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REVIEW OF NATURE-INSPIRED OPTIMIZATION ALGORITHMS APPLIED IN CIVIL ENGINEERING

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Abstract: Nature has always been an example of perfection and inspiration. In nature, everything has reasons why it is happening exactly the way it does. Nature-inspired optimization algorithms have become a rapidly growing area of research in all areas of life. Ant colonies find the shortest path to food, the evolution of the living world shows adaptation to the world around it. For example, bees find the optimal path to food and back to the hive. Optimization algorithms contribute significantly to solving many complex issues and achieving optimal results. This research paper outlines nature-inspired optimization algorithms, such as ant colonies, artificial immune systems, artificial neural networks, flocks of bats, bee swarms, firefly algorithms, genetic algorithms, and particle swarms. The purpose of this brief overview is to provide an easy-to-understand list of the basic features of the most common nature-inspired optimization algorithms as well as the potential applications of the aforementioned algorithms in civil engineering.

Keywords: algorithm; civil engineering; heuristics; nature-inspired; optimization

PREGLED OPTIMIZACIJSKIH ALGORITAMA NADAHNUTIH PRIRODOM, PRIMIJENJENIH U GRAĐEVINARSTVU

Sažetak: Priroda je oduvijek bila primjer savršenosti i nadahnuća. Sve što se događa u prirodi, događa se na taj način s određenim razlogom. Prirodom nadahnuti optimizacijski algoritmi postaju brzo rastuće područje istraživanja u svim područjima života. Kolonije mrava pronalaze najkraći put do hrane, evolucija živog svijeta pokazuje prilagođavanje svijetu koji ga okružuje, pčele pronalaze optimalan put do hrane i natrag do košnica itd. Optimizacijski algoritmi daju veliki poticaj za rješavanje mnogo složenih problema te pronalaženje optimalnog rezultata. U ovom radu, ukratko će se prikazati prirodom inspirirani optimizacijski algoritmi kao što su kolonije mrava, umjetni imunološki sustav, umjetne neuronske mreže, jato šišmiša, roj pčela, algoritam krijesnica, genetski algoritam i roj čestica. Svrha ovog kratkog pregleda je dati lagano shvatljivi popis te osnovne karakteristike najčešćih optimizacijskih algoritama koji imaju nadahnuće u prirodi te moguću primjenu prethodno navedenih algoritama u građevinarstvu.

Ključne riječi: algoritam; građevinarstvo; heuristike; prirodom nadahnuti; optimizacija

1 INTRODUCTION

Nature is a great source of inspiration in the development of intelligent systems, and it also enables the solution of complex problems [1]. This is why so many researchers are attracted to nature. The algorithms developed with inspiration from nature are known as nature-inspired algorithms. Nature-inspired algorithms (also known as biological systems) have become very popular because of their ability to adapt to any changing environment [2]. Further, nature-inspired algorithms have gained popularity in the optimization of complex problems [3] because optimization problems in the real world are often very challenging to solve [4]. An optimization problem consists of maximization or minimization of a function in relation to a set, which represents the possibility of available choices in a given situation. The function allows the comparison of different choices, so that one can decide which choice might be the best [5].

To solve optimization problems that are very difficult to solve, complex and "fuzzy" (they cannot be well-formulated mathematically) [6] heuristic and metaheuristic techniques (algorithms) are used. Heuristic techniques can be used to solve a wide variety of optimization problems [7]. The term "heuristic technique" implies any technique that is used to find a specific acceptable solution to the observed problem. However, the solution found does not have to be optimal, but must be permissible, and it is considered that such a technique can find a solution much quicker than if the exact solution is sought using some other technique. Moreover, if there is more than one solution, heuristic methods are used to find only some of these solutions, but not all possible solutions. Hence, heuristic methods seek the balance between optimality, completeness, and accuracy of a solution on one hand and the time of execution on the other hand. The quality of a specific heuristic method used depends on the above-mentioned factors [8]. Heuristic methods that are not specially designed for a particular problem, but are, with certain adaptations, applicable to a large number of problems, are called metaheuristic methods [8]. In addition, as extensions to main heuristic methods, hyperheuristic and stochastic techniques are known [7]. The term "metaheuristics" was first coined by Glover in 1986 [9].

A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms. The term is also used to refer to a problem-specific implementation of a heuristic optimization algorithm according to the guidelines expressed in such a framework [10]. Most heuristic and metaheuristic methods (if not all of them) are listed in the paper authored by Venkrbec, Galić, and Klanšek [7] and in the paper authored by Fister et al. [4] Therefore, for the purpose of further study, it is advisable to read the two aforementioned papers. The described heuristic and metaheuristic methods are used to solve real-world optimization problems, the so-called NP-hard problems. To solve such problems, optimization techniques should be used, though there is no guarantee that the optimal solution can be obtained. In fact, for NP-problems, there are no efficient algorithms at all [4].

Optimization is applicable and useful in many areas of human life. Obviously, the goal of an optimization can vary, such as minimizing energy consumption and costs, maximizing profit, minimizing the project completion time, minimizing risk, maximizing the effects of a machine. As resources, time, and money are always limited in real life, our job is to find solutions that optimally use these valuable resources under different conditions [11].

Generally, an optimization algorithm is an iterative process, starting from some initial assumption. After a certain (sufficiently large) number of iterations, the solution begins to converge towards a stable solution, ideally the optimal solution of the observed problem [12-14]. In essence, an algorithm is a set of symbols and a general procedure, which explains how to solve a task stepwise. Many algorithms are of iterative nature. Correct steps and procedures depend on the algorithm used and the area of interest [11]. Among nature-inspired algorithms, a special type of algorithm has been developed with inspiration by swarm intelligence (SI). Algorithms based on SI are among the most popular ones [4]. SI is the collective behavior of natural or artificial decentralized, self-organizing systems. SI systems are usually made of populations of simple agents (particles) that communicate with each other and with their environment [15]. To find the optimum solution in the solution space for each particle, particle swarm optimization (PSO) allows the particles to communicate; each particle that is a candidate for the solution seeks an optimal solution simultaneously using mutual interaction and cognitive knowledge [16-18].

The rest of this paper provides the selected nature-inspired optimization algorithms, some of which are more or less known. The main objective of this paper is to provide a list of some (more frequent) optimization algorithms, their possible application in civil engineering, and the most basic characteristics thereof, without elaborating on any of them, because the length of such a paper would exceed the expected length of a review paper. Moreover, one of the main goals of this paper is to familiarize potential users with optimization algorithms and to arouse their interest encouraging them to use the algorithms to a greater extent as compared to their present use.

2 SELECTED NATURE-INSPIRED OPTIMIZATION ALGORITHMS

2.1 Ant colony optimization

Ant colony optimization (ACO) is a method inspired by natural systems [19, 20]. The ACO algorithm is based on the hypothetical behavior of an ant collective when the ants are looking for food [21-23]. If there are no available traces of pheromones, the ants move randomly. However, if the pheromones are present, the ants follow the trace of the pheromones [24]. During their search for food, the ants secrete pheromones in order to mark their path, but the pheromones evaporate over time. In nature, ants use the shortest path to reach their colony as quick as possible, so this (the shortest, i.e., the fastest) path is marked by a higher concentration of pheromones. This path serves as bait for other ants, and over time all ants from a specific colony choose this optimal (shortest) path [21-23]. The amount of released pheromones is proportional to the quality of the solution, which affects the probability that other ants will use the components (portions) of that solution in creating their own, personal solution. This contributes to the global search for a solution in the ACO algorithm [25].

The key to the success of the ACO is in its construction of new solutions [26]. The ACO algorithm was first introduced by Dorigo et al. in the 1990's [27, 28]. ACO algorithms are shown to be effective problem-solving strategies for a wide range of problem domains, including multiple-objective optimization [29].

2.2 Artificial immune system

The natural immune system is a complex system adapted to the identification of pathogens, foreign microorganisms. It protects the body from various foreign pathogens such as bacteria or viruses [30-32]. One of the main purposes of the immune system is to keep the organism healthy [33]. An artificial immune system (AIS) appeared in the 1990's as a new branch in computational (artificial) intelligence. AISs are inspired by immunology, the immune function, and principles observed in nature [32, 34, 35]. AISs mimic biological principles of clone generation, proliferation, and maturation. The main steps of AISs based on the clonal selection principle are the activation of antibodies, proliferation, and differentiation on the encounter of cells with antigens, maturation by carrying out the affinity maturation process, elimination of old antibodies to maintain the diversity of antibodies and to avoid premature convergence, and selection of those antibodies whose affinities with the antigen are greater [36].

The field of AISs is a diverse area of research, which bridges the disciplines of immunology and engineering. AIS algorithms are typically developed from the abstraction of immune system theories, processes, and agents, and they are applied to a wide variety of engineering applications including computer security, fault tolerance, data mining [37] and optimization [37-39].

2.3 Artificial neural network

An artificial neural network (ANN) can be described as a massive, parallel, distributed data-processing system that consists of simple elements and has a natural tendency to store experiential knowledge, which can be used later, and is similar to the brain in the way it acquires and stores knowledge [40, 41]. The study of neural networks was started by the publication by McCulloch and Pitts [42]. In their work [42], they created a computational model for neural networks based on mathematics and algorithms called threshold logic. Single-layer networks, with threshold activation functions, were introduced by Rosenblatt. These types of networks are called perceptrons. In the 1960's, it was experimentally shown that perceptrons could solve many problems, but many problems, which did not seem to be more difficult, could not be solved. Neural networks make an attempt to simulate the human brain [43].

In 1986, a group of three authors described a new learning procedure, back-propagation, for networks of neuron-like units [44]. ANNs offer an alternative to classic computation for the real-world problems that use natural knowledge (which may be uncertain, imprecise, inconsistent, and incomplete) and for which the development of a conventional program that covers all possibilities and eventualities is unlikely or at least very laborious and expensive [45].

2.4 Bat algorithm

Bat algorithms (BAs) belong to a class of SI algorithms [46, 47]. The BA was developed by Yang [48, 49]. BAs are based on the echolocation behavior of microbats [49, 50] with varying pulse rates of emission and loudness. A multi-objective BA was developed to solve design optimization problems such as welded beam design problems [51]. Bats use a type of sonar, the so-called echolocation, to detect their prey, avoid obstacles, and locate cracks where they live in the dark. Bats emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects [51, 52]. During roaming, microbats emit short pulses; however, when a potential prey is nearby, their pulse emission rates increase and the frequency is tuned up [49]. They have the ability to automatically adjust the wavelength or frequency of the pulses, and can automatically control the degree of pulse transmission depending on the distance between them and the prey [52, 53]. The increase of the frequency, namely frequency-tuning, together with the speedup of the pulse emission shortens the wavelength of echolocations and thus increases the detection accuracy [49].

BAs are successfully applied to a number of very different problems such as large-scale optimization problems [54, 55], multi-objective optimization [51], economic load and emission dispatch problems, data mining [54], etc.

2.5 Bee colony optimization

Teodorović et al. developed a method of bee colony optimization (BCO) [56-58]. The basic idea of BCO is to create a colony of artificial bees that will be able to solve difficult combinatorial optimization problems effectively. A swarm of artificial bees is flying in the space of possible solutions, seeking possible, favorable solutions. Each bee generates one solution to the problem. In order to find good solutions, artificial bees cooperate and exchange information [59, 60]. Using collective knowledge and sharing information between themselves, bees concentrate on better solution spaces and slowly leave worse solutions [61]. Artificial bees create and improve their solutions together [59]. The BCO algorithm, based on the principles of SI [62, 63], provides excellent, promising results for solving complex engineering problems [57].

BCO has many applications in several different fields. One of the most interesting applications is the training of neural networks [64]. BCO was also used by some researchers for solving discrete optimization problems in the design of trusses [64, 65], for minimizing the weight of lattice structures [56], etc.

2.6 Firefly algorithm

In the firefly algorithm (FA or also called FFA), the objective function of a given optimization problem is based on differences in light intensity. It helps fireflies to move towards brighter and more attractive locations in order to obtain optimal solutions [66]. In the FA, there are two important variables: light intensity and attractiveness [67]. The movement of a firefly is determined by a brighter firefly (than itself) to which it is attracted [67, 68].

Multiple fireflies are randomly distributed in the whole search space, and all fireflies have their light intensity, corresponding to the fitness value of the optimization problem. Then each individual flies following the firefly with higher light intensity in its visual range. After multi-iterations, all individuals gather around the best firefly, which represents the final optimization [69]. The FA is a swarm-based metaheuristic algorithm introduced by Yang [70-72].

2.7 Genetic algorithm

The genetic algorithm (GA) is an algorithm based on natural selection and mechanisms of population genetics [73]. It was proposed (invented) by Holland in the early seventies [74, 75]. The GA is a stochastic technique to find a solution that mimics the principles of natural genetics [76, 77]. The GA is inspired by biological evolution, Charles Darwin's theory of natural evolution [78], which uses propagation, random mutation, genetic diversity, and natural selection [79]. This algorithm reflects the process of natural selection where the best individuals are selected for breeding to give offspring in the next generation [72].

The advantage of the GA compared to conventional solution-searching techniques is that it starts with an initial set of random solutions of the named populations. Each individual in the population is called a chromosome, and represents a solution to a problem [77].

2.8 Particle swarm optimization

Particle swarm optimization (PSO) is one of the most popular nature-inspired optimization algorithms because of its simplicity and ease of use [80, 81]. This algorithm is inspired by the movement of birds and fish in their groups, i.e., the social behavior of feeding birds and fish [82, 83]. PSO solves optimization problems through a series of searches performed by a group of individuals [82, 84]. In PSO, potential solutions, called particles, fly through the space, in which a solution to a problem is searched by following the current optimal particle [85].

In nature, there is always a leader (the main bird or fish) that leads a flock of birds or fish. PSO is successfully applied in many areas such as optimization of functions, training of ANNs, system control, optimization of time and cost in project execution, etc. [85].

Table 1 lists some of the main characteristics (including the algorithm name and its abbreviation, the source of inspiration, and its authors, year, and reference) of the aforementioned nature-inspired algorithms.

Table 1 Short list of the selected nature-inspired algorithms in alphabetical order

Algorithm	Inspiration	Authors	Year	Reference
Ant colony optimization, ACO	behavior of ant colonies	Colorni, Dorigo, and Maniezzo	1991	[28]
Artificial immune system, AIS	human immune system function	Kephart	1994	[86]
Artificial neural network, ANN	biological neural networks and brain	McCulloch and Pitts	1943	[42]
Bat algorithm, BA	echolocation behavior of microbats	Yang	2010	[48]
Bee colony optimization, BCO	bees' foraging principles	Lučić and Teodorović	2001	[58]
Firefly algorithm, FA or FFA	flashing characteristics of fireflies	Yang	2010	[70]
Genetic algorithm, GA	natural mechanisms of population genetics	Holland	1975	[75]
Particle swarm optimization, PSO	social behavior of feeding birds and fish	Kennedy and Eberhart	1995	[82]

3 APPLICATION OF NATURE-INSPIRED OPTIMIZATION ALGORITHMS IN CIVIL ENGINEERING

The applications of nature-inspired optimization algorithms in civil engineering are widespread. Civil engineering is a professional engineering discipline, which deals with the design, construction, and maintenance of physical and naturally built environments, including houses, skyscrapers, canals, bridges, dams, airports, sewerage systems, pipelines, roads and railways, schools, hospitals, etc. [87, 88].

This section will provide a brief overview of some potential applications of nature-inspired optimization algorithms in the field of civil engineering. The names of specific algorithms, studied problems, main findings and conclusions, and their origin are shown in alphabetical order (of algorithms) in Table 2.

To keep the overview as recent as possible and of an appropriate length (not too long), it will be limited to the time period from 2010 to onward. In addition, approximately five applications will be provided for each nature-inspired algorithm found in the available literature.

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Table 2 List of the selected nature-inspired algorithms and some of applications in civil engineering

Algorithm	Studied problem	Main findings and conclusions	Origin
Ant colony optimization, ACO	optimal design of storm sewer networks	The applicability and efficiency of ACO in the studied problem are excellent. The used methods are shown to be very effective in locating the optimal solution and in terms of the convergence characteristics of the resulting algorithms.	[89]
	efficient routing of piping networks	ACO provides a powerful means of performing network optimization through the shortest-path calculations, as it is able to construct the shortest-path solutions efficiently. Moreover, ACO exhibits quick convergence to the final solution.	[90]
	performance-based optimal seismic design of frame structures	The results obtained indicate that the ACO algorithm can find the optimum seismic design of structures successfully.	[91]
	determination of the ultimate bearing capacity of shallow foundations on granular soil	The algorithm will find wide application in the calculation of the ultimate bearing capacity of foundations.	[92]
	solving the stochastic time–cost trade-off optimization problem	The model attempts to minimize the time and cost of a project as two objectives. The results show that the algorithm is adequately reliable.	[93]
	decision-support system for construction time–cost optimization	The results show that the model based on the ant colony system techniques can generate better solutions without utilizing excessive computational resources. The model provides an efficient means to support planners and managers in making better time–cost decisions efficiently.	[94]
	optimization of the pumping schedule in water distribution networks	The optimization results showed that the proposed heuristic approaches considerably improved the quality of solutions and enhanced the navigation of the optimization process.	[95]
Artificial immune system, AIS	flexible job-shop scheduling problem	The proposed algorithm was tested on 162 benchmark problems and results showed that the presented algorithm is effective in overcoming those problems.	[31]
	project scheduling problem under resource constraints	The computational results show that the proposed algorithm has competitive results of solving real-world problems compared to the existing benchmark algorithms.	[96]
	analysis of structural integrity of a building	The results obtained using the present method are efficient, robust, and accurate. The paper presented a new method to analyze failures in structures.	[97]
	structural health monitoring (SHM)	The high success rate shown by this approach has great potential for SHM tasks. The results showed that the proposed AIS could reach a relatively high accuracy with limited training antigens.	[98]
Artificial neural network, ANN	methodology for determining the execution time and cost of earthworks	The results presented in the paper confirm the fact that trained ANNs can be used in designing earthwork organization in construction to determine the time necessary to carry out earthworks and to calculate the costs involved.	[99]

	determination of the ultimate bearing capacity of shallow foundations on granular soil	The algorithm will find wide application in the calculation of the ultimate bearing capacity of foundations.	[92]
	damage identification in civil engineering structures	Compared with modal-based approaches, the used method requires much less post-processing of the recorded data. Especially, there is no need for manual processing, which makes the developed method more suitable for on-line health monitoring.	[100]
	energy analysis of a building	Results presented in this paper confirm the potential of ANNs as a design tool in many areas of building service engineering.	[101]
	measuring and predicting construction-labor productivity	A model for measuring and predicting labor productivity in construction projects was developed by utilizing ANNs. The developed model was successful.	[102]
	calibration of a microsimulation traffic model	Presented results clearly show that a neural network is not an alternative to a microsimulation model. The neural network accurately predicted the traveling time, but not the queue parameters.	[103]
Bat algorithm, BA	capacitated vehicle routing problem (CVRP)	In this paper, a hybrid BA with path relinking for solving the CVRP was presented. Results show that the methodology is able to provide fine-quality solutions, which can compete with the ones provided by some exact and heuristic approach.	[104]
	layout optimization of steel frames with steel plate walls	The results reveal the effectiveness of the proposed method for optimization of steel frames with steel plate walls.	[105]
	size optimization of skeletal structures consisting of truss and frame structures	Results presented in the paper show the suitability and efficiency of the present algorithm for optimal design of skeletal structures.	[106]
	optimum design of large-scale truss structures	The paper presents an improved BA for optimizing large-scale structures. The capability of the algorithm is examined by comparing the resulting design parameters and structural weight with those of other methods from the literature.	[107]
Bee colony optimization, BCO	production scheduling for dispatching ready-mixed concrete (RMC) trucks	The experimental results showed that the BCO approach can quickly generate efficient and flexible solutions to dispatch RMC trucks. Furthermore, the obtained results had higher quality solutions and faster computational time than those obtained from the conventional approaches.	[108]
	job-shop scheduling problems	In this study, three modifications of BCO are proposed, i.e., global evolution of some bees, dynamic parameters of the colony, and special treatment of the best bee. The computer simulation shows that the modified BCO performs quite better than the BCO for some job-shop scheduling problems.	[109]
	transit network design	The numerical experiments are performed on known benchmark problems. The approach, based on the BCO algorithm, is competitive with other approaches in the literature, and it can generate high-quality solutions.	[59]

Firefly algorithm, FFA	optimal design of truss structures	Numerical results indicate the robustness and efficiency of the proposed method in the optimum design of truss structures.	[110]
	determining the optimum design of tower-shaped structures	This method is effective in improving the convergence and also suitable for expensive optimization tasks such as large-scale structures. Three tower structures are selected to evaluate the performance of the algorithm. The results are better than other results proposed in the literature and confirm the validity of the proposed algorithm.	[111]
	optimization of queueing systems	In this paper authors have tested FFA to the multiobjective maximization problem of cost function. The FFA is a very powerful technique used to solve the problems of queueing system optimization.	[66]
	shape and size optimization of truss structures considering dynamic constraints	FFA could find the optimal solution in a relatively short computational time. For the tested examples, considering the same number of iterations, harmony search (HS) found the optimal solution in a slightly shorter time than FFA; however, in all cases, FFA found solutions slightly better than HS.	[112]
	minimum weight design of new-generation steel beams with sinusoidal openings	The results obtained by the application of firefly search algorithms demonstrate that new-generation sinusoidal steel beams produce a more cost-effective solution than other two beams as a result of their sleek, transparent, and flexible geometry, and they increase the efficacy of the relation capacity.	[68]
Genetic algorithm, GA	optimum cost of prestressed and reinforced concrete beams	The comparison showed that the GA models were efficient in moving towards the beam optimum cost.	[113]
	optimization model for generating optimal schedules for repetitive projects	A GA optimization model was developed for generating optimal schedules for repetitive projects. This developed model is capable of offering valuable support to project team members in minimizing the overall cost of the project.	[114]
	optimization design of high-performance concrete	The GA could reduce the cost, save the energy, and provide better use value in the engineering practice.	[115]
	overall cost optimization of prestressed concrete (PC) bridges	It is concluded that the GA can be effectively used in the overall cost optimization of PC bridges.	[116]
	multi-objective optimization for scheduling a multi-storey building	The developed model enables construction planners to generate, from a set of feasible alternatives, optimal/near-optimal construction plans that minimize project duration, number of synchronized crews, and crew work interruptions. The transparency of the model and its versatile performance will hopefully encourage project managers to utilize it in the planning of repetitive projects.	[117]
	construction project schedule	In this paper, the authors demonstrate a novel approach of retrieving enough information from the building information model (BIM) of a project and then develop construction sequencing for the installation of the project elements.	[118]

Particle swarm optimization, PSO	multi-objective construction site layout planning	The evaluation indicates that the proposed model provides effective and rational solutions, in response to decision parameters and problem constraints, and that it results in more robust layout planning than previous methods both qualitatively and quantitatively.	[119]
	structural truss mass optimization on size and shape with dynamic constraints	The results show that the particle swarm algorithm performed similar to other methods and even better in some cases.	[120]
	beam-slab layout design problems	The results from the example problem show the validity of the proposed algorithm. PSO can be a good alternative to the GA for solving the beam-slab layout design problem.	[121]
	optimum design of unbraced steel frames to load and resistance factor design, American Institute of Steel Construction	The efficiency of the algorithm is demonstrated considering a number of design examples, and it is satisfactory.	[122]
	determination of optimum time and costs	The PSO method can be successfully used for optimizing the realization of construction projects. The use of this method is recommended for optimization of global critical path diagrams for projects with smaller number of project-significant activities.	[81]
	PSO-trained neural network for structural failure prediction of multistoried reinforced concrete (RC) buildings	The work proposed a PSO-based approach to train a neural network (NN). PSO is employed to find the weight vector with the minimum root-mean-square error for the NN. The experimental results established the dominance of the proposed model for detecting the structural status of a multistoried RC building structure.	[123]

4 SUMMARY AND CONCLUSION

In this paper, the following optimization algorithms are briefly presented: ACO, AIS, ANN, BA, BCO, FFA, GA, and PSO. The purpose of an optimization is to find the best, optimal, solution to a specific observed problem, meaning a solution that will mostly satisfy the conflicting objectives. Nature-inspired optimization algorithms help to solve many complicated problems we face in real life. The common feature of all the aforementioned algorithms is that they are inspired by the behavior of the living world in nature, such as ants and bees, which find the shortest path to food and back to the nest, and then the functioning of the immune system, etc.

In the above-mentioned work (Section 2), the intention was to explain the basic concept of the optimization algorithms as briefly as possible, whereas for the further study, it is recommended to use the references listed in the bibliography section at the end of this paper. Section 3 provides an overview of the potential applications of nature-inspired algorithms in civil engineering. Papers related to the selected algorithms, found in the period from 2010 until now, are briefly presented. As they clearly show, each subsequent year brought new metaheuristics, and the existing metaheuristics are improved every year. However, it is important to emphasize that the development and improvement of metaheuristics come with the necessity to preserve the simplicity of their operational principles. One of the aims of this paper is to fill in the void that is present in the literature regarding the application of nature-inspired algorithms in civil engineering.

In addition, the purpose of this overview is to inform the readers about nature-inspired optimization algorithms and to arouse their interest in further research of this topic. The potential users should be more thoroughly introduced into nature-inspired algorithms and their potential applications, not only in the field of civil engineering, but in all areas of human activity. Artificial intelligence and the related technologies (including optimization algorithms) are changing every day, and as computers become more popular and more advanced, the use of optimization algorithms is expected to increase in all areas of human life, as well as in civil engineering.

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