem	Continuous	Discrete	Discrete
Possible metaheuristics	Genetic Algorithm African Vultures Optimization Algorithm Bacterial Colony Chemotaxis Optimization Flower Pollination Algorithm Gravitational Search Algorithm Grey Wolf Optimizer Selfish Herd Optimizer Swine Influenza Models-Based Optimization Whale Optimization Algorithm	Genetic Algorithm Ant Colony Optimization Artificial Immune System Chemical Reaction Optimization Golden Ball Algorithm Harmony Search Hybrid Metaheuristic Particle Swarm Optimization Sine Cosine Algorithm Water Cycle Algorithm	Genetic Algorithm Ant Colony Optimization Artificial Immune System Chemical Reaction Optimization Golden Ball Algorithm Harmony Search Hybrid Metaheuristic Particle Swarm Optimization Sine Cosine Algorithm Water Cycle Algorithm

7. Operational testing

After defining the selection structure, the effectiveness must be examined on a specific example with specific algorithms. These steps are shown in **Figure 5**.

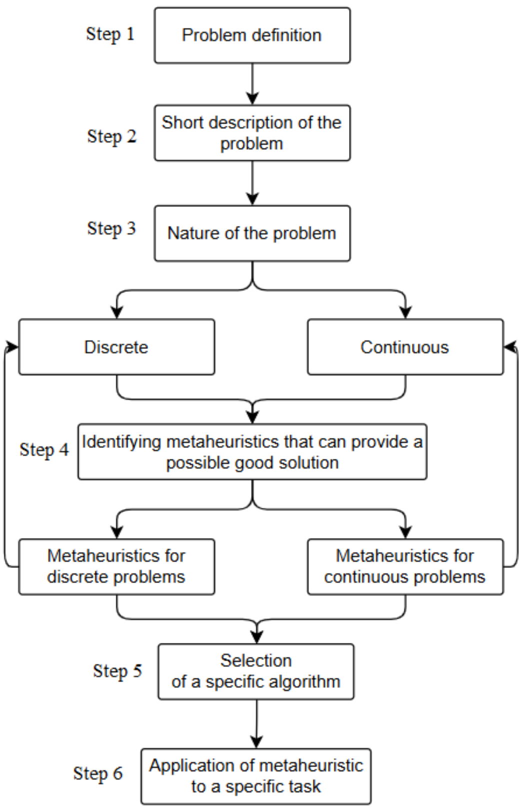

Figure 5. Selection steps.

The task is described below using the model. The goal is to identify a potential good solution algorithm:

Step 1: Defining the problem: Determining the optimal location of facilities.

Step 2: Brief description of the problem: Determining the optimal location of facilities and assigning customers to these facilities by minimizing the total cost. Total cost is the sum of facility opening/operating and delivery costs. Customers are in a specific location.

Step 3: The nature of the problem in terms of the solution: Continuous optimization task, with continuous variables (facilities can be anywhere).

Step 4: Identifying metaheuristics that can provide a possible good solution: It was necessary to identify metaheuristics that, based on the literature, have already effectively solved tasks of a continuous nature. (Examples in **Table 8**.)

Step 5: Choosing a specific algorithm: We chose the African Vultures Optimization Algorithm (AVOA) (based on **Table 8**).

Step 6: Application of metaheuristics to a specific task.

Representation of the problem:

- n customers, each with a fixed location;
- m facilities that must be located somewhere in the space (facilities are not limited to predetermined locations);
- cost function: cost related to opening/operating a facility + delivery cost (the cost of transporting the goods from the facility to the customers).

Constraints:

- each customer must be assigned to exactly one facility;
- a facility can only serve customers when it is open.

Mathematical representation:

$$\text{minimize} \sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} x_{ij} + \sum_{j=1}^{m} F_j \, y_j,$$

where

c_{ij}: the cost of transporting the goods from facility *j* to customer *i*;

x_{ij}: binary variable, which is 1 if customer *i* is assigned to facility *j*, otherwise 0;

F_j: fixed cost of opening facility *j*;

y_j: binary variable, which is 1 if facility *j* is open, 0 otherwise.

Constraints:

$$\sum_{f=1}^{F} x_{cf} = 1 \quad \forall c \in \{1, 2, \ldots, C\},$$

where

x_{cf}: binary variable that is 1 if customer *c* is assigned to facility *f*, otherwise 0;

F: set of available facilities.

$$x_{cf} \leq y_f \quad \forall c \in \{1, 2, \ldots, C\}, \quad f \in \{1, 2, \ldots, F\},$$

where

y_f: binary decision variable that is 1 if facility *f* is open and 0 if not.

Example parameters:

- location (coordinates) of customers in a two-dimensional space: [(2, 3), (5, 6), (8, 8)];
- opening each facility has a fixed cost: $F1 = 10$, $F2 = 10$;
- cost per unit distance: 1;
- maximum number of iterations: 100;
- number of agents (vultures): 10.

An algorithm inspired by the African Vultures Optimization Algorithm (AVOAn) was tested in Python. The results are shown in **Table 9**.

Table 9. Comparison of AVOAn and ACOn.

Metaheuristic	Short general description	Problem nature*	References	Task solution result
African Vultures Optimization Algorithm (AVOA)	The African Vultures Optimization Algorithm (AVOA) - like countless other algorithms - was inspired by collective intelligence and the foraging of creatures living in nature. AVOA was inspired by the lifestyle of African vultures: it simulates their foraging and navigational behavior (Abdollahzadeh et al., 2021).	Continuous	Abdollahzadeh et al., 2021; Diab et al., 2022; Ghafari and Mansouri, 2023; Rajaguru and Annapoorani, 2023	Optimal Facility Locations: [[4.34698593 6.82859876], [4.99789714 5.99690372]] Optimal Total Cost: 17.85
Ant Colony Optimization (ACO)	ACO is a popular algorithm based on mimicking the foraging behavior of ants. Ants essentially find and follow the shortest path between their colony and food sources. They use pheromones to mark the tracks, as well as information on the quantity and quality of the food. This natural behavior of ants was the main motivation for the creation of ACO (Blocho, 2020).	Discrete	Chaharsooghi and Kermani, 2008; Cui et al., 2024; Skinderowicz, 2022; Wu and Gao, 2023	No location was founded Best Cost = 24.43

* The nature of the tasks/problems, which have already been effectively solved by the given metaheuristic based on the literature.

However, it is not enough to test a selected metaheuristic on a problem, it is also worth examining what kind of result we get in the event that we do not choose an algorithm that was identified based on the selection model. Therefore, we tested the task with a method suitable for discrete problems. We chose Ant Colony Optimization (ACO), which can efficiently solve discrete tasks based on **Table 8**. The method and testing data are identical to the procedure used for the African Vultures Optimization Algorithm. The results of the ACO-inspired algorithm (ACOn) can also be seen in **Table 9**.

The **Table 9** also shows a short description of the selected algorithms, as well as some references to already solved problems. It should be noted here that the result obtained with AVOA can most likely be further improved by fine-tuning the parameters and an even better result can be achieved. However, the fine-tuning of the parameters is not the focus of this paper.

Based on the results, it can be concluded that an algorithm that we identified with the help of the selection model presented in the paper really performed better.

8. The impact of the framework on the logistics infrastructure

Table 10. Analysis of tasks related to logistics infrastructure.

Problem	Field	Key variable(s)	Type of problem	Metaheuristics
Global supply chain network design	infrastructural	Binary or integer decision variables for placing different facilities.	discrete	ACO, AIS, CRO, GBA, HS, HM, PSO, SCA, WCA, GA
Determining the location of distribution centers	infrastructural	A finite set of integer decision variables (if predefined locations are considered)/an infinite range of values if the distribution centers can be anywhere in a defined space.	discrete/continuous	ACO, AIS, CRO, GBA, HS, HM, PSO, SCA, WCA, GA/AVOA, BCCO, FPA, GSA, GWO, SHO, SIMBO, WOA, GA
Determination of the optimal number of warehouses	infrastructural	Number of warehouses to be opened: integer variables.	discrete	ACO, AIS, CRO, GBA, HS, HM, PSO, SCA, WCA, GA
Determination of optimization techniques for different subareas	efficiency improvement	It involves the selection of optimization techniques from a predefined set (e.g. exact or metaheuristic methods): discrete variables representing the chosen techniques.	discrete	ACO, AIS, CRO, GBA, HS, HM, PSO, SCA, WCA, GA
Development of long-term efficiency-enhancing strategies	sustainability/efficiency improvement	Optimizing performance indicators with different measurements: continuous variables.	continuous	AVOA, BCCO, FPA, GSA, GWO, SHO, SIMBO, WOA, GA
Monitoring the fuel consumption of transport vehicles	sustainability	Continuous variables for fuel levels and consumption rates.	continuous	AVOA, BCCO, FPA, GSA, GWO, SHO, SIMBO, WOA, GA

One of the most important tasks of logistics systems and network planning is to determine the optimal location of various facilities (e.g. warehouses, distribution centers). These are complex optimization problems that can be efficiently solved with metaheuristics. The rethinking and development of existing infrastructures or the appropriate optimization of planned infrastructures all contribute to the efficiency of the entire logistics network. The **Table 10.** contains some infrastructural and efficiency-enhancing tasks, the nature of which we determined using the most important variables, which is one of the most important tasks of the framework. The metaheuristics defined in **Table 7.** can be assigned to individual tasks after their classification into discrete or continuous classes has been identified.

The use of metaheuristics in logistics optimization also has many advantages in an infrastructural context. Thanks to the flexibility and adaptability of the algorithms, these methods can be properly adapted to the optimization of different infrastructural elements. Thanks to their robustness, they are able to adapt to changes in the environment, which makes them suitable for solving dynamic and real-time logistics problems. In logistics systems, metaheuristics are able to find the near-optimal solution to a specific problem, which helps reduce the operating cost of the entire network and improves the overall performance of the entire supply chain. Metaheuristics offer an efficient, flexible approach to optimizing logistics operations at all decision levels, for all complex, high-volume, many-constrained tasks. The framework primarily helps with how existing techniques can be adapted to tasks. This means both a reduction in development costs and a reduction in the time devoted to optimization. This not only facilitates the effective solution of specific tasks, but also contributes to sustainable logistics practices by optimizing resource use or supporting economic development. The use of advanced algorithms is essential in the decades of the Fourth Industrial Revolution and in maintaining the competitiveness of companies.

9. Discussion

Selecting and applying a metaheuristic suitable for a given problem is a difficult task. Metaheuristics basically provide a solution of adequate quality within an acceptable calculation time. But what if there is a relatively short time available for optimization, for choosing an optimization technique? How can the results and suggestions of thousands of scientific works be applied in practice? We were looking for a solution proposal for these problems, because we saw that unexpected events happen in countless cases in the industry, which affect the predetermined scenarios. In the case of real, complex problems, the uncertain environment and, in many cases, the expected result within a short period of time influence the choice and effectiveness of the optimization method. The trade-off between the quality of the solution and the speed of the calculation time can be seen in practice in countless cases. Depending on whether a problem belongs to a strategic, tactical or operational level, it is possible to decide on the procedure used: more emphasis is placed on the accuracy of the solution in the event that there is a lot of time available in the decision-making process, and accepting one possible good solution can mean promoting efficient work in the case of operational tasks. For this, we were looking for a solution that would facilitate and speed up the time devoted to optimization while ensuring an acceptable result.

For this reason, we investigated metaheuristic algorithms and logistic problems and found that it is very difficult to find the right algorithm for a task type among thousands of research materials. As a solution, we proposed the use of a framework and presented the steps necessary to select a metaheuristic. We classified logistic problems and metaheuristics according to a similar, novel principle: the common denominator was the aspects of discrete and continuous concepts. This makes it easier to identify the right optimization method for a given task, and the framework also reduces the time allocated to the optimization process. We also demonstrated the suitability and applicability of the selection system through a specific example. The results showed that the categorization and matching of logistics tasks and algorithms along a novel principle has many advantages: it provides a good framework to facilitate the decision-making process; can contribute to more frequent reuse of metaheuristics; and can promote the real industrial application of these algorithms. All this can increase efficiency in the field of optimization and make processes more sustainable.

Based on our current research, several additional directions and goals can be formulated. We extend the study to several metaheuristics and to the solution of additional logistics tasks. Our goal is also to identify even more common points of connection between a task and an algorithm, which can be used to further narrow down the methods that provide a good solution.

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