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Investigation of Artificial Intelligence Based Optimization Algorithms

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A B S T R A C T

In this study, the concept of artificial intelligence (AI), deep learning and machine learning are explained and the relation between AI and optimization algorithms are examined. By defining the basic stages and the content of deep learning and machine learning, the relationship of AI with optimization is investigated. In the light of this study, four optimization algorithms were considered. The steps and the operations of these artificial intelligence-based optimization algorithms which were widely used in the literature have been examined in detail. All the algorithms discussed in this study are related to nature. These algorithms are; Bacterial Foraging Optimization, Flower Pollination Optimization, Genetic Algorithm and Artificial Bee Colony Algorithm. The studies in the literature carried out by modelling the life cycle of bacteria known as koli basil in Bacterial Foraging, the pollination event in flower pollination plants in Flower Pollination, genetics in Genetic Algorithm and the formation of genes that lead to the formation of a high quality population and bees' behavioural logic in Artificial Bee Colony. While the studies except the Artificial Bee Colony were the direct models of the phenomenon in nature, the Artificial Bee Colony was put forward by adding a comment about how the behaviours of bee colonies can be separated from the expected and unexpected values in a sample space. In this study, the stages of all these algorithms and the logic used in each step are examined. Some recent important application domains related to these algorithms are also discussed. In the conclusion part, what can be done in the light of these studies as a future work is mentioned.

ÖZ

Bu çalışmada yapay zeka, derin öğrenme ve makne öğrenmesi kavramları açıklanmış ve yapay zekanın optimizasyon algoritmaları ile ilişkileri incelenmiştir. Derin öğrenme ve makine öğrenmesinin temel aşamaları ve içeriği tanımlanarak, yapay zeka'nın optimizasyon ile olan ilişkisi araştırılmıştır. Bu inceleme ışığında dört adet optimizasyon algoritması ele alınmıştır. Literatürde sıklıkla kullanılan bu yapay zeka tabanlı optimizasyon algoritmalarının adımları ve işlemleri ayrıntılı olarak incelenmiştir. İncelenen algoritmaların hepsi doğa ile ilgili olarak geiştirilen algoritmaları içermektedir. Bu algoritmaları sayacak olursak; Bakteri Yiyecek Arama Optimizasyonu, Çiçek Tozlaşması Optimizasyonu, Genetik Algoritma ve Yapay Arı Kolonisi algoritmalarıdır. Literatürde yapılan çalışmalar, Bakteri Yiyecek Arama'da koli basili olarak bilinen bakterilerin yaşam döngüsünin modellenmesi, Çiçek Tozlaşmasın'da çiçekli bitkilerde meydana gelen tozlaşma olayının modellenmesi, Genetik Algoritma'da biyolojide çeşitliliği ve kaliteli bir populasyonun oluşmasını sağlayan genlerin oluşumunun modellenmesi ve Yapay Arı Kolonisi'nde arıların davranış mantıklarının modellenmesi ile gerçekleştirilmiştir. Bu çalışmalardan Yapay Arı Kolonisi dışındaki çalışmalar doğrudan doğada gerçekleşen olayların modellemesiyken, Yapay Arı Kolonisi arı kolonilerinin davranışlarıyla bir örnek uzayının içerisindeki beklenen ve beklenmeyen değerler kümesinin nasıl ayrılabileceği ile ilgili bir yorum eklenerek ortaya atılmıştır. Bu çalışma içerisinde tüm bu algoritmaların aşamaları ve her adımda uygulanan mantık irdelenmektedir. Bu algoritmalarla ilgili bazı yeni önemli uygulama alanları da ele alınmıştır. Sonuç kısmında ise bu çalışmalar ışığında gelecek çalışmalar için neler yapılabileceği ifade edilmiştir.

1. Introduction

AI is the simulation of human intelligence processes with machines, especially computer systems. These processes include learning (acquiring knowledge and rules for obtaining information), rationalizing (using rules to achieve approximate or final results), and self-correction. AI's specialized applications include specialized system speech

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recognition and artificial vision. AI was born at a meeting in the summer of 1956 in Dartmouth (USA), the main researchers of the region. For the preparation of the meeting, J. McCarthy, M. Minsky, N. Rochester, and CE Shannon drafted a draft proposal, in which the term "artificial intelligence" first appeared. Apparently, the name was given on the orders of J. McCarthy (McCarthy, 2006).

The topics around the artificial intelligence, the components of artificial neural networks, expert systems, fuzzy logic, genetic algorithms. There are many disciplines that possess artificial intelligence. Some of them are computer science, philosophy, cognitive science, electronics. There are not many Turkish sources about artificial intelligence. If this small volume of work can help in correcting the confusion in the minds of the information owners, the point of giving the self-knowledge without any knowledge about this matter will be achieved. AI is now a name with many operations and various applications. Artificial Intelligence is mainly divided into two areas: Machine Learning and Deep Learning.

Machine Learning

Machine Learning "combines algorithms learned from examples and data". This makes it possible to "estimate the values in the data sets presented as examples". Conclusion: The quality of the results depends on the quality of the data given to the learning system (Makridakis, 2017):

Controlled learning provides examples to learn the system and give the right answer. This type of AI is used to define video content, to estimate the price of a house based on the past, or to predict medical risks.

Unsupervised learning is to provide many examples to the system, but this time without giving good answers. Separating customer groups by similarities, detecting anomalies (banking fraud), or identifying correlations (for example, to place two products side by side on a store shelf) and what the machine learns.

Semi-audited learning is to give many examples to the system and give the right answer for some. Google or Facebook's services are enough to "recognize" the people in the photos.

Reinforcement learning allows a system to develop in a physical (ie, a robot) or virtual environment. The system is evolving with penalties and prizes. This is when a robot learns to walk alone or a bot develops in a video game.

Deep learning

Deep learning is based on the ability of a technology to learn from raw data. Word processing, voice or face recognition; There are a large number of applications. Yann LeCun and Geoffrey Hinton are the two leading experts who use neural networks inspired by biological neurons in this area. If these neuronal neurons can be connected in various ways, the neural networks consist of overlapping layers in most cases. The neural network is trained to recognize the contents of an image. Depending on the results, the "link force" between each neuron is corrected. Thus, the neural network was perfected until further recognition error disappeared. Cigref's guide says "Deep Learning is very powerful but also very expensive". Olik It should be kept for the most important classes, and other machine learning algorithms should be used at a lower cost, which can result in sufficient results. Oliv The AI machine is learning to learn and deep learning warns Olivier Ezratty in a new blog post. "There are a number of limitations: best AI solutions often combine together various techniques," he said, including other techniques including programming and rule engines and silenced them due to resonance in deep learning(Buchanan, 2005).

2. Artificial Intelligence And Optimization

The time that has taken place since the first foundations of the AI has been in the direction of developing this research area within the framework of different problem solving issues. The penetration of the field into different problem solving subjects has led to the discovery of more multi-disciplinary aspects and the formation of more subspaces. These sub-specializations are sometimes referred to by their own names such as Machine Learning, and sometimes by the basic problem.

Among the candidates in optimization, we choose the optimum solution to our problem and we do this under certain limitations and acceptances. Yang(Yang, 2010b) likens optimization to a kind of eyi treasure hunting av process in general and focuses on the role of genel hunters olarak who seek 1 treasure ’in particular. When we take into account the processes within optimization, we can understand how humanistic aspects are actually related to behaviors. That's why, for this reason, AI has been the perfect solution for optimization problems. It is enough for us to understand the point where optimization is the subject of decision making, AI and optimization.

It is also possible to discuss and interpret the expressed relationship from a more technical point of view. According to this, as a result of our experience with the literature and experience gained in this study, we can list the main reasons why AI area is preferred in optimization problems (Yang, 2010b)(Karaboğa, 2014)(Geem, 2001)(Lee, 2008)(Weise, 2009)(Zelinka, 2012).

Classic optimization approaches, methods and techniques are not sufficient in advanced optimization problems [eg; the problem of local optimum values in the problems, the need for long calculating and processing processes, the optimum values with large differences ere and so on. - For more information on classical optimization, readers can refer to the following sources (Bayraktar, 2003)(Floudas, 2013)(Kaplan, 2011)(Kaymaz, 2016)(Kearfott, 2013)(Rao, 2009)(Das, 2009):

- Effectiveness, speed and efficiency advantages of this area in solving optimization problems
- The simplification of various approaches (intuition, random behaviors, etc.), which are unique to people (and sometimes other living things) in advanced optimization problems, can be done easily and more effectively by the relevant field.
- A more effective approach to deliver highly flexible, feasible solutions, always with an improved structure.
- AI is built on a set of broad approaches and methods that can transfer the intended logical and mathematical processes to the practice in a practical and flexible manner.

3. Optimization Algorithms

3.1 Bacterial Foraging Optimization

To better understand the basics of BFO, it is worth mentioning briefly about the movements and life processes of the Koli Basili bacteria. Accordingly, a coli bacterium may be present in various chemotaxis depending on the density of the medium (substance) and its living conditions. Koli Basili bacteria carrying whips on them, rotating their whips counterclockwise in environments suitable for food sources, movements based on swimming, tumbling, and vice versa. by rotating these movements to include more rolling (Passino, 2012)(Yang, 2010a). During these processes, Koli Basili bacteria can be divided into two or can be reproduced or the presence of harmful sources in the environment or according to the average life processes of these bacteria can end their lives. In addition, Koli Basili bacteria secrete a substance in order to attract the other coli bacteria in the appropriate environment and the bacterial density of the environment increases with this spreading method (Passino, 2012)(Yang, 2010a) . BFO also employs a variety of solution processes, inspired by all these processes and using the particles that they accept as bacteria, in a herd-oriented manner in the solution space. In this context, chemotaxis includes a mixture of different phases such as Rolling, Swimming, Reproduction and Elimination - Distribution.

We can describe the algorithmic solution steps of BFO which are designed in the context of the described features and functions (Yang, 2010a).

Step 1 (Installation Phase): Randomly dispense N pieces of bacteria particles (potential solution variables) into solution space. Algorithm parameters (eg Nk: maximum number of chemotaxis, Nyus: number of swimming motions, Nudes: number of replicates, Ne: maximum elimination number, tensile and repulsive coefficients, oed: probability of elimination). Perform the necessary arrangements for the problem to be solved.

Step 2: Calculate the objective function value (fitness) according to the locations of the bacteria (potential solution variables).

Step 3: Perform the following steps, Repeat until: (in the context of each objective function size)

Step 3.1 (Chemotaxis Phase): Perform the following steps for each bacteria, up to the Nk value:

Step 3.1.1: Calculate the objective function value (fitness) according to the position of the next bacteria (potential solution variable).

Step 3.1.2: The objective function of the bacterium related to the (fitness) cell to cell attractive effect of the update. Hold this value until swimming phase.

Step 3.1.3 (Rolling Phase): Generate random numbers up to the purpose function size in the range [-1, 1]. Run the rolling process for the respective bacteria.

Step 3.1.4: Calculate the objective function value (fitness) according to the location of the bacteria (potential solution variable). The purpose of the relevant bacterium is to update the value of the function function (fitness) from cell to cell with attractive effect.

Step 3.1.5 (Swimming Phase): Perform the following steps for the related bacteria, up to the Nyush value.

Step 3.1.5.1: If the final objective function value (fitness) of the bacteria is better than stored before the Swimming Phase, keep this new value.

Step 3.1.5.2: Update the held objective function value (fitness) of the relevant bacteria according to the displacement value to be calculated.

Step 3.1.6: If all bacteria have not been treated yet, switch to the next bacterium and return to Step 3.1.1.

Step 3.2 (Reproduction Phase): Calculate the health status of each bacterium and sort them all from small to small according to these values.

Step 3.3: Eliminate the worst bacteria according to the set criteria. Let the bacteria grow in the best condition. New bacteria are in place of their parents.

Step 3.4: If the nu value has not yet been reached, increase the counter for that value and go back to Step 3.1 and continue with the next generation.

Step 3.5 (Elimination - Distribution Phase): Transfer each bacterium to a new location according to the value oed.

Step 4: At the end of the processes, the value (s) obtained by the global best position is considered to be the optimum value (s).

There are many studies and applications that are related with this optimization algorithm. In Hezer (2013), to determine the routes to be followed by the vehicles used in distribution and collection activities and to minimize the logistics costs, an algorithm has been developed with this optimization to solve the stated problem.

3.2 Flower Pollination Optimization

Flower Pollination Optimization (FPO) is another technique developed by Yang (Yang, 2012). In this study, only GKO and FPO should be included, sufficient space for different techniques, proven successes of ICC, and FPO are also newer than Fire techniques. FPO's main source of inspiration, as understood, is the pollination in nature. As with similar techniques, this technique is the focal point of the pollination event related to the concepts and phenomena benefit. These concepts and facts about FPO can be summarized as follows:

- Approximately 80% of the plant species in nature are known as flowering plants, at which point in flowering plants; The process called pollination can be explained as a series of natural dynamics which are carried out by various alternative means and reproducing the related plants and ensuring the continuity of their species (Yang, 2014)(Darwin, 2015). In this context, it is possible to observe the pollination process in two different ways, biotic and abiotic. Biotic pollination processes can be defined as 'carrier' elements placed on (or near) flowers such as insects and animals. 2014). Taking into account the relevant factors, pollination, which can occur between biotic elements and between different flowers, is called cross-pollination, and the pollination between the same flower or the same kind of flowers is called self-pollination(Yang, 2014).

The algorithm details of the RTO technique which were brought to the multi-purpose optimization level (Darwin, 2015) after gaining the first literature (Yang, 2014) are as follows:

Step 1 (Installation Phase): Randomly distribute N-flower-particle (potential solution variables) in solution space. Assign algorithm values, specify the transition probability parameter (go). Perform the necessary arrangements for the problem to be solved.

Step 2: Calculate the objective function value (fitness) according to the position of the flowers - particles (potential solution variables). Find out what's best.

Step 3: Repeat the following steps throughout the iterative process (eg until you reach a certain number of iterations or until you reach a desired value in the objective function): (For each particle; for each purpose function size)

Step 3.1 (Global - Local Pollination Phase): Generate a random value. If the value produced is less than the value of equation and Levy Flights (step vector: L). If the value produced is equal to or greater than the value of go, uniform distribution in the range [0, 1]. Run the local pollination process in the context.

Step 3.2: Calculate the purpose function value (fitness) according to the updated position of flowers - particles (potential solution variables).
Step 3.3: Update the global best value (and hence the variable position) if the best objective at that time is found to be better than the function value.
Step 4: Iteration - At the end of the cycle the value (s) obtained according to the global best position is considered to be the optimum value (s).
In a recent study (Korkmaz, 2018), the Flower Pollination Algorithm which is known as one of the most popular optimization methods of recent times, is used to model car ownership in Turkey and to make predictions for the future. With this algorithm in this study, models have been developed to estimate the number of vehicles per 1000 inhabitants. Models in linear and force forms have been proposed using 3 independent parameters.

3.3 Genetic Algorithm

Genetic Algorithm is the first technique developed by Charles Robert Darwin (1859; 2015 (Trans.))(Holland, 2012), Inspired by the basic elements and facts of the Theory of Evolution. GA (1992: 1975) brought to the literature by GA, based on the concept of genetic concepts and explained by the Theory of Evolution, selection (selection), mutation and crossover processes to solve real-life-based problems are also known as an EH technique. In fact, the representation of particles used in the solution process in GA unlike the techniques described so far is the way of coding (Kramer, 2017)(Mitchell, 1998)(Fisher, 1958). This coding, as expressed by Holland (Kramer, 2017), is inspired by approaches by Ronald Aylmer Fisher (Baker, 1985), which explain the transfer of genes throughout a population in mathematical structure.
In the GA technique solution process, the genetic processes such as mutation and crossing applied to the coded individuals to change genetically in the genetically modified populations and thus to reach the solution process are as follows (Kramer, 2017)(Mitchell, 1998)(Fisher, 1958):

- Crossover: In this process, the predetermined individuals are in a sense reproduced to create a new individual. For this purpose, new individuals are obtained by exchanging reciprocal gene - code according to GA's related parameters and determined crossing pattern. In this connection, for example, approaches such as changing the codes of symmetrically mutually opposite genes or performing changes at regular intervals can be followed.
- Mutation: In order to increase the potential of successful individuals to some more successful solutions within the algorithm, mutation is also applied. In the individuals selected for mutation, changing the codes with the relevant parameters of GA is performed. The simplest example of this procedure is that in an individual encoded with 0 and 1, some 0s are 1 and some 1s are 0.

Another important issue in the algorithmic process of GA is the crossing and mutation processes. This situation is tried to be solved by performing the selection process just before the relevant genetic procedures are applied. For this purpose, selection is carried out in different ways from the current population, among individuals returning from the objective function structure of the problem with successful results. When we examine the liteature, it is possible to see alternative ways such as the biased roulette wheel, proportional reproduction, tournament selection, and ranking selection (Karaboğa and Akay, 2007). Among these, among the studies, the preferred solution of individuals' solutions, based on the preferred choice of rinsed roulette wheel, is placed on a representative wheel based on the quality of the population to the average solution, and the individuals to be subjected to reproduction by rotating this wheel are determined by the luck factor (Karaboğa, 2014).
We can describe the algorithmic solution steps of GA as follows (Kramer, 2017)(Karaboğa, 2014)(Mitchell, 1998):
Step 1 (Installation Phase): Build a population of N individuals according to the problem and the preferred coding scheme. Identify the methods of the initial algorithm parameters (eg, the crossing ratio, the mutation rate) and the methods to be followed in processes such as selection, crossing, mutation.
Step 2: Repeat the following steps throughout the iterative process (eg until you reach a certain number of iterations or until you reach a desired value in the objective function): (For each individual; for every purpose function size)
Step 2.1: Calculate the objective function value (fitness) within the relevant structure.
Step 2.2: Carry out the selection process in the context of the preferred methods for identifying individuals to be involved in the reproductive process, with the calculated objective function value (fitness) values.
Step 2.3: Apply the crossover process to the identified individuals within the relevant algorithm parameters and preferences.
Step 2.4: Apply mutation to related individuals within the scope of algorithm parameters and preferences.
Step 3: Iteration - At the end of the cycle the value (s) obtained according to the global best position is considered to be the optimum value (s).
One of the optimization problem class in which genetic algorithms are applied is the optimization problems associated with efficient allocation of limited resources to achieve the desired objectives. These resource limits are generally related to labor, procurement or budget. The word “combination” implies only to the existence of a finite number of alternative suitable solutions. Combination optimization is the process of finding one or more optimal solutions in a well-defined problem space. Such problems arise in all branches of management (finance, marketing, production, stock control, database management, etc.). Traveling problem, vehicle routing problem, Chinese postman problem, work workshop scheduling problem, assignment problem, layout design problem and backpack problem are some examples of combination optimization problems (Hoffman, 2002).

3.4 Artificial Bee Colony

Artificial Bee Colony (ABC) is a AI-based optimization algorithm that is mainly based on the idea of modeling the bee's food search behavior of Karaboğa (Karaboğa, 2014) and has been introduced to the literature by Karaboğa and Baştürk (Karaboğa, 2007). ABC is known to be one of the effective techniques that offer an optimization process in the evolutionary process solution approaches, Although it is not specifically used in the role-based solution and direct evolution theory functions. When the foundations of the ABC are examined, it is suggested by Tereshko (Tereshko, 2000) that under the components such as food sources, duty-free bees, the food-based model is based on functions such as food source orientation, resource-dropping, and in this context, Tereshko and Loengarov (Tereshko, 2005). the effects of the collective decision-making approach in the bees they propose are at stake (Karaboğa, 2014).

When the algorithmic structure is examined, it can be seen that there are three different roles: a solution process in which the particles that can be transformed into worker bees, scout bees and exploratory bees are included in the solution space (Karaboğa, 2014)(Karaboğa, 2007). The particles in these roles generally simulate the bee's food search behavior. On the other hand, in order to simplify the solution process mathematically and logically, the algorithm adheres to the following assumptions (Karaboğa, 2014):

- In the solution process, the sources reached by bees in the food search correspond to the possible optimum values. In the algorithm, nectar quantities are taken into consideration. The nectar concept is used in response to the quality of the solution values obtained from the sources.
- The nectar in each source can only be taken by one worker bee. In this case, the total number of food sources and worker bees are considered as equal.

Generally, the number of worker bees is considered equal to the number of beekeepers. Briefly, we can express the general structure of the algorithm as follows (Karaboğa, 2014)(Karaboğa, 2007):

Step 1 (Installation Phase): Build N food sources. Specify the corresponding bee particles as numbers in this context. Set the initial algorithm parameter values (eg resource incapacity counter, extinction limit). Make arrangements for the problem.

Step 2: Repeat the following steps during the iterative process (eg until you reach a certain number of iterations or until you reach a desired value in the objective function): (For each bee; for each purpose function size)

Step 2.1: (Worker Bee Phase): Ensure that worker bees select and send food source regions, taking.

Step 2.2: Calculate the objective function value (fitness) depending on the location of the food source and determine the nectar (quality) in the food sources with the objective function values (fitness) found. Increase or decrease the counters of nonfood food sources according to nectar values.

Step 2.3 (Observer Bee Phase): According to the information from the worker bees to the beekeepers, the nectars in the food sources, perform the probabilistic selection process for the food sources (solutions) to be chosen by the beekeepers. To do this, determine the probability of selection of each source. After the beekeepers choose the food source zones and are sent to these areas as workers, Perform the processes described in step 2.2.

Step 2.4 (Exploring Bee Phase): Check the development counters in the food sources and turn the worker-in-source worker into an explorer bee (usually an explorer bee is formed in each cycle). Make the explorer call the food source.

Step 3: Iteration - At the end of the cycle the value (s) obtained according to the global best position is considered to be the optimum value (s).

Artificial Bee Colony is one of the popular and preferred algorithm to solve optimization problems. In (Küçüksille, 2011), a program has been developed which can perform automatic timetabling by using this algorithm.

4. Conclusion

In this study, artificial intelligence is explained in the perspective of deep learning and machine learning. The relationship between deep learning and artificial intelligence and its effects on optimization algorithms in the context of this relationship are mentioned. The relationship between machine learning and artificial intelligence is also discussed. In the light of these definitions, artificial intelligence based optimization algorithms which mimic nature are examined and the detailed stages of these algorithms are discussed. The algorithms examined are the Bacteria Foraging Optimization, the Flower Pollination Optimization, the Genetic Algorithm and the Artificial Bee Colony Algorithm. While explaining each stage of these algorithms, it is realized that there are stages related to Flower Pollination Optimization, Bacteria Foraging Optimization and Genetic Algorithm directly related to the samples in nature. Artificial Bee Colony mimics the movement of bees while detecting anomalies in nature and using the logic of natural movements. As seen in many of the studies in the literature, these algorithms are used to support the solutions of the problems in our daily lives such as developing automated systems such as scheduling and planning, determining the route of vehicles.

In future studies, these algorithms and other optimization algorithms can be compared by using the same data sets. New steps can also be added to the existing algorithms or some of the steps may be omitted from the existing stages to increase the accuracy rates.

References

Baker, J. E., 1985, Adaptive selection methods for genetic algorithms, Proceedings of an International Conference on Genetic Algorithms and their applications, 101-111.

Bayraktar, D. ve Çebi, F., 2003, Yöneylem Araştırması-1 – Ders Notları (İstanbul Teknik Üniversitesi – İşletme Fakültesi), http://web.itu.edu.tr/~cebife/TUM_YA1notlari.pdf.

Buchanan, B. G., 2005, A (Very) Brief History of Artificial Intelligence. AI Magazine, 26(4), 25th Anniversary Edition. 53-60, http://www.aaai.org/ojs/index.php/aimagazine/article/view/1848/1746.

Darwin, C., 2015 (Çev.), Türlerin Kökeni, İstanbul, Evrensel Basım Yayın.

Das, S., Biswas, A., Dasgupta, S. ve Abraham, A., 2009, Bacterial foraging optimization algorithm: theoretical foundations, analysis, and applications, In: Foundations of Computational Intelligence, Eds: Springer, p. 23-55.

Fisher, R. A., 1958:1930, The Genetical Theory of Natural Selection, (1930: Clarendon Press) Oxford University Press.

Floudas, C. A., 2013, Deterministic Global Optimization: Theory, Methods and Applications, Springer Science & Business Media.

Geem, Z. W., Kim, J. H. ve Loganathan, G., 2001, A new heuristic optimization algorithm: harmony search, Simulation, 76 (2), 60-68.

Hezer, S., & Kara, Y. (2013). Eşzamanli Dağıtımlı ve Toplamalı Araç Rotalama Problemlerinin Çözümü için Bakteriyel Besin Arama Optimizasyonu Tabanlı bir Algoritma. Journal of The Faculty of Engineering & Architecture of Gazi University, 28(2).

Hoffman K. ve Padberg M., "Combinatorial and Integer Optimization", www.iris.gmu.edu/~khoffma/papers/newcomb1.html. (07/05/2002)., s. 1-10.

Holland, J. H., 2012, Genetic Algorithms. Scholarpedia, 7(12), 1482, http://www.scholarpedia.org/article/Genetic_algorithms.

Kaplan, W., 2011, Maxima and minima with applications: practical optimization and duality, John Wiley & Sons.

Karaboğa, D., Akay, B. ve Öztürk, C., 2007, Artificial bee colony (ABC) optimization algorithm for training feed-forward neural networks, International Conference on Modeling Decisions for Artificial Intelligence, 318-329.

Karaboğa, D. ve Baştürk, B., 2007, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, Journal of global optimization, 39 (3), 459-471.

Karaboğa, D., 2014, Yapay Zekâ Optimizasyon Algoritmaları, Ankara, Nobel Akademik Yayıncılık.

Kaymaz, İ., 2016, Optimizasyon Teknikleri – Ders Notları (Atatürk Üniversitesi – Fen Bilimleri Enstitüsü), http://194.27.49.11/makine/ikaymaz/optimizasyon/.

Kearfott, R. B., 2013, Rigorous global search: continuous problems, Springer Science & Business Media.

Korkmaz, E., Akgüngör, A. P., Türkiye'deki Araç Sahipliğinin Çiçek Tozlaşma Algoritması ile Tahmini, Gazi Mühendislik Bilimleri Dergisi 2018, 4(1): 39-45.

Kramer, O., 2017, Genetic Algorithm Essentials, Springer.

Küçüksille, E. U., Tokmak, M., 2011, Yapay Arı Kolonisi Algoritması Kullanarak Otomatik Ders Çizelgeleme, Süleyman Demirel Üniversitesi, Fen Bilimleri Enstitüsü Dergisi, 15-3(2011),203-210.

Lee, K. Y. ve El-Sharkawi, M. A., 2008, Modern heuristic optimization techniques: theory and applications to power systems, John Wiley & Sons.

Makridakis, S., 2017, The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms. Neapolis University - HEPHAESTUS Repository, http://hephaestus.nup.ac.cy/bitstream/handle/11728/9254/THE_FORTHCOMING ...2017_Full.pdf?sequence=1&isAllowed=y.

McCarthy, J., Minsky, M. L., Rochester, N. ve Shannon, C. E., 2006:1955, A proposal for the dartmouth summer research project on artificial intelligence, 31 Ağustos 1955. AI Magazine, 27(4), 12, http://www.aaai.org/ojs/index.php/aimagazine/article/view/1904/1802.

Mitchell, M., 1998, An Introduction to Genetic Algorithms, MIT Press.

Passino, K. M., 2012, Bacterial foraging optimization, Innovations and Developments of Swarm Intelligence Applications, 219-233.

Rao, S. S., 2009, Classical optimization techniques, In: Engineering Optimization: Theory and Practice, Eds, p. 63-118.

Tereshko, V., 2000, Reaction-diffusion model of a honeybee colony’s foraging behaviour, International Conference on Parallel Problem Solving from Nature, 807-816.

Tereshko, V. ve Loengarov, A., 2005, Collective decision making in honey-bee foraging dynamics, Computing and Information Systems, 9 (3), 1.

Weise, T., 2009, Global Optimization Algorithms – Theory and Application, http://www.it-weise.de/projects/book.pdf.

Yang, X.-S., 2010a, A new metaheuristic bat-inspired algorithm. Nature inspired cooperative strategies for optimization (NICSO 2010): 65-74.

Yang, X.-S., 2010b, Nature-Inspired Metaheuristic Algorithms, Luniver Press.

Yang, X.-S., 2012, Flower pollination algorithm for global optimization, International Conference on Unconventional Computing and Natural Computation, 240-249.

Yang, X.-S., Karamanoglu, M. ve He, X., 2014, Flower pollination algorithm: A novel approach for multiobjective optimization, Engineering optimization, 46 (9), 1222- 1237.

Zelinka, I., Snasel, V. ve Abraham, A., 2012, Handbook of optimization: from classical to modern approach, Springer Science & Business Media.