ACTA TECHNICA CORVINIENSIS – Bulletin of Engineering | e–ISSN: 2067 – 3809
Tome XVII [2024] | Fascicule 4 [October – December]

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OPTIMIZATION IN LOGISTICS: INCREASING EFFICIENCY WITH METAHEURISTICS

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Abstract: The wide application of metaheuristics and the continuous development of algorithms is currently one of the most researched areas in the field of optimization. Hundreds of algorithms already exist and their number is constantly increasing. There is almost no area where intelligent methods are not used. Numerous metaheuristic algorithms help optimization in the field of logistics as well. Despite the popularity of metaheuristic algorithms, they are rarely used in industrial practice. A wide range of different procedures is available to perform optimization tasks, traditional, e.g. from gradient–based algorithms to metaheuristics. The authors of the paper give suggestions to facilitate this.

Keywords: Logistics, metaheuristics, optimization, efficiency

INTRODUCTION

Optimization is very important in many fields: from engineering, to business, to medicine, different techniques are used to find the best solution. The goal of optimization can be essentially anything: minimizing costs, waste, scrap, travel time, energy consumption or maximizing efficiency, performance, profit. In practice, however, we always find limiting conditions when solving problems, which can be time, money, available resources, and other complex constraints. In addition to these, different techniques must find the optimal solution when solving a task [1].

During optimization, the definition of the objective function is one of the most important tasks, since the problem can be solved by minimizing or maximizing this function. Different algorithms and optimization techniques help this, especially intelligent methods, since most real problems are non–linear and multi–constrained. A wide range of different procedures is available to perform optimization tasks, traditional, e.g. from gradient–based algorithms to metaheuristics. Nondeterministic polynomial–time difficult (NP–hard) problems are usually not efficiently solved by traditional, exact algorithms, so approximate heuristic methods are the appropriate way to deal with the challenges in this case [1].

We can distinguish two common meanings of the term metaheuristics. One is a set of high–level frameworks, concepts and strategies that provide a basis for developing optimization algorithms. The other means the concrete implementation of an algorithm based on such a framework [2]. Metaheuristics arrive at the final solution iteratively, but they do not guarantee the best optimal solution. Therefore, the aim of the developments is to find a "good enough" solution in a short calculation time. This eliminates the "combinatorial explosion" (the computation time required to optimally find NP–hard problems increases exponentially depending on the size of the problem). Metaheuristics therefore represent a good compromise between the quality of the solutions and the calculation time, especially when a very complex problem with a large number of instances has to be solved. This has already been proven by the scientific community, and it can be said that metaheuristics can be effectively applied in the field of optimization. In many cases, it is an excellent alternative where exact methods (e.g. linear or dynamic programming) are no longer able to find a solution within an acceptable time. Another advantage of metaheuristics is that they do not impose specific requirements when formulating an optimization problem. Thus, the ability to obtain acceptably good solutions where other methods cannot guarantee this has made metaheuristics the choice for solving the majority of real–world multifactorial optimization problems in both academic research and practical applications [3].

The rapid growth rate of new–generation metaheuristic algorithms and new proposals, continuous developments, has induced the publication of thousands of studies in recent years. In many cases, these algorithms are not evaluated based on their usefulness or their performance values, but they emphasize the novelty of modeling a given problem or task. Due to this, similar new methods can appear at the same time [4] and "double discoveries" [5] can be made.

Another problem is that, contrary to the hypotheses, countless algorithms do not provide the appropriate efficiency and do not bring the expected results in solving real tasks [6]. Although metaheuristic algorithms are clearly considered the pioneering method for solving complex and real–world problems, most of the publications present the techniques at a theoretical level and there are few depictions of specific engineering solutions in real–world situations. Of course, the number of successful and efficient algorithms is also large and several metaheuristics have become popular in optimization research.

The paper contributes to getting a comprehensive picture of the latest results of metaheuristic publications and applied methods in the field of logistics. The authors propose a technique to assign an algorithm to a given problem. In this way, the practical application of metaheuristics and the appearance of these techniques on real problems can be facilitated.

The paper is structured as follows: in part 2, with the literature review, the authors present the latest scientific works thematically. In the third section, a group of metaheuristic algorithms already used in the field of logistics is reviewed, and then the increase/facilitation of their use/application can be found in the fourth section. In the 5th part, the authors present the effectiveness of the implementation of the algorithms with the help of an examination. In the 6th section, the conclusion and further research directions are formulated.

LITERATURE REVIEW

Hundreds of metaheuristic algorithms have already been developed, but their number is constantly increasing. On the one hand, by continuously creating new methods, and on the other hand, by improving, existing algorithms and crossing different techniques (hybridization).

The authors have divided the literature dealing with metaheuristics into 3 large areas and based on these, they present the current state of research in the following groups:

a. comprehensive analyzes of the area,
b. possible classification of metaheuristics and
c. other research materials that are considered good practice in the field.

Comprehensive analyzes

Tens of thousands of scientific works have been published in the field of metaheuristics in the last few years and decades. In many cases, a detailed (or less detailed) presentation of special tasks or an algorithm was made in a given publication. Searching through research materials is very difficult. If, for example, we want to propose a heuristic solution to a problem, it is not easy to find previous works, ideas, and suggestions due to the variety and huge amount of articles. Therefore, several useful and at the same time well–usable, comprehensive analytical works on metaheuristics have already been prepared.

Hussain et al. [7], for example, conducted a survey by analyzing 1222 studies (research works published between 1983 and 2016) to determine the amount of research conducted in the field of science and to present the current state of the field. Critical questions related to the concerns of the field were also formulated, which could also be potential research topics.

Ma et al. [8] collected more than 500 metaheuristics and presented some of them in detail from two main aspects: the source of inspiration and the basic operators needed to generate solutions. They also examined the publication numbers of some very popular algorithms, and the metaheuristics were placed in ascending order according to the year of their publication. The latter is rare because in most comprehensive studies the algorithms are arranged in ABC order based on their names.

Rajwar et al. [9] examined 540 algorithms and provided statistical information. Several possible classification structures were presented, as well as the areas of application and most important parameters of the most popular metaheuristics were collected. Based on the number of algorithms examined, the study is outstanding and unique, as it currently contains perhaps the most examined and collected metaheuristics.

The work of Ezugwu et al. [4] is also outstanding from the point of view of the analysis of metaheuristics: they listed nearly 300 algorithms with the following most important data: author, source of inspiration, class, field of application. Perhaps there is no other summary study at the moment that presents the application areas of nearly 300 different algorithms in broad outlines, but in such detail. The advantages and disadvantages of some algorithms have been examined before, which can also contribute to the success of further research and practical applications [6]. It would also be worthwhile to extend this kind of comparative analysis to many more metaheuristics.

Mohammadi and Sheikholeslam [10] presented in detail the field of intelligent optimization and published a comprehensive analysis containing more than 320 algorithms, which was described as follows: the algorithms were grouped according to classes taking into account numerous specifications: author, year of publication, source of inspiration, most important regulatory parameters, areas of application. Various analyzes and publication measurements are included in their work.

Systematic classification of metaheuristic algorithms

Presenting a systematic classification of all metaheuristic algorithms available in the literature is an extremely difficult task and a great challenge [4]. Fister et al [11] gave a brief overview of nature–inspired algorithms and listed the following classes: algorithms based on swarm intelligence, biologically inspired algorithms that are not based on swarm intelligence, algorithms inspired by physical and chemical processes and mentioned another category that may include all other algorithms that do not fit into the previous categories.

Ma et al. [8] describe that the most popular taxonomy is based on sources of inspiration. They describe a rough classification "in which metaheuristics are divided into population–based optimization algorithms and single–solution–based optimization algorithms according to the number of solutions generated during each iteration" [8]. In their article, they primarily deal with population–based algorithms, so this class was further divided into evolutionary algorithms, algorithms based on swarm intelligence, and algorithms based on physical or chemical processes.

In their article, Rajwar et al. [9] present several classification techniques: according to source of inspiration, according to the number/size of elements (population) of the search space, according to the movement/operation of the population, according to the number of parameters. The latter – excluding the source of inspiration – are considered a new type of classification structure in the scientific field of metaheuristics.

Molina et al. [12] also classified algorithms based on the sources of inspiration. They proposed a comprehensive taxonomy for nature–inspired optimization algorithms in a new, different approach.

Brownlee analyzed metaheuristic algorithms inspired by nature and collected a lot of parameters and important information about the individual metaheuristics, which can be of great help primarily for programming [13].

A new classification of metaheuristic algorithms was introduced by Abdel–Basset et al., which focuses on the type of inspiration. According to this, the techniques were classified into metaphor and non–metaphor based algorithms. The metaphor–based class was further divided into different subcategories: biology–based, physics–based, swarm intelligence–based, social behavior–based, music–based, chemistry–based, sports–based and mathematics–based metaheuristics are distinguished. The non–metaphor–based class was not broken down into further subcategories. All but one of the subcategories of metaphor–based algorithms (mathematical–based) belong to the additional class inspired by nature, while the non–metaphor–based class and the metaphor–based–mathematical–based algorithms are metaheuristics not inspired by nature [14].

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. Nature–based algorithms were classified according to the source of inspiration and actually, Abdel–Basset et al. can be interpreted as an extended version of his classification. Nine main categories are distinguished: bio–based, ecosystem–based, social–based, physics–based, chemistry–based, music–based, sport–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 [15].

The largest group of different metaheuristic algorithms are algorithms inspired by nature. This is primarily due to their excellent performance and relatively simple structure. Hundreds of animals, plants, natural formations and phenomena were used as a source of inspiration to develop an algorithm. Natural phenomena and behavioral patterns serve as the basis for algorithms, such as: food–seeking behavior of certain species, the water cycle, movement characteristics of animals, behavioral patterns of team sports, etc. There are at least – approximately – 400 algorithms that belong to the group of algorithms inspired by nature [15]. Table 1 shows some algorithms and their sources of inspiration [16].

Table 1: Some metaheuristics and their sources of inspiration

Metaheuristics	Sources of inspiration
Particle Swarm Optimization (PSO)	Intelligent social behavior of a flock of birds
Monkey Search (MS)	The process of monkeys climbing trees while searching for food
Mine Blast Algorithm (MBA)	Mine bomb explosion
Artificial Algae Algorithm (AAA)	The lifestyle of microalgae
Shark Smell Optimization (SSO)	A shark's ability to find its prey by smell
Dolphin Swarm Optimization Algorithm (DSOA)	Mechanisms of dolphins in detecting, chasing and preying on schools of sardines
Virus Colony Search (VCS)	Viral infection and dissemination strategies
Crow Search Algorithm (CSA)	Intelligent food hiding behavior of crows
Grasshopper Optimization Algorithm (GOA)	Swarming behavior of grasshoppers
Electro–Search Algorithm (ESA)	The orbital motion of electrons around the nucleus
Spotted Hyena Optimizer (SHO)	Social behavior of spotted hyenas
Butterfly–inspired Algorithm (BA)	The mating mechanism of the butterfly
Squirrel Search Algorithm (SSA)	Dynamic foraging behavior and efficient locomotion of southern flying squirrels
Red Deer Algorithm (RDA)	Imitating the behavior of the Scottish red deer
Simulated Annealing (SA)	Annealing process in metallurgy

Research materials

When we want to optimize, depending on the size of the problem and the number of parameters and constrained conditions, there are many methods available to solve a task efficiently. Among the exact and heuristic techniques, the former is effective for problems with a smaller number of instances, while the latter can also handle large data sets, but can "only" provide a good enough solution. At what point is it worth investing time and money in developing an intelligent algorithm and is it worth using? The general comparison of exact methods and metaheuristic solutions is discussed in few scientific works, each example is typical for the solution of a specific problem. For example, Chandra et al.'s paper [17] compares the Branch and Bound (B&B) method with the Fruit Fly Optimization Algorithm (FOA) and the Artificial Atom Algorithm (A^3) metaheuristics. In terms of processing time, the difference between the two methods is more than 12 days, however, if certain conditions are met, B&B performed better. It should therefore be considered to carry out comparative analyzes in this direction during the practical application of a new metaheuristic method.

Another strong contribution to the scientific field of metaheuristics is the collection of solution proposals collected and thematically arranged for individual specific problems in one work. A good example of this is the article by Golab et al. [18], in which metaheuristic approaches applied to resource–constrained project scheduling problems were presented. This also provides a good basis for further research and can contribute to the identification of the most suitable solution method for the task.

In the scientific field of metaheuristics, several problems have already been formulated in the research community, for example, that there are no uniformly accepted standards in the field of operations research. This fact also damages the credibility of the results dealing with metaheuristics. To eliminate this, several researcher have already suggested that the optimization research community should adopt certain standards. Kendall et al. [19] formulate a specific proposal and draft for the unification of many areas, including the presentation of algorithms, solutions, calculation speed, software features, etc. By doing so, they hope to further improve the quality of research by adhering to the same minimum standards. This can contribute to and improve the reproducibility and comparability of results, as well as the efficiency of individual researchers and research groups.

Another good practice is the complete analysis of each algorithm: the basics of metaheuristics, general presentation, hybrids, application possibilities, etc. A good example of this is Neshat et al.'s article [20], in which the Artificial Fish Swarm algorithm is presented, or Teodorović's work [21] with the analysis of Bee Colony Optimization, but the work of Zebari et al. [22] with a complete overview of the Bat Algorithm can also be classified here.

Another area for improvement in studies and research on metaheuristics is that relatively few concrete engineering problems are presented at an adequate level, if at all. Even in the case of the presented problems, it often happens that the problem is not represented properly, with few parameters and an incomplete mathematical description. In their article [23], Zhao et al. describe the engineering solutions, decision variables, limiting conditions, etc. of the Artificial Hummingbird Algorithm: they examine the effectiveness of the algorithm for 10 specific small engineering tasks, comparing it with other algorithms. In the study by Agárdi et al. [24], the specific engineering problem is properly formulated and described.

Tens of thousands of studies related to metaheuristics are available in scientific databases. Research, results, and developments are continuous, but there is a need to improve the quality of the field, to provide accessible, uniform summary and comparative works in order to make the field of science more clearly understandable and unambiguous for future researchers.

METAHEURISTICS IN LOGISTICS

Metaheuristics perform well for complex, complicated problems. In the field of logistics and supply chains, the processes are extremely complex and their proper coordination and global optimization is also necessary in addition to the optimization of the individual sub–processes. Therefore, metaheuristic algorithms are also used in these areas and there are many procedures for solving complex tasks (e.g. [25], [26], [27]). There is a wealth of research and results to effectively solve a logistics or supply chain problem. However, due to the variety and quantity of articles, it is difficult to find the best solution for a specific problem and the details and reasons for the method used.

Few scientific works have been published that focus on a particular problem, and optimization techniques suitable for the problem have been systematically collected. From this approach, the authors focus on the problems.

Ezugwu et al. determined in the case of almost [4] 300 algorithms, in which area the given algorithm has already been applied. With the help of this, already used metaheuristics for some logistics problems could be easily identified, here are some examples:

- **Travelling salesman problem:** African Buffalo Optimization, Ant colony optimization, Artificial bee colony algorithm, Artificial Ecosystem Algorithm, Bean Optimization Algorithm, Bumble Bees Mating Optimization, Chicken swarm optimization, Clonal Selection Algorithm, Consultant–Guided search, Crystal Energy Optimization Algorithm, Egyptian Vulture Optimization, Elephant Search Algorithm, Firefly algorithm, Fish swarm algorithm, Genetic algorithm, Golden ball, Harmony Search Algorithm, Honey–bees mating optimization algorithm, Hunting search algorithm, Hydrological cycle algorithm, Intelligent Water Drops Algorithm, Invasive Weed Optimization, Memetic Algorithm, Penguins Search Optimization Algorithm, Photosynthetic Learning Algorithm, River Formation Dynamics, Shuffled Frog Leaping Algorithm, Simulated annealing, Swallow Swarm Optimization Algorithm, Tabu Search algorithm, The scientific algorithms, Variable Neighborhood Descent Algorithm, Water Wave Optimization, Water–flow Algorithm
- **Knapsack problem:** Artificial Algae Algorithm, Artificial Chemical Reaction Optimization Algorithm, Cuckoo search, Egyptian Vulture Optimization, Fruit Fly Optimization Algorithm, Glowworm swarm optimization, Intelligent Water Drops Algorithm, Migrating Birds Optimization, Monarch Butterfly Optimization Algorithm, Monkey search algorithm, Multi–verse Optimizer, Viral systems
- **Transportation problem:** Keshtel Algorithm, Sheep Flocks Heredity Model, Viral systems
- **Scheduling:** African Buffalo Optimization, Ant colony optimization, Ant Lion optimization, Artificial bee colony algorithm, Bat Algorithm, Biogeography Based Optimization, Bird mating optimizer, Brain Storm Optimization, Bumble Bees Mating Optimization, Cat swarm optimization, Earthworm Optimization Algorithm, Firefly algorithm, Fruit Fly Optimization Algorithm, Gases Brownian motion Optimization, Genetic algorithm, Imperialist Competitive Algorithm, Intelligent Water Drops Algorithm, Invasive Weed Optimization, League championship algorithm, Migrating Birds Optimization and Monkey search algorithm, Particle swarm optimization, Raven Roosting Optimization Algorithm, Saplings Growing Up Algorithm, Sheep Flocks Heredity Model, Shuffled Frog Leaping Algorithm, Symbiotic Organisms Search, Virus Optimization Algorithm, Water Wave Optimization, Water–flow Algorithm, Whale Optimization Algorithm, Wind Driven Optimization
- **Job scheduling:** Artificial Chemical Reaction Optimization Algorithm, Artificial Fish Swarm Algorithm, Fish swarm algorithm, Harmony Search Algorithm, Particle swarm optimization, Tabu Search algorithm, Variable Neighborhood Descent Algorithm
- **Flowshop scheduling problem:** African Wild Dog Algorithm, Anarchic Society Optimization, Artificial Immune System, Golden ball, Memetic Algorithm, Monkey search algorithm
- **Job–shop scheduling problem:** Anarchic Society Optimization
- **Flexible job scheduling problems:** Camel herd Algorithm
- **Production scheduling problem:** The Bees Algorithm

- **Routing problem:** Cultural algorithm, Genetic algorithm, POPMUSIC: Partial Optimization Metaheuristic Under Special Intensification Conditions, Simulated annealing, Variable Neighborhood Descent Algorithm
- **Multicast routing problem:** Animal Migration Optimization Algorithm, Bumble Bees Mating Optimization
- **Vehicle routing problems:** Ant colony optimization, Bumble Bees Mating Optimization, Egyptian Vulture Optimization, Golden ball, Honey–bees mating optimization algorithm, Intelligent Water Drops Algorithm, Monarch Butterfly Optimization Algorithm, Saplings Growing Up Algorithm, Simulated annealing, Tabu Search algorithm, Variable Neighborhood Descent Algorithm, Water Wave Optimization

Of course, this does not mean that only these algorithms were used to effectively solve the listed problems, since the number of metaheuristics and scientific works is growing exponentially every year. However, the question can legitimately arise, why is there little reuse of algorithms in a field that develops so quickly? Why are there few actual applications of these algorithms in practice? There are critical elements that have already been formulated by other researchers, for example, Swan et al summarized some problems that can hinder development in the field of metaheuristics. They also formulated the shortcomings of the published works (for example: the description of the algorithms in the articles dealing with metaheuristics is not precise enough and this hinders independent re–implementation, or that the main processes of algorithm design are rarely documented), the improvement of which could increase the practical application of metaheuristics [5].

INCREASING THE PRACTICAL APPLICATION OF METAHEURISTICS

Metaheuristic algorithms perform well in solving complex, complicated, high–volume tasks. Nowadays, their application in the field of optimization is significant, but at the same time, the practical use and reuse of algorithms is less realized. The primary goal of theoretical research and scientific work should be to make metaheuristics more widespread in practice and appear as a real technique. Both the work of the specialist and the solution of the tasks must be promoted in the field of optimization. Scientific works can provide a suitable basis for this, but an important research question is how can this really be implemented? What does it take a method to work effectively in practice? What are the possibilities of integrating these techniques into the field of logistics?

After reading hundreds of scientific papers, the authors make the following conclusions – especially regarding the pseudocodes of metaheuristics:

- In order to increase the reuse of metaheuristic algorithms, it is necessary to define the basic properties and most important elements that are necessary for the proper application of an optimization technique or the implementation of the basics.
- Based on the pseudocodes of the metaheuristics, the framework of the algorithm can be translated into a chosen programming language so that it is syntactically correct. Of course, this does not mean that the program will work and is able to provide a solution to a specific problem. However, it is already a big help for programmers if the framework of a metaheuristic is easier to implement. Metaheuristic algorithms and their transfer to different programming languages are extremely complicated without a basic concept. Only a few programming mathematicians have the appropriate knowledge for this. This also proves that it is not easy to apply a metaheuristic optimization procedure in practice, although due to the complexity of real engineering problems, general use would be necessary in many cases.
- If the program runs in the selected programming language written from the pseudocode, it can be said that it is syntactically correct, but it cannot output a result. The reason for this is that this code only provides the framework of the metaheuristics, however, exact parameters and the mechanisms of the behaviors need to be clarified in order to demonstrate a solution.

The example below clearly illustrates what data a randomly selected algorithm needs to function properly.

In order for the Artificial Fish Swarm Algorithm (AFSA) [28] program to function effectively and efficiently, the following data, parameters and operations are generally required:

≡ Definition of problem–specific data: the problem to be solved, special requirements, decision variables, objective function and constraints.

- Determination of the size and dimensions of the solution space.
- Determination of population size (number of artificial fish) for each iteration.
- Determination of the maximum number of iterations.
- Defining the preying, the swarming and the following behavior: defining the logic of the behavior based on the characteristics of the problem.
- Definition of initialization method (random, problem–specific approach).
- Determination and adjustment of crowd factor (how neighboring artificial fish interact with each other).
- Determination of stop conditions.
- Additional parameters: there are other dependent problem–specific and algorithm–specific parameters that must be taken into account (e.g. exploration–exploitation trade–off).
- Selecting appropriate data structures for displaying information.
- Testing with different parameters to determine the performance indicators, efficiency, and robustness of the algorithm to achieve the optimal configuration.

— In programming, semantics includes questions of content. Essentially, it is a set of rules for the operation of the program. A program is semantically correct if it runs and produces results. Of course, this does not mean that it works correctly for a specific problem, since it is necessary to check the final result and if it is not correct or does not give the expected result, then some parameter setting or operating mechanism is incorrect and must be corrected. Specialists in the given field are able to provide appropriate assistance for the latter.

— If a detailed and correctly formulated pseudocode of an algorithm is given, as well as a description of the mechanisms that basically determine the operation of the algorithm and the most important data, then we can obtain executable, syntactically and semantically correct program codes in different programming languages. However, it is extremely important to precisely define the task to be solved with strictly defined data, information and parameters, as well as to take into account the special properties of the chosen algorithm. The performance of an algorithm can be further improved by evaluating the results and by fine–tuning the settings and parameters related to the particularities of metaheuristics. Based on these, it is likely that an optimization procedure using metaheuristics can be carried out with the help of the above. However, this also requires the knowledge of specialists in the specific field.

It can be seen that a lot of data and mechanism definition are needed for the actual application and efficient operation of a metaheuristic procedure. In the case of complex problem solving, a high level of theoretical and practical knowledge and the serious expertise of a programming mathematician are required to solve the task. However, if the variables, the objective function, the operating mechanisms, and all other parameters and information are properly defined, then the use of the algorithm and its practical applicability are easier with their help.

PROMOTING IMPLEMENTABILITY AND EXTENDING PRACTICAL APPLICATIONS

In the fields of logistics, there are countless complex problems and optimization tasks for which the application of these algorithms provides and could provide an optimal solution within an appropriate calculation time. In practice, however, it is not an easy task to choose which metaheuristic to choose for a given problem. The reasons for this are essentially the same as those described earlier: there are many different metaheuristic algorithms for countless problems, and in the absence of few practical, real–world examples, it is difficult to say which method to choose for a given problem. Furthermore, metaheuristics have not been grouped so far based on their components and structural elements, which are responsible for the basic optimization performance of the given method, and it has not been revealed why the method works well, or what is the relationship between the properties/components of the metaheuristic and the structure of the problem to be solved.

The adaptation of an algorithm is based on close cooperation between the programmer and the logistician. So far, it has been presented which data help the programmer to implement an algorithm, but all this is not enough to properly solve a problem without the professional knowledge of the logistician. The task of the logistician is to tell the specifications of the problem, the exact parameter settings, their modification if necessary, and the real operational efficiency of the algorithm based on the accuracy of the results.

In terms of variables, optimization problems can basically be divided into two broad categories: discrete and continuous. Many logistic problems are combinatorial optimization problems, which can usually be traced back to discrete sets, but this does not mean that all combinatorial optimization problems have discrete variables. In light of these, the authors classified logistics problems according to these three categories: combinatorial, discrete and continuous. Metaheuristics were also classified into the same categories in light of the types of problems they have already effectively solved based on the literature. Of course, an algorithm can efficiently solve both continuous, discrete and combinatorial problems, but the authors believe that if an algorithm is able to solve the largest number of combinatorial problems, it is likely that it can be used to solve several other types of combinatorial problems. Some examples are presented below according to the described classification principle.

Problems:

- Continuous Capacity Planning (CLP) – continuous
- Discrete Facility Location Problem (DFLP) – discrete
- Economic Order Quantity (EOQ) – continuous
- Job Scheduling (JS) – combinatorial
- Knapsack Problem (KP) – combinatorial
- Traveling Salesman Problem (TSP) – combinatorial
- Vehicle Routing Problem (VRP) – combinatorial
- Metaheuristics:
- African Buffalo Optimization (ABO): combinatorial [29]
- African Vultures Optimization Algorithm (AVOA): continuous [30], [31], [32], [33]
- Ant Colony Optimization (ACO): combinatorial [34], [35], [36], [37]
- Artificial Bee Colony (ABC): combinatorial [38], [39]
- Artificial Fish Swarm Algorithm (AFSA): continuous, combinatorial [40], [41]

The authors assume that more emphasis should be placed on the nature of the problem when connecting the optimization technique and the problem. This can provide a starting point and help you find the right way to solve the problem. According to their assumption, if an algorithm worked effectively in solving combinatorial problems based on the literature, it is likely that it will also be suitable for solving logistic combinatorial problems. The goal is to determine which of the metaheuristics chosen at random can be suitable for solving a chosen logistics problem. The method is suitable for promoting the industrial use of metaheuristics, because the goal here is not to prove the efficiency and capabilities of an algorithm against other algorithms. The (most) suitable solution method must be found for a given problem.

EFFICACY STUDY

If we compare the problems and metaheuristics presented in the previous chapter, then a possible matching can be the following (Hypothesis 1): Continuous Capacity Planning problem (Eq. 1) can be efficiently solved by the African Vultures Optimization Algorithm (AVOA).

Objective function:

$$\text{Minimize} \int_0^T \left[k_1 \left(P(t) - P(t-1)\right)^2 + k_2\, I(t)^2\right] dt$$

where T is is the planning horizon, k_1 and k_2 are cost coefficients, $P(t)$ is the production rate and $I(t)$ is the inventory level at time t.

In the first step, the previously described technique must be used, i.e. a method capable of solving a Continuous Capacity Planning problem can be adapted based on the information found in scientific works, expert knowledge and the pseudocode and most important operating mechanisms of the selected algorithm.

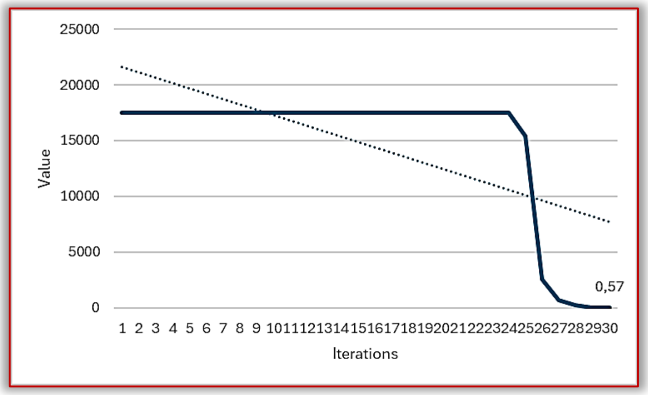

Figure 1: Results of an AVOA–based procedure

A characteristic of metaheuristic procedures is that it is necessary to experiment with the appropriate setting of parameters and different mechanisms. Even in the case examined by the authors, several modifications were needed to obtain acceptable values. Initially, the algorithm did not improve the fitness value above the initial value found in the first iteration. After the modified parameters and mechanisms, the algorithm significantly reduces the fitness value in the first few iterations. However, it converges quickly, suggesting that it is trapped in a local minimum and is not looking any further to find a potentially better global minimum. Further fixes and modifications proved to be successful. Fig. 1 shows that the adaptation was successful. The metaheuristic approach achieved an extremely good result in the 30th iteration. The following can be said about the previous iterations: In the beginning, the algorithm converged quickly, but it successfully got out of the trap of the local minimum and effectively reduced the fitness value in later iterations. This indicates that the parameter modification and the diversity mechanism performed effectively.

CONCLUSION AND FUTURE WORK

Nowadays, the development, usefulness and success of metaheuristic optimization procedures are unquestionable. Hundreds of algorithms have already been developed and demonstrated their success based on various efficiency tests. However, the number of metaheuristics applied to specific, real–world problems and the scientifically acceptable, detailed presentation of solving a real engineering task with metaheuristics are still few. This would require the provision of data and parameters that actually promote practical applicability and adaptability to problems in other areas. The primary goal of the paper was to show how the results of scientific works and industrial practice can be brought closer together.

The authors examined metaheuristic optimization procedures and the possibilities of how they can be adapted and implemented to solve various logistics tasks and problems. It was determined how important it is to have the detailed pseudocode of a metaheuristic and other important parameters and operating mechanisms available in a given paper. With the expert knowledge that can be obtained from scientific works, an optimization procedure can be created, which is able to effectively solve the problem while retaining the special properties of a chosen metaheuristic. It can be concluded that a program written based on AVOA's pseudocode and other parameters performed well in a continuous optimization problem. Of course, there are parameters that can be fine–tuned to achieve even better performance and results, and the efficiency of the algorithm can be gradually improved.

Another result is that a working optimization method can be implemented in practice and is suitable for solving real logistics tasks. With a similar novel classification of logistics tasks and metaheuristics, the authors facilitated the assignment of an optimization technique to a given task. In relation to the parameter settings of the algorithms, it was pointed out how important the contribution of the logistician is during the adaptation of an optimization procedure into practice. With the help of all these, the practical usefulness of the paper contributes to a great degree of promotion of the logistical applicability of metaheuristic algorithms, as well as to bringing empirical theory and industrial practice closer to each other. With the help of the presented techniques, the implementability of an algorithm was facilitated not only in the field of logistics, since the method can be adapted to other fields as well.

Based on the paper, it is clear that there are countless possibilities for further research in the area. Further development and expansion of the methods presented in this work is a primary task for the future. In addition to these, adding additional information to the organization of pseudocodes can contribute to even more effective implementability. A database supplemented with mathematical formulas can also be a defining task of a further research direction.

References

[1] Yang, X.–S., & Karamanoglu, M. (2020). Nature–inspired computation and swarm intelligence: a state–of–the–art overview. Nature–Inspired Computation and Swarm Intelligence, 3–18

[2] Sörensen, Kenneth & Sevaux Marc & Glover, Fred. (2013). A History of Metaheuristics. in R. Martí, P. Pardalos, and M. Resende, Handbook of Heuristics, Springer, 2016. (https://www.researchgate.net/)

[3] Kenneth Sörensen, Fred Glover: Metaheuristcs, Encyclopedia of Operations Research andManagement Science (3e) Springer, New York. (https://www.researchgate.net/publication/237009172_Metaheuristics)

[4] Ezugwu, A.E., Shukla, A.K., Nath, R. et al. Metaheuristics: a comprehensive overview and classification along with bibliometric analysis. Artif Intell Rev 54, 4237–4316 (2021)

[5] Jerry Swan, Steven Adriaensen, Alexander E.I. Brownlee, Kevin Hammond, Colin G. Johnson, Ahmed Kheiri, Faustyna Krawiec, J.J. Merelo, Leandro L. Minku, Ender Özcan, Gisele L. Pappa, Pablo García–Sánchez, Kenneth Sörensen, Stefan Voß, Markus Wagner, David R. White: Metaheuristics “In the Large”, European Journal of Operational Research, Volume 297, Issue 2, 2022, Pages 393–406

[6] Ezugwu, Absalom & Adeleke, Olawale & Akinyelu, Ayo & Viriri, Serestina. (2019). A conceptual comparison of several metaheuristic algorithms on continuous optimization problems. Neural Computing and Applications. 32

[7] Hussain, K., Mohd Salleh, M.N., Cheng, S. et al. Metaheuristic research: a comprehensive survey. Artif Intell Rev 52, 2191–2233 (2019)

[8] Zhongqiang Ma, Guohua Wu, Ponnuthurai Nagaratnam Suganthan, Aijuan Song, Qizhang Luo: Performance assessment and exhaustive listing of 500+ nature–inspired metaheuristic algorithms, Swarm and Evolutionary Computation, Volume 77, 2023, 101248.

[9] Rajwar, K., Deep, K. & Das, S. An exhaustive review of the metaheuristic algorithms for search and optimization: taxonomy, applications, and open challenges. Artif Intell Rev 56, 13187–13257 (2023)

[10] Ali Mohammadi, Farid Sheikholeslam, Intelligent optimization: Literature review and state–of–the–art algorithms (1965–2022), Engineering Applications of Artificial Intelligence, Volume 126, Part D, 2023, 106959

[11] Fister Jr, Iztok & Yang, Xin–She & Fister, Iztok & Brest, Janez & Fister, Dušan. (2013). A Brief Review of Nature–Inspired Algorithms for Optimization. Elektrotehniski Vestnik/Electrotechnical Review. 80(3): 1–7.
[12] Molina, D., Poyatos, J., Ser, J. D., García, S., Hussain, A., & Herrera, F. (2020). Comprehensive Taxonomies of Nature– and Bio–inspired Optimization: Inspiration Versus Algorithmic Behavior, Critical Analysis Recommendations. Cognitive Computation
[13] Brownlee, J. (2011). Clever algorithms: nature–inspired programming recipes. Jason Brownlee
[14] Abdel–Basset, M., Abdel–Fatah, L., & Sangaiah, A. K. (2018). Metaheuristic Algorithms: A Comprehensive Review. Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications, 185–231
[15] Darvishpoor S, Darvishpour A, Escarcega M, Hassanalian M. Nature–Inspired Algorithms from Oceans to Space: A Comprehensive Review of Heuristic and Meta–Heuristic Optimization Algorithms and Their Potential Applications in Drones. Drones. 2023; 7(7):427
[16] Kumar, Neetesh & Singh, Navjot & Vidyarthi, Deo. (2021). Artificial lizard search optimization (ALSO): a novel nature–inspired meta–heuristic algorithm. Soft Computing. 25. 1–23
[17] A. Chandra, C. Natalia and A. Naro "Comparative Solutions of Exact and Approximate Methods for Traveling Salesman Problem", Lámpsakos, no. 25, pp. 1–12., 2021
[18] Golab, Amir & Sedgh Gooya, Ehsan & Falou, Ayman & Cabon, Mikael. (2022). Review of conventional metaheuristic techniques for resource–constrained project scheduling problem. Journal of Project Management. 7. 95–110. 10.5267/j.jpm.2021.10.002.
[19] Kendall, Graham & Bai, Ruibin & Blazewicz, Jacek & De Causmaecker, Patrick & Gendreau, Michel & John, Robert & Li, Jiawei & Mccollum, Barry & Pesch, Erwin & Qu, Rong & Sabar, Nasser & Vanden Berghe, Greet & Yee, Angelina. (2015). Good Laboratory Practice for Optimization Research. Journal of the Operational Research Society. 67. 10.1057/jors.2015.77.
[20] Neshat, M., Sepidnam, G., Sargolzaei, M. et al. Artificial fish swarm algorithm: a survey of the state–of–the–art, hybridization, combinatorial and indicative applications. Artif Intell Rev 42, 965–997 (2014)
[21] Teodorović, D. (2009). Bee Colony Optimization (BCO). Studies in Computational Intelligence, 39–60
[22] Zebari, Amar & Almufti, Saman & Abdulrahman, Chyavan. (2020). Bat algorithm (BA): review, applications and modifications. International Journal of Scientific World. 8. 1
[23] Weiguo Zhao, Liying Wang, Seyedali Mirjalili: Artificial hummingbird algorithm: A new bio–inspired optimizer with its engineering applications, Computer Methods in Applied Mechanics and Engineering, Volume 388, 2022, 114194.
[24] Agárdi, A.; Nehéz, K.; Hornyák, O.; Kóczy, L.T. A Hybrid Discrete Bacterial Memetic Algorithm with Simulated Annealing for Optimization of the Flow Shop Scheduling Problem. Symmetry 2021, 13, 1131
[25] Pedro Coelho, Cristovão Silva: Parallel Metaheuristics for Shop Scheduling: enabling Industry 4.0 Procedia Computer Science 180 (2021) 778–786
[26] Farshid Keivanian, Raymond Chiong: A Novel Hybrid Fuzzy–Metaheuristic Approach for Multimodal Single and Multi–Objective Optimization Problems Expert Systems with Applications Available online 16 November 2021, 116199
[27] Robert Pellerin, Nathalie Perrier, François Berthaut: A survey of hybrid metaheuristics for the resource–constrained project scheduling problem European Journal of Operational Research 280 (2020) 395–416
[28] Faeq, I.F. & Duaimi, Mehdi & Sadiq, Ahmed. (2018). An efficient artificial fish swarm algorithm with harmony search for scheduling in flexible job–shop problem. Journal of Theoretical and Applied Information Technology. 96. 2287–2297.
[29] Julius Beneoluchi Odili, Mohd Nizam Mohmad Kahar, Shahid Anwar: African Buffalo Optimization: A Swarm–Intelligence Technique, Procedia Computer Science, Volume 76, 2015, Pages 443–448
[30] Benyamin Abdollahzadeh, Farhad Soleimanian Gharehchopogh, Seyedali Mirjalili: African vultures optimization algorithm: A new nature–inspired metaheuristic algorithm for global optimization problems, Computers & Industrial Engineering, Volume 158, 2021, 107408
[31] R. Ghafari, N. Mansouri: E–AVOA–TS: Enhanced African vultures optimization algorithm–based task scheduling strategy for fog–cloud computing, Sustainable Computing: Informatics and Systems, Volume 40, 2023, 100918
[32] V Rajaguru, K Iyswarya Annapoorani: Virtual synchronous generator based superconducting magnetic energy storage unit for load frequency control of micro–grid using African vulture optimization algorithm, Journal of Energy Storage, Volume 65, 2023, 107343
[33] Ahmed A. Zaki Diab, Mohamed A. Tolba, Ali M. El–Rifaie, Kotin A. Denis: Photovoltaic parameter estimation using honey badger algorithm and African vulture optimization algorithm, Energy Reports, Volume 8, Supplement 10, 2022, Pages 384–393
[34] S.K. Chaharsooghi, Amir H. Meimand Kermani: An effective ant colony optimization algorithm (ACO) for multi–objective resource allocation problem (MORAP), Applied Mathematics and Computation, Volume 200, Issue 1, 2008, Pages 167–177
[35] Junguo Cui, Lei Wu, Xiaodong Huang, Dengpan Xu, Chao Liu, Wensheng Xiao: Multi–strategy adaptable ant colony optimization algorithm and its application in robot path planning, Knowledge–Based Systems, Volume 288, 2024, 111459
[36] Hongguang Wu, Yuelin Gao: An ant colony optimization based on local search for the vehicle routing problem with simultaneous pickup–delivery and time window, Applied Soft Computing, Volume 139, 2023, 110203
[37] Rafał Skinderowicz: Improving Ant Colony Optimization efficiency for solving large TSP instances, Applied Soft Computing, Volume 120, 2022, 108653
[38] Syed Fawad Hussain, Adeel Pervez, Masroor Hussain: Co–clustering optimization using Artificial Bee Colony (ABC) algorithm, Applied Soft Computing, Volume 97, Part B, 2020, 106725
[39] Dervis Karaboga, Celal Ozturk: A novel clustering approach: Artificial Bee Colony (ABC) algorithm, Applied Soft Computing, Volume 11, Issue 1, 2011, Pages 652–657, ISSN 1568–4946
[40] Bin Sun, Tong Guo: A physics–informed artificial fish swarm algorithm for multiple tunnel fire source locations prediction, International Journal of Thermal Sciences, Volume 199, 2024, 108939
[41] Genrang Zheng, ZhengChun Lin: A Winner Determination Algorithm for Combinatorial Auctions Based on Hybrid Artificial Fish Swarm Algorithm, Physics Procedia, Volume 25, 2012, Pages 1666–1670

ISSN: 2067-3809