Article

Application of Evolutionary Artificial Intelligence. An Exploratory Literature Review

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Received: 01 May 2022
Accepted: 11 June 2022
Online: 31 August 2022

Abstract. Evolutionary processes found in nature are of interest to developers and practitioners of artificial intelligence because of the ability to optimize, detect, classify, and predict complex man-made processes. Evolutionary artificial intelligence (EAI) is examined from various perspectives to evaluate the main research directions and the trend of the decade. Co-occurrence networks were used to visualize data and find key sub-themes in a dataset consisting of article titles. The literature review covers the following aspects of EAI applications: methods, detection, data, approach, and colony. The resulting co-occurrence networks show a huge increase in diversity in research methods, data and function application possibilities, and approaches. Although simulating the behaviour of colonies is not as popular as it was a decade ago, the scope of applications for known algorithms has not been diminished.

JEL: C6; C8.

Keywords: colony; co-occurrence network; detection; differential evolution; evolution; multi-objective optimization; swarm intelligence.

Citation: Nijole Maknickiene (2022) Application of Evolutionary Artificial Intelligence. An Exploratory Literature Review. – *Applied Business: Issues & Solutions* 1(2022)22-31 – ISSN 2783-6967.
https://doi.org/10.57005/ab.2022.1.4

Introduction

The advent of programming languages has created new opportunities for human expression and communication with machine. Mathematical logic can be supplemented by logic created from nature using programming language operators, loops, objects, and so on. Evolutionary processes in nature characterize change in the heritable characteristics of biological populations over successive generations and ensure biodiversity. Why did nature choose such a goal? Why not copy/paste? It would be a simple algorithm to replicate the most perfect population and its behaviour; in an ever-changing world, however, a biological species must adapt to survive. Imitation of evolution by artificial intelligence is the main object of investigation.

The purpose of this article is to classify and evaluate different aspects of simulating evolutionary processes in scientific articles of the Scopus database [1]. One database contains not all scientific works on a certain topic, but rather the unified management of the bibliography of articles; the search system provides equal opportunities for selected articles to enter the author's field of interest. The first section of this paper discusses the methodology of finding main aspects in certain topic of articles. Text analysis and co-occurrence network algorithms are used for analysis and visualization. The second section describes the data found in the Scopus database. The data includes the titles of articles from 2021–2022 in the Scopus database, sorted by keywords 'application', 'evolutionary', 'artificial', 'intelligence'. This data was compared with data from 2011–2012 with the aim of identifying trends in scientific research topics. The third section includes a literature review from five different perspectives.

1. Application of textual analysis to review

For exploratory literature review, we selected a co-occurrence network [2]; this visualisation method is typically used for investigation of social networks. Research directions, processes and changes are also analysed using the networks. Notably, Rajita et al. [3] used machine learning to explore the collaborative relationships among researchers with the goal of predicting changes in research topics. Classical collaborative distance (CCD) and refined classical collaborative distance (RCCD), together with other community-specific estimates, are sufficiently accurate predictors of change in studies. Networks of co-authorship of researchers in different disciplines were drawn by Newman [4]; Zhang et al. [5] analysed the ethical issues of artificial intelligence using the co-authorship network method. An article by Elmsili and Outtaj [6] inspired us to use co-occurrence networks to select scientific papers on evolutionary artificial intelligence for review.

Titles of articles during the two periods were taken for the study with the aim of visualizing trends in selected research aspects. The algorithm organizes the text, removes stop words, and creates a bag-of-word matrix using a model. This action allows us to assign certain numerical characteristics to words, such as the frequency of repetition of the word. Counting word co-occurrence estimates relationships between words. Graphs model relationships between words visually: nodes are assigned to words, and edges are assigned to connections. The strength of the connection between the nodes is determined by the weight and thickness of the line. The code presents a limited number of nodes and connections in the final visualization because the comprehensive graph is too confusing and uninformative, so it allows the user to select a keyword in the set and find its neighbours.

2. Overview of data used in the study

We selected articles exclusively from the Scopus database [1] for review to ensure that the data would be selected and classified in the same way. For 2011–2012, the database returned 260 articles; for 2021 and approximately the first half of 2022, it returned 206

Table 1. Distributions of articles according to scientific field.

Scientific Field	Part, % 2011–2012	Part, % 2021–2022
Computer Science	49	35
Mathematics	23	15
Engineering	15	26
Decision Sciences	2	5
Biochemistry, Genetics, Molecular Biology	2	4
Energy	2	3
Social Sciences	2	4
Agriculture and Biological Sciences	1	1
Environmental Sciences	1	3
Physics and Astronomy	1	5

articles by selected keywords: *application*, *evolutionary*, *artificial*, *intelligence*. The distribution of articles by assigned topics is presented in Table 1. The last ten years have seen an expanded application of Evolutionary Artificial Intelligence (EAI) in a variety of fields. Ten years ago, research was more focused on computer science, mathematics, and engineering, whereas in recent years, application in almost all other fields of science has doubled. This trend indicates that newly developed models of EAI are being successfully applied in various fields.

Evolution represents the term that describes the unique object of a selected article that unites all aspects of Evolutionary Artificial Intelligence. The network of titles of scientific articles (Fig. 1) obtained by Matlab code [2] revealed that the centre contains nodes with higher weights close to the keywords: *evolution* (52), *intelligence* (31), *based* (30), *artificial* (26). Important nodes are found farther from the centre: *differential* (26), *method* (20), *detection* (24), *research* (23), *analysis* (20), *data* (20), *optimization* (20), *colony* (12), *approach* (17).

In addition to the most popular words in the centre, Fig. 1 shows three larger and two smaller wings of word combinations, each representing different aspects of the topic.

1. The first large group covers method and is mostly related to the word 'differential'. It is easy to infer that many scientists are developing new (or improving upon known) methods of evolutionary artificial intelligence (EAI). The differential evolution method is one of the most popular in this field.
2. The second large group combines articles with 'feature' and 'detection'. EAI is usually associated with optimization, so detection is an interesting area of research.
3. The third large group of articles is related to 'date', 'research' and 'analysis'. Data is used in every study, but in recent years new aspects of data use, security and analysis have emerged.
4. The first smaller group deals with 'approach'. This finding was surprising and made us look at EAI as a heuristic or even meta-heuristic application.
5. The second smaller group is related to 'optimization' and 'colony'. This aspect is closely related to the imitation of evolutionary processes in nature.

The resulting network became the basis for the structure of the literature analysis. It is important to note that in the initial phase of the study, more word networks were obtained with the keywords 'application', 'evolutionary', 'artificial', 'intelligence' and others. The information in these networks is interesting, but it remains insufficiently clear.

3. Literature review

3.1. Methods

Co-occurrence network by the word 'methods', presented in Fig. 2, clearly shows that in ten years, the variety of application of methods has expanded significantly. Thicker lines in the 2011–2012 graph show two popular methods: differential evolution and ant colony optimization; in 2021–2022, more methods are used, which already need to be classified.

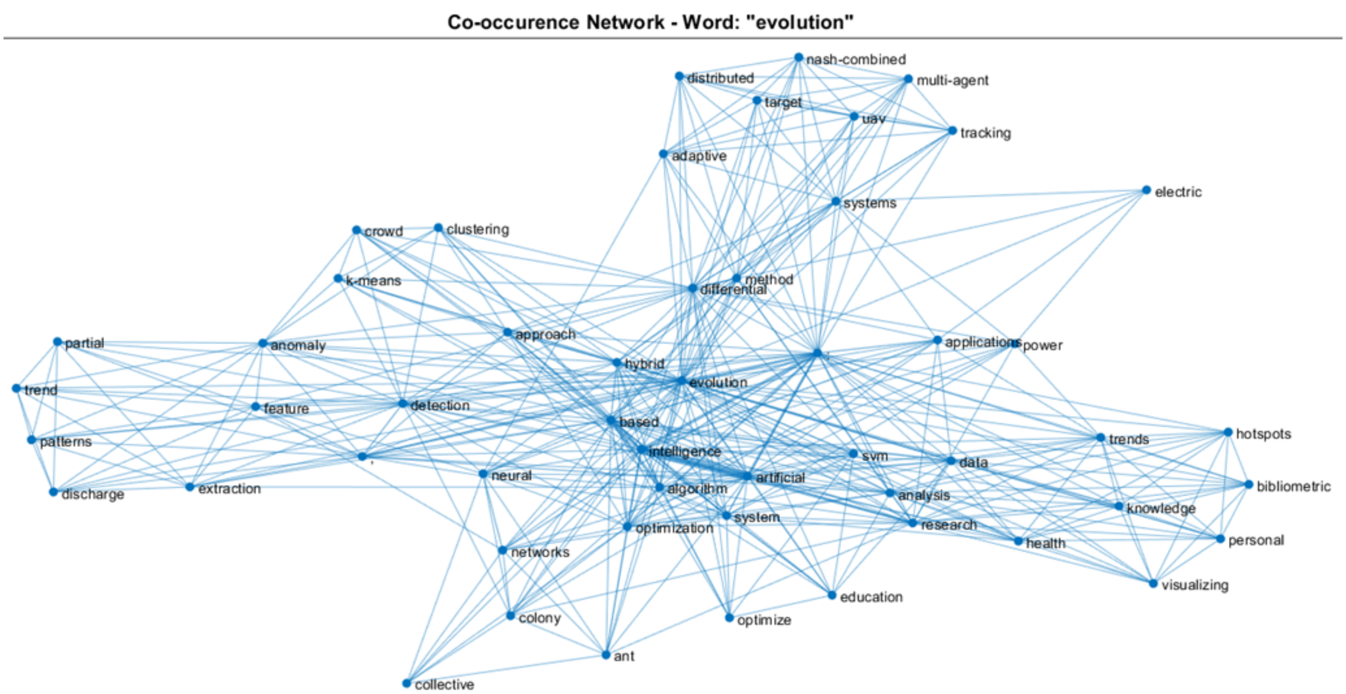

Fig. 1. Co-occurrence network for 'evolution'.

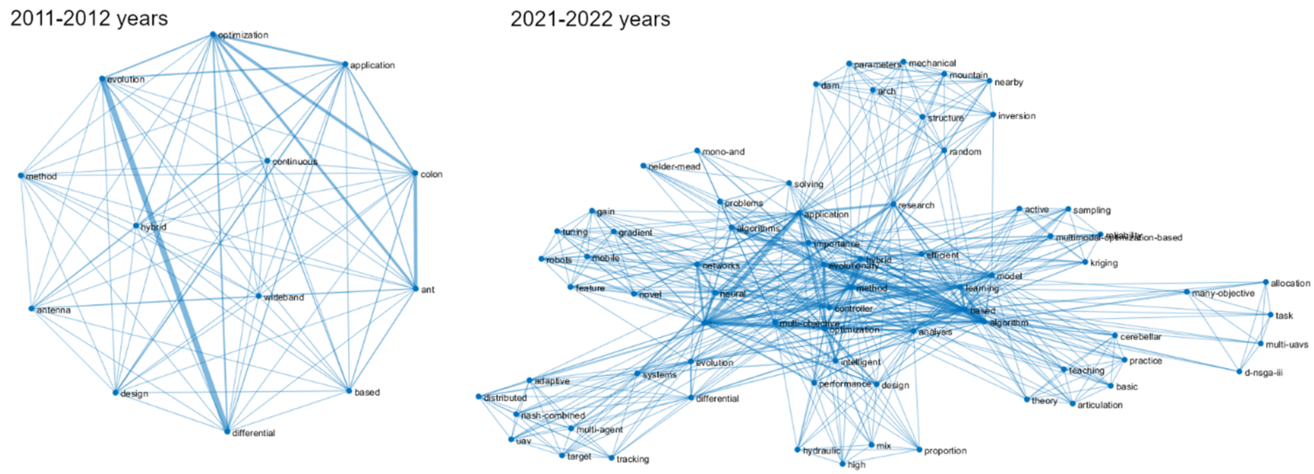

Fig. 2. Co-occurrence network for 'method' (left: 2011–2012, right: 2021–2022).

Evolutionary computation is a subset of artificial intelligence that is most commonly used for optimization by extracting certain variances from large data sets using several important estimates. These are usually genetic algorithms, evolutionary or genetic programming, or swarm intelligence. Because all these methods are heuristic, researchers are constantly striving to improve them and adapt them to new problems. Ahli et al. [7] combined three evolutionary computational methods – global optimization methods (GOM), the genetic algorithm (GA), and particle swarm optimization (PSO) – and applied them to hydrological modelling. Differential evolution (DE) is a method that solves the problem of optimization, in the form of multiple iterations, in order to improve a possible solution. DE first was proposed by Storn and Price [8] and outperformed other optimization algorithms, because it is a very simple and straightforward strategy. DE is one of the most popular evolutionary methods due to its easy adaptation, simple design, low number of parameters and fast operation. Jebaraj [9] adapted DE to address energy issues, namely: reactive power planning, congestion management, transmission capability, cost-effective load shedding, generating equipment commitment, power flow optimization, and optimal reactive power supply. Yan et al. [10] adopted this method for the design optimization of x-ray source beam optics. Long and Gao [11] studied an artificial intelligence training system consisting of training need, training data, training characteristics, model, and application to training.

In that research, DE initiates the population and then uses mutation, crossover, and selection to obtain the optimal combination of SVM parameters. In recent years, researchers have sought to combine genetic algorithms with other known methods with the goal of increasing the efficiency of solutions, the speed of calculations, and adapting them to new data sets. The resulting hybrids facilitate solving a wider range of problems. Liu et al. [12] combined the DE method with the K-mean classification algorithm to identify anomalies in artificial crowd intelligence. The differential evolution of parameter adaptive schemes is known as adaptive differential evolution (ADE). Another hybrid was proposed by Yu et al. [13]; it combines the ADE algorithm with Nash optimization, and then proposes a Nash-combined ADE method for unmanned aerial vehicle (UAV) systems. The MAP-elite algorithm looks for the best solution in a large space by evaluating certain criteria at each point in the space. Choi and Togelius [14] merged DE with MAP-elites, thereby obtaining higher-quality solutions.

In real life, it is not enough to have a clear goal when making decisions; oftentimes the decision-maker must compromise. Sometimes the goals contradict each other, and sometimes optimization results only in a set of 'good-enough' decisions, and the choice of the result depends on the decision-maker. In optimization tasks, this problem is solved by classifying the tasks into single-objective optimization (SOO) and multi-objective optimization (MOO). The use of evolutionary algorithms in combination with SOO and MOO algorithms has allowed Lambrinidis and Tsantili-Kakoulidou [15] to increase their chances of success in developing new, more effective drugs. For the distribution of various unmanned aircraft tasks, a multi-objective evolutionary algorithm named D-NAGA-III was proposed, which effectively optimizes military tasks. Boukhari et al. [16] improved the hybrid approach of evolutionary strategies and multi-objective optimization to accelerate the speed of convergence and applied it to two-objective portfolio optimization.

A new method of MMO was proposed by the Nie and Luo [17]. They did not aim to simplify the multi-objective task; rather, they developed a method for finding solutions in parallel. The complex model of rare events can be solved by the complex model proposed by Wang et al. [18], known as evolutionary multimodal-based multi-objective optimization (EMO-MMO), which recognizes the most probable failure points. For antenna engineers, alignment can be greatly simplified using the methodology proposed by De Melo et al. [19], which incorporates the non-dominated sorting genetic algorithm (NSGA-II) and multi-objective evolutionary algorithm based on decomposition (MOEA / D) to easily reconcile several objectives. In recent years, more scientific articles have been written in the field of computer science than in any other field (Table 1). Such articles usually involve the development of methods or methodologies that combine the construction of hybrid models with known models.

3.2. Detection

There is also a clear difference in the variety of research aimed at detecting certain properties using EAI between a decade ago and now (Fig. 3).

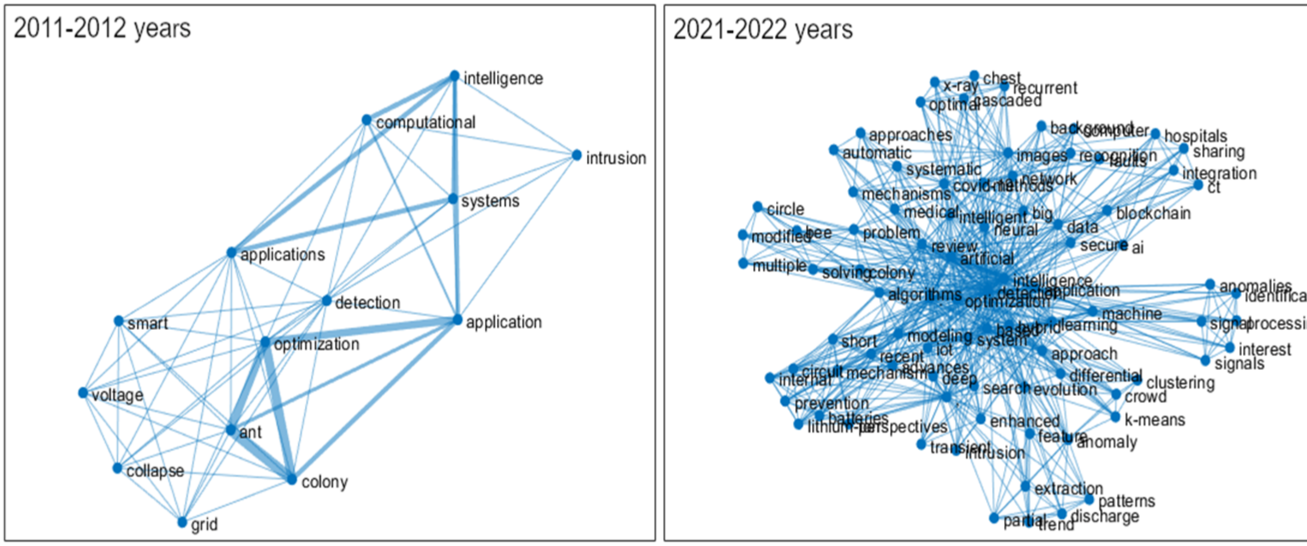

Fig. 3. Co-occurrence network for 'detection' (left: 2011–2012, right: 2021–2022).

Detection is the specific cognitive ability of a person to recognize useful information in the flow of information. This operation is difficult to describe with mathematical formulas or statistics, although a large amount of data is available in this case. Artificial intelligence algorithms are successfully applied to detect near other imitations of human cognitive functions. An important area of application for detection algorithms is medicine, where early detection of disease is very important. Kumar et al. [20] proposed how to identify cancer-affected regions at an early stage in magnetic resonance imaging. This work combined deep learning with a blockchain and applied the bat algorithm. The benefits are early cancer detection and easy information sharing without compromising client privacy.

Furthermore, the global COVID-19 pandemic has challenged doctors to quickly diagnose the virus. Shankar et al. [21] proposed a barnacle mating optimization (BMO) algorithm with a cascaded recurrent neural network (CRNN) model named BMO-CRNN, which can detect a virus from chest x-ray images using an algorithm that simulates the barnacle life cycle from eggs to adult life. The proposed BMO-CRNN model detects COVID-19 with an average accuracy of 94.82%. Afza et al. [22] proposed a more accurate and faster method for detection skin cancer by incorporating a hybrid deep features selection (HDFS) method in a classification algorithm.

Detection is also very important in identifying fraudulent behaviour. The detection of cyber-attacks in the field of the Internet of Things (IoT) has been investigated by Fatani et al. [23]. Their transient search optimization (TSO) generates a population, and operators such as recombination and mutation of the differential evolution (DE) algorithm are used in conjunction with convolutional neural networks that act as extractors of certain properties. The result of this combination of algorithms is a significantly improved accuracy in classifying fraudulent events. A multi-step process consisting of an evolutionary bag-of-ngram approach, a genetic algorithm (GA), and a convolutional neural network (CNN) is used to detect malware in cloud computing [24].

The action of detection is related to rare events, also called anomalies. Florkowski [25] proposed segmentation techniques for feature extraction, anomaly detection, and trend evolution using convolutional neural networks for the detection of coherent forms in the images. With the help of business analytics, companies, suppliers, and customers are connected into a single system where information and data are shared. It is therefore important that computer networks run smoothly. Computer network failure detection is the focus of a study by Ge [26], who improved particle swarm optimization (PSO) and merged it with radial neural network function (RBF). Improvements in evolutionary algorithms have resulted in good (89.3%) accuracy as well as shorter computer network failure detection times.

Business analytics also seeks to extract information from a huge stream of textual data. Textual and sentiment analysis allows us to measure customer or employee opinions and make more useful decisions. Erfanian et al. [27] used textual data from Twitter for the purpose of detecting certain events and their evolution on the social network. Their proposed evolutionary approach involves two steps: in the first stage, events are detected in the text, and in the second stage, changes in the terms associated with the events are detected. Social networks are also of interest to researchers as a source of community dissemination and exchange.

The mechanism of community discovery on social networks is combined with community change in the work of Rajita et al. [28]. In their work, community change is detected as an event using the Cuckoo search algorithm, and it involves three steps: detection of the communities for each timeframe, identification of a proper fitness function, and computation of the similarity and events. Knowledge of social networking communities can be successfully applied in marketing, politics, disaster recognition and management, and more.

EAI algorithms improve solutions to field-specific problems, such as the circle detection problem in images by using Bee Colony algorithms [29], detection of internal short circuit (ISC) within lithium-ion batteries [30], and detection of students who complete their undergraduate studies on time by predicting student's attrition rates [31]. In conclusion, it can be said that EAIs are not only optimization algorithms but are also increasingly applied to detection.

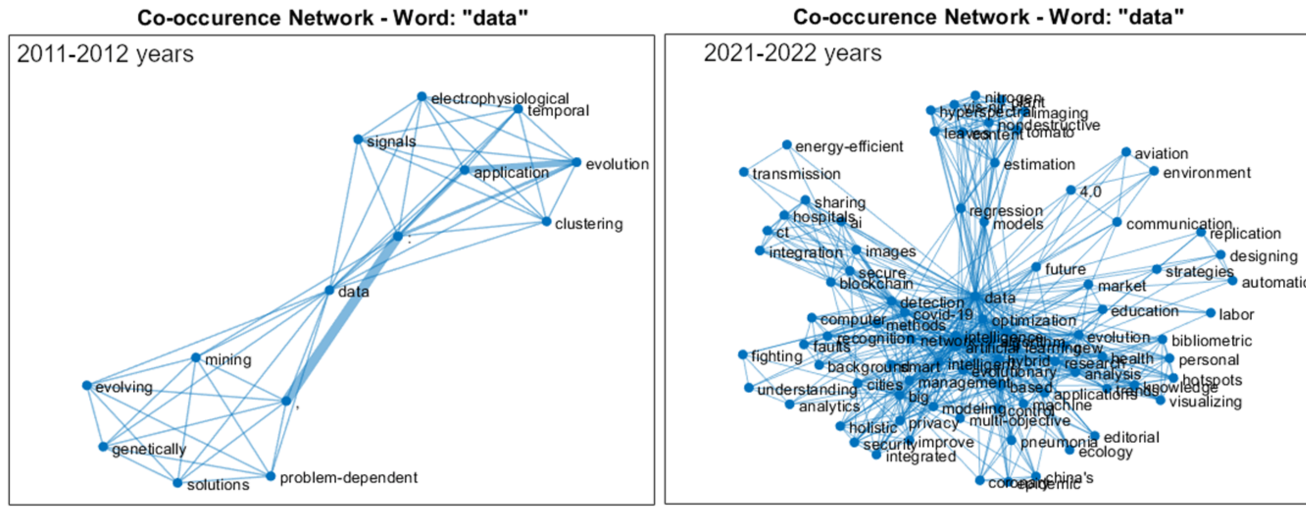

Fig. 4. Co-occurrence network for 'data (left: 2011–2012, right: 2021–2022.

3.3. Data

In the scientific articles of 2011–2012, data were analysed in two directions: data extraction and application. In 2021–2022, we even see several clusters of nodes (Fig. 4) that are associated with different methods, new technologies and novel application possibilities.

In each study, the choice, availability, or lack of data plays an important role. In the application of EAI, the data determine not only the application sector but also the heuristic nature of the solutions. The growing use of big data for community purposes is also creating new challenges, such as data integrity, privacy, security, and reliability. Data usage issues are particularly acute in smart city applications. Chen et al. [32] used evolutionary algorithms to solve data management problems, adopting good data availability and process optimization practices from big data analytics. The use of big data faces data transfer challenges such as security and resource savings. Chaitra and RaviKumar [33] solve these problems by creating a model and incorporating evolutionary algorithms into it. Secure data sharing is also very important in medicine. Kumar et al. [20] combined blockchain technology with convolutional deep learning algorithms, and applied data pre-processing techniques to the data, which include the bat algorithm and data augmentation technique. This adaptation made it possible to eliminate noise and improve the efficiency of the calculations. This study is useful for hospitals, testing labs, research centres and other institutions.

In computer networks, where countless requests occur simultaneously, reliability is very important in data distribution systems. Bokhari and Theel [34] solve this problem by using evolutionary algorithms that make it possible to reduce cost without significantly reducing data availability. Data communication, data transfer and data security are very important in building the aviation of the FUTURE 4.0 Project. These data usage issues have been addressed by Sekera and Novák [35], who reviewed the possibilities of using new technologies. The use of personal health data (PHD) in the three aspects of medicine, computer science, and management has been examined by Gong et al. [36]. Although their article examines how knowledge about PHD has evolved over the past 20 years, it remains relevant to the development of new safe PHD technologies. Scientific research uses not only numerical data, but also other forms of data such as pictures [21,37], hyperspectral imaging [38] and mapping [39-40]. In the information age, data challenges users to balance the cost of resources used and return opportunities, data privacy, security, and fast and convenient data availability.

3.4. Approach

Networks according to the word approach are shown in Fig. 5. In 2011–2012, the most popular approach was ant colony optimization, and in 2021–2022, we can identify several clusters: optimization, artificial intelligence, machine learning, proteins, and classification.

The optimization approach means that the solution method does not guarantee an exact solution with mathematical formulas, but rather provides a potentially useful heuristic approach to the optimal solution. Almosnino and Cappelletto [41] proposed an optimization system based on an evolutionary algorithm that allows the modelling of human motion functions. The obtained scenarios mimic various doctors' decisions and facilitate predictions of the course of treatment. The many layers transfer learning genetic algorithm (MLTLGA), developed and tested by De Lima Mendes et al. [42], is an evolutionary approach that has found application in medicine for the classification of pneumonia from chest x-ray images. The application of evolutionary and particle swarm optimization algorithms by Polkowski et al. [43] allowed them to obtain a better optimization approach during observation of query plans along with database servers. The machine learning approach is perceived as a rough learning from the data presented, lacking reference to a predetermined equation or model. Adeleke et al. [44] used compounds of genetic algorithms to determine seasonal changes in the composition of physical waste, which could be very beneficial for optimizing municipalities' waste management approaches, although the study was conducted only in South Africa.

The artificial intelligence (AI) approach includes the capabilities of computer algorithms such as acting humanly, thinking humanly, thinking rationally, and acting rationally. Nayeri et al. [45] classifies techniques based on artificial intelligence into three groups: evolutionary algorithms, machine learning algorithms, and combinatorial algorithms; they further divide the application of evolutionary algorithms in the fog computer into swarm intelligence, genomic

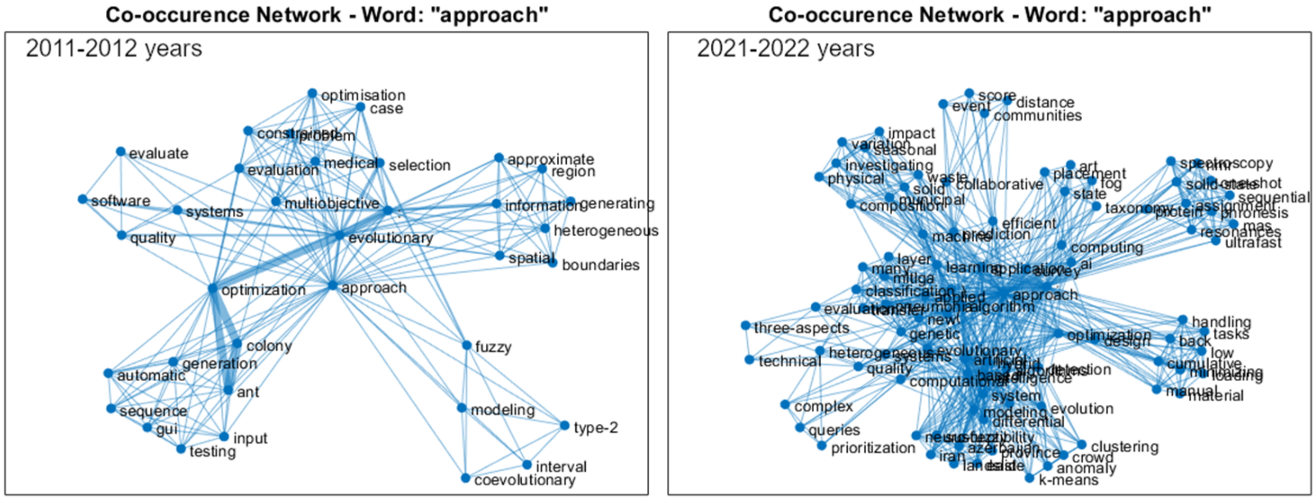

Fig. 5. Co-occurrence network for 'approach' (left: 2011–2012, right: 2021–2022).

mimetic and search based. The review article summarizes the research of many authors to solve fog computing problems and concluded that evolutionary algorithms have focused on providing efficient load balancing methods, whereas EAI solves fog computing problems best in conjunction with machine learning algorithms.

Abdollahizad et al. [46] modelled susceptibility to landslides by comparing three metaheuristic methods including grey wolf optimization (GWO), particle swarm optimization (PSO), and shuffled frog leaping algorithm (SFLA). The approach of artificial intelligence can successfully predict phenomena such as landslides.

Knowledge of microbiology has inspired scientists to create artificial intelligence systems that mimic processes in protein cells. Repecka et al. [47] developed an artificial intelligence network that generates new protein sequences from a complex family of amino acid sequences. Rives et al. [48] integrated the knowledge of protein sequences into a model based on unsupervised AI, which can convey information about the main properties of proteins. Gopinath et al. [49] performed multidimensional experiments by creating artificial multidimensional pulse sequences.

The classification approach is also associated with EAI. Czajkowski et al. [50] developed an evolutionary heterogeneous decision tree, whose application to cancer detection yielded relatively good accuracy. Afza et al. [22] used classification by extreme learning machine for detecting and classifying skin cancer.

3.5. Colony

Fig. 6 shows that ten years ago, the word 'colony' was significantly more popular than in recent years. The reason may be that many new algorithms simulating the behaviour of living things were developed ten years ago, and now researchers are already using a selection of these known and tested colony algorithms.

Swarm intelligence is a term derived from biology; it describes the collective behaviour of living things – specifically their self-regulation in optimizing the use of resources and in preserving and propagating the population. With the development of programming languages, logical operators can use not only mathematical logic but also logic created by nature. Particle swarm optimization (PSO), colony optimization (CO) and their variants are the most common heuristic descriptions of artificial intelligence algorithms [51], although colony simulation is not limited to optimization, also being used for detection and prediction. Kadkol [52] has explored the mathematical side of the PSO algorithm in depth. Mittal et al. [53] compared the characteristics and application possibilities of different PSO modifications and hybrids with other optimization algorithms. Chen et al. [54] conducted a comprehensive review of the optimization capabilities of PSO algorithms.

Ant colony optimization (ACO) is an algorithm that mimics ants' ability to transfer pheromones to food sources outside the anthill. Artificial intelligence mimics this behaviour through the interaction of agents. Since the late 1980s, when the ACO algorithm was first developed, ACO has been used to graphically find the best path to a goal. In recent years, however, researchers have been tackling other challenges. Liu et al. [55] use ACO to optimize two goals: distance and time. For this purpose, agents are assigned different properties of the ant elite and the ant lion using the mutation algorithm. Li [56] improved the selection of path nodes and the regulation and control of pheromone concentration in ACO, which improves the quality of path optimization. Kounte et al. [57] examined the evolution of evolutionary algorithms with a stronger focus on solving the vehicle routing problem and traveling salesman problem with ACO. Qi et al. [58] combined ACO with genetic algorithms and obtained an improved algorithm that can develop each individual's collective intelligence and force them to evolve along with swarms.

The artificial bee colony (ABC) algorithm was first proposed by Karaboga [59] for single- and multi-target optimization. Artificial bees, which have different targets, fly in a multidimensional space and search for food sources with the greatest amount of food. If one bee finds an amount of food greater than that found by the other bees, it captures that location and passes the information on to other bees. In recent years, researchers have been refining the ABC algorithm. Zhang et al. [60] applied the improved fitness function and improved update strategy of food source and improved the quality of the solution. Aslan [29] supplemented the ABC algorithm with two improvements; the first used only the most abundant food sources found by artificial bees, and the second used all food sources, even those left by bees. The combination of these improved solutions enables the use of an algorithm not only for optimization but also for detection. Over time, scientists have developed many different

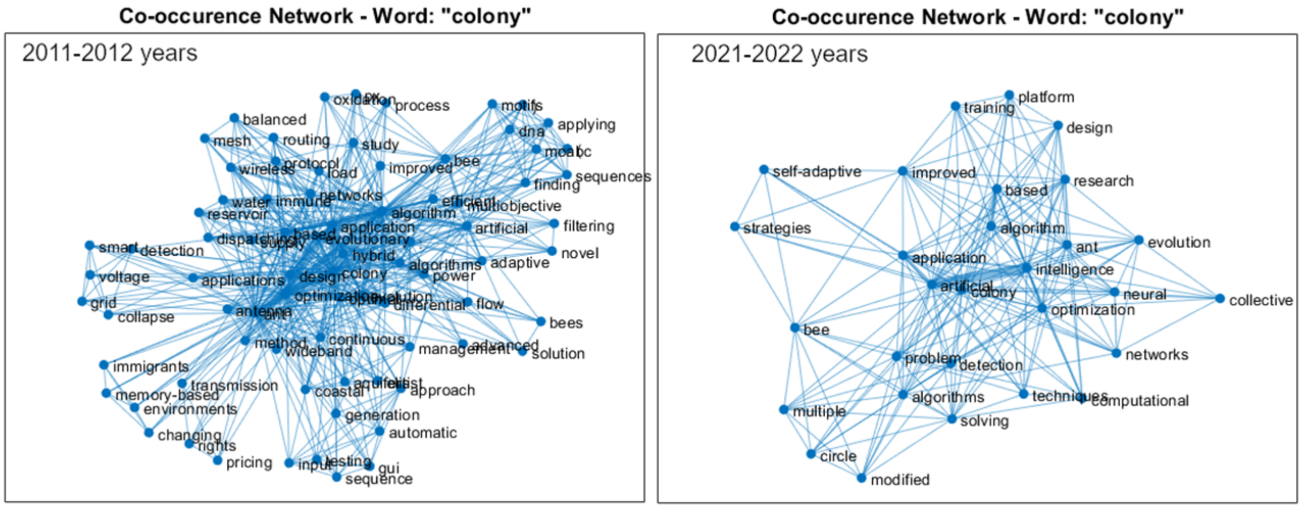

Fig. 6. Co-occurrence network for 'colony' (left: 2011–2012, right: 2021–2022)

algorithms. Solgi and Loáiciga [61] compared the bee system (BS), mating bee optimization (MBO), bee colony optimization (BCO), bee evolution for genetic algorithms (BEGA), bee algorithm (BA), artificial bee colony (ABC), and bee swarm optimization (BSO) global optimization and perceived that ABC is best suited for all seven purposes, whereas others specialize in optimizing certain features.

The firefly algorithm (FA) was proposed by Yang [62]. Kaur et al [63] investigated FA to efficiently apply this algorithm to the relay coordination problem. The authors have studied and applied to the new field three main behavioural features of fireflies.

1. One firefly attracts the other irrespective of their sex because they are unisex in nature.
2. Fireflies' attractiveness is inversely proportional to distance and directly proportional to brightness.
3. The brightness obtained depends upon the fitness function of the firefly.

Yang and Deb [64] developed a cuckoo search algorithm based on information collected by biologists about cuckoos' aggressive breeding strategy. This optimization algorithm can be multi-objective because the nest can contain several eggs that represent different solutions. Rajita et al. [28] applied the cuckoo search (CS) algorithm to social network research, which first detects a certain community, then identifies selected features, and then counts community group similarities and events. The authors compared CS with the already-known particle swarm optimization (PSO) and ant colony optimization (ASO) algorithms for solving a selected social network problem.

Yang [65] developed a bat algorithm (BA) that mimics microbats' use of echolocation, flight, and the ability to emit and recognize sounds of different frequencies. Huang et al. [66] applied the bat algorithm to improve the study process by using multiple intelligence tasks and assessment methods. The monarch butterfly optimization (MBO) algorithm was descripted by Wang et al. [67] and Ghetas et al. [68]; its novelty is that it relied on the migration behaviour of individuals. Self-adaptive crossover (SAC) operator creates new, more perfect individuals in the population, as selecting the best can significantly speed up processes. Feng et al. [69] summarized the contributions of many authors in improving MBO, creating new modifications and hybrids, and evaluated the field of application of this algorithm. Pierezan and Coelho [70] were the first to develop and study an optimization algorithm based on coyote behaviour. The proposed coyote optimization algorithm (COA) is an extension of grey wolf optimizer (GWO), from which it differs in that it does not use hierarchy and related rules in the population, but rather divides it into small groups that exchange experience rather than simply hunting for prey. Li et al. [71] improved COA and applied it to image segmentation based on fuzzy multilayer thresholding. The results obtained show a very good potential for their use in medicine, where accuracy is crucial. Sulaiman et al. [72] proposed a new barnacle mating optimizer, which achieved efficient optimization results by testing 23 mathematical equations. Barnacle is a marine crustacean with an external shell, which feed by filtering particles from the water using their modified feathery legs. Shankar et al. [21] applied BMO in an artificial intelligence-based diagnosis model for Covid-19.

Microbiology and medical knowledge have also inspired scientists to create algorithms that simulate the behaviour of viruses [73] and the processes of changes in immunity [74].

The use of colony logic in algorithms has been criticized by scientists for using easy-to-remember, imaginative names borrowed from nature that can obscure scientific novelty. However, the marketing appeal of such algorithms makes it easier to recognize the differences and purposefully choose them for application.

4. Discussion and limitations

Several choices were made that determined the content of this article. The first choice is that of selecting the Scopus database of scientific articles, which stands out for its high-quality requirements and wide coverage of topics. Because there are many other databases available, the choice to use a single database is a major limitation of this article. In addition, because it takes longer to publish articles than to give a seminar, the latest scientific achievements are perhaps first presented at conferences. The price of publications also plays a significant role, which is especially relevant for scientists with fewer economic resources.

A second choice was the use of a collaborative network for article classification and selection. The main dilemma here is whether to leave the review writing to a machine. Before writing the review, the author had a different idea of the distribution of articles and a different understanding of the main subtopics. The network created other priorities, and comparing articles from a decade ago and now, aspects of EAI from network are on the newer side.

The third choice is the use of the keyword 'evolution'; this choice is the most subjective. The keywords by which the articles were selected are not suitable here, so a word was searched to combine the topics. As a result, five sub-themes were obtained. Methods, colony, and detection are the topics most often associated with EAI. Data is also a very important aspect of EAI, but articles in this area have given rise to nuances such as data security and privacy. Approach is the most unexpected – but no less interesting – subsection.

A graphical comparison of co-occurrence networks a decade ago and now reveals a growing diversity of research directions. The single topic of swarm intelligence has narrowed.

Our research can be extended in several directions. This could be done first by looking at more databases of scientific articles, or by comparing this database articles to the research results of another very well-known database, Clarivate Analytics Web of Science. Another approach would be to look through the mapping of EAI application sectors.

Conclusions

In this study, we used information from the Scopus database on 206 articles from 2021–2022 and compared them with scientific articles from a decade ago. For research use, co-occurrence networks have identified five important research subtopics in recent years: methods, detection, data, colonies, and approach. During the decade, research directions increased in all subtopics, except for the field of colonial intelligence.

The differential evolution method remains the most popular; however, there is a need to use not only single-objective optimization but also multi-objective optimization. Furthermore, researchers use hybrid methods, combining EAI with other methods.

EAI has optimization as well as detection functions. It has been successfully applied in medicine, in recognizing anomalies and fraudulent behaviour, and in identifying and solving business and social problems.

In recent years, scientists have helped businesses confront the challenge of balancing data privacy, security, and reliability with the opportunities that big data provides for businesses and customers.

In scientific articles, EAI is found in different approaches: optimization, machine learning, artificial intelligence, classification, and protein. All of them reflect the heuristic or meta-heuristic nature of EAI.

Algorithms that simulate the behaviour of swarms or colonies are assigned the name of a particular animal species by scientists. The best known are the ant colony optimization and the artificial bee colony algorithms. Algorithms that are less well known – but which nevertheless offer specific advantages – are the firefly, cuckoo search, and bat algorithms. Recent colony optimization algorithms include monarch butterfly optimization (MBO), which simulates the migration phenomenon, and the coyote optimization algorithm, which abandons the colony hierarchy.

Co-occurrence networks revealed that the scope of topics, methods, and application areas of evolutionary artificial intelligence is growing rapidly.

Abbreviations

ABC	-	Artificial Bee Colony
AI	-	Artificial Intelligence
BA	-	Bee Algorithm
BCO	-	Bee Colony Optimization
BEGA	-	Bee Evolution for Genetic Algorithms
BS	-	Bee System
BSO	-	Bee Swarm Optimization
EAI	-	Evolutionary Artificial Intelligence
IoT	-	Internet of Things
MBO	-	Mating Bee Optimization

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