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Overview of evolutionary algorithms and neural networks for modern mobile communication

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Abstract

The sixth generation (6G) of mobile networks must support the huge growth of mobile connections and provides various intelligent services in future mobile networks. For that, designing high-performance network architecture and communication systems (CSs) as well as finding coherent solutions for the determined problems is critical demand that needs to be achieved in 6G networks. Optimal solutions are mainly sought by using modifiable, smart, and perceptive algorithms aimed at optimizing more specific tasks. Therefore, advanced optimization methods are highly required to accommodate the requirements of CSs efficiently. That will be in various parts of the future networks such as advanced mobility management, multi communication links, efficient power consumption, ultra-lower latency, ultra-security, high speed, and reliable connectivity. Accordingly, highly accurate and smart functions must be modeled to optimize the required communication parameters in the network. This study provides a comprehensive overview of optimization methods that may need further investigations and developments to be applied in 6G networks at various parts of networks. A detailed theoretical description for each method is presented and discussed to elucidate future research directions for optimizing specific characteristics with multi-objective optimizations. Moreover, this article illustrates the conceptual and structural viewpoints of reported optimization methods. Also, the capability of various optimization methods that can offer industrial solutions in 6G is discussed. The potential applications of each method are also analyzed. Finally, this article presented the research issues and future directions of optimization technology and research gaps that need to be addressed before the standardization of 6G networks.

1 | INTRODUCTION

Recently, innovative solutions of communication systems (CSs) have been developed impressively, as data traffic is increasing exponentially by more than 50% per year.[1] Several factors will contribute for increasing data demand massively, for example, as predicted by CISCO, the video will make up 82% of the all IP traffic by 2022.[2,3] This massive increase in data traffic will cause several new issues that will facing the implementation of future mobile networks. That will include a dramatic increase for wider spectrum need,[4] the necessity for big system capacity,[5] further mobility issues,[6,7] and higher energy consumption,[8] in which cannot be handled efficiently by the current cellular networks.

Addressing these various issues lead to rapid developments in mobile technologies which have attracted many researchers to focus on the next mobile communication field, recognizing the need for new innovative approaches which can only be developed by combining advanced techniques in various technologies. Fifth generation (5G),[9-13] and sixth generation (6G) of mobile networks[14] provide significant advancements that lead to transformative changes in telecommunication systems[3,15] including the next generation of the Internet of Things (IoT), TeraHertz (THz) communications, and drone-based communications. The 6G technology combines many up-to-date tendencies and welcome higher data rates for CSs.[16] Furthermore, millimeter wave (mmWave) communications with massive multi-input-multi-output (MIMO) technologies,[17] transceiver design,[18] and channel modeling[19] are important key technologies for enabling 5G and 6G Mobile communication networks. Hence, these networks need resources to provide operations and require optimal management for networks because they suffer from specific drawbacks. For instance, the mobile edge computing (MEC)[20] and centralized-radio access network (C-RAN) architectures suffer from speed and data storage capabilities. MEC is an advancement of mobile cloud computing (MCC) technology with cloud computing capabilities. It is worth to note that, C-RAN architectures are candidates for 5G and 6G Mobile networks development.[21] Therefore, advanced *optimization methods* are required for supporting 5G and 6G technologies. The optimization method is a mathematical formulation, algorithm or specific procedure used for selecting the best elements and optimal solutions, thus achieving desired goals by minimizing and/or maximizing the objective functions. Optimization simply implies "the best or most favorable point" for obtaining the highest achievable performance by iterative execution.[22] In the advanced 5G/6G technologies, there are various specifications to be considered and optimized as: latency, peak data rates, number of mobile connections, channel bandwidth, frequency band, uplink waveform, and user equipment transmitted power.[23] Providing a set of optimal solutions in terms of all nominated specifications is not straightforward and it requires multi-objective optimization methods for trading-off between various required outputs.

The 4G and 5G technologies facilitate a technological breakthrough by reducing latency[24,25] and increasing reliability with speed in application environments such as IoT.[26] However, there are various optimization metrics and numerous features in wireless technology that include latency, connectivity, reliability, and speed where they must be optimized concurrently. For conflicting different communication requirements, multi-objective optimization algorithms are desired to evaluate key performances as well as realizing ambitious and impressive goal performance.[27,28] In particular, the optimization process must be cost effective, providing stable and productive outcomes to ensure an effective system and to improve an immense measure of information.[29]

Considering the limitations in conflicting multiple features and constrains, there is a growing consensus for determining accurate and fast multi-objective optimization methods. To tackle these challenges, the study of various multi-objective optimizations applied to 4G and 5G technologies has become a necessity for the present and future multi-mode terminals[30] and future 6G networks. With the rapid evolution of communication technologies, network topologies and services are becoming complicated. Therefore, in many communication areas, various optimization methods facilitate progress by solving the aforementioned challenges and use advanced methodologies to attract attention from both academia and industry. To solve optimization problems, multi-objective optimizations can determine optimal solutions by striking trade-offs among objectives and constraints with the assurance of the best solutions and time-to-market processes.[31-33]

Two different optimization methods are generally used namely as: exact optimization method and heuristic optimization methods. Optimal and best solutions are achieved in the exact optimization methods. In contrast, the heuristic optimization methods provide no guarantee about the obtained outcomes as they are used to solve NP-complete problems. In the field of heuristic methods, evolutionary algorithms (EAs) have garnered the attention of researchers at their role in developing evolutionary programming, and strategies.[34] Particle swarm optimization (PSO),[35,36] ant colony optimization (ACO),[37] artificial bee colony (ABC),[38] differential evolution (DE),[39] and genetic algorithm (GA)[40] are some of the EA-based approaches used in CSs. As the optimization engine in this study, we describe in detail some of the recently used methods including intelligent optimization methods (ie, optimization algorithms based on animals, plants or insect behaviors, optimization algorithms based on human treatments, and optimization algorithms based on the evolution process), self-optimization (SO), Markov approximation algorithm (MAA), joint optimization (JO), closed-loop optimization (CLO), and convex optimization (CO).

Some surveys related to optimization were recently published in the communication field providing comprehensive reviews for determining the relevant principles, methods, and applications. We focus on the main contents of the recently published survey papers and summarize some of them in Table 1. In contrast to existing surveys, our work aims to discuss various and general state-of-the-art optimization methods that can be employed in the future 6G networks. In particular, we provide the basic theory of each method and as practical applications we determine recently published papers

TABLE 1 Summary of recently published surveys related to optimization in the communication field

Ref.	Year	Content description of each survey
34	2014	Describing evolutionary algorithms
41	2016	Discussing physical layer operations in the mobile environment
42	2017	Explaining the features of 5G wireless CSs developed for use in millimeter wave frequency bands
43	2018	Clarifying the necessity of mobility prediction and intrinsic characteristics
44	2019	Demonstrating optimization approaches on each research topic of the physical layer security
45	2019	Improving handover performances and fast handovers for mobile Internet protocol version 6 (IPv6) (FMIPv6)
46	2019	Describing radio access mobility in LTE, heterogeneous networks and 5G new radio
15	2020	Exploring the expected new technologies for 6G networks
47	2020	Presenting online big data analytics, cloud-edge computing, statistical machine learning, and proactive network optimization in a common cross-layer wireless framework
3	2020	Describing intelligent management design techniques with a combination of ultra-dense networks and 5G-enabling technologies
48	2020	Developments in slice admission control objectives, strategies, and algorithms

that these algorithms are used in their problems. Considering the importance of practical communication networks, herein, we provide a well-rounded overview of the applied optimization methods and their practical applications in the next-generation networks (ie, 6G networks).

This article aims to provide a comprehensive summary on optimization methods that can be employed in 6G mobile networks. In particular, this study is describing explicitly each method and identify technical challenges for the state-of-the-art reported techniques. Additionally, the advantages and disadvantages of each nominated optimization method are briefly explained such that readers can easily determine a suitable algorithm for their problems. Furthermore, the applications of each optimization method are briefly discussed and their features are compared. Study also is describing the suggesting possible future open challenges. Such kind of survey study will contribute for enabling the researchers to figure out which methods need in-depth study on its impacts to find out the most optimal methods can be efficiently applied in 6G systems.

The remainder of the article is organized as follows. In Section 2, we provide general descriptions about the concept and structures of the optimization methods. In Section 3, we present a comprehensive overview of the different optimization methods applied in recently used communication technologies and the applicable possibility in the future 6G networks. In Section 4, we investigate the challenges around the optimization methods and discuss the future work. Section 5 devotes to summarize the authors' own outlook and thoughts regarding the optimization methods. Finally, Section 6 concludes this article.

2 | BACKGROUND

Before theoretically explaining various optimization methods, we firstly aim to provide an overview of the optimization terms. The concept of optimization and a common optimization structure used in various methods are described below.

2.1 | Concept of optimization

Optimization is the process of minimizing and/or maximizing some functions corresponding to some datasets. Some common applications can include minimal cost, minimal error, optimal design management, and maximal profit. The goal of the subject is to consider the optimization problems, advantages and disadvantages of optimization, and the problem categorization. Numerical methods can provide solutions using iterative computation schemes. In addition to numerical methods, different solution techniques can be compared and evaluated.

The system level designs and circuits have considerably benefited from increased applications and performance. However, meeting constraint is challenging and multi-modal black-box optimization problems are encountered owing to system complexity. Tens of thousands of function evaluations are required in simulation designs. In interactions, various optimization methods have been considered for solving design problems that lead to compact, low-cost, and low-profile structures. The validity of different optimization methods is measured in terms of robustness, simple implementation, and satisfied optimization performance. Suitable optimization methods with sufficient tools for handling the problems of electromagnetic design drawbacks are selected by considering the advantages and disadvantages of each method. The targeted design parameters can be accounted by focusing on full-wave and electromagnetic simulations. Optimization methods generally lead to optimal solutions in an evolutionary manner.

The 5G and next-generation technologies will be an important key for the future digital world that will support ultra-wide band data transmission. The future 6G technology will need the evolutionary methods to be used in various use-cases such as extreme mobile broadband, massive machine-type communication, and ultra-reliable machine-type communication. Hence, providing potential algorithms for enhancing the flexibility of 5G and 6G systems to be used almost everywhere becomes a significant step.[49] Evolutionary algorithms and neural based networks perform well approximating solutions to various types of problems that garnered the attention of researchers owing to their attractive features and suitable generalization capability.[50,51] Hence, various intelligent and evolutionary based algorithms are used in the analog, radio frequency, and telecommunication domains in the recent years.[52-54]

2.2 | Optimization structure

Over the past decade, the structural optimization has been presented as a remarkable tool in the design process. Many optimization problems are encountered in the domain of next-generation networks. Therefore, seeking the best and suitable optimization solver for the determined problems is an important concern of researchers. Hence, it would be fruitful for applying new optimization methods to solve the determined problems.

The use of numerical optimization techniques requires an optimal design mechanical structure, and yields cost-effective structures. The optimization process reduces the construction and engineering costs, thus leading to innovative design solutions. The optimization process is divided into three groups, namely, size optimization, shape optimization, and topology optimization wherein the dimensions, shapes, and spatial distribution of structural components are optimized, respectively. In these three groups, determining the objective function with boundary conditions is a vital process. Figure 1 shows various optimization concepts (ie, size, shape, and topology optimizations) for optimizing a single microstrip patch antenna. For deep illustration, in the size optimization width and length of the antenna are altered where in the shape optimization the construction and topology are updated and in the topology optimization the constituent parts with biasing points of antenna are arranged.

Figure 2 presents the general and comprehensive optimization loop for achieving desired output performances in any system-level designs. In 5G networks, some of the specifications that can be attempted to be optimized can be latency, power consumption, and so on. After determining the optimization goals, the suitable optimization technique will be selected by considering the advantages/disadvantages of each method. Finally, after careful evaluation the optimized output performances are obtained.

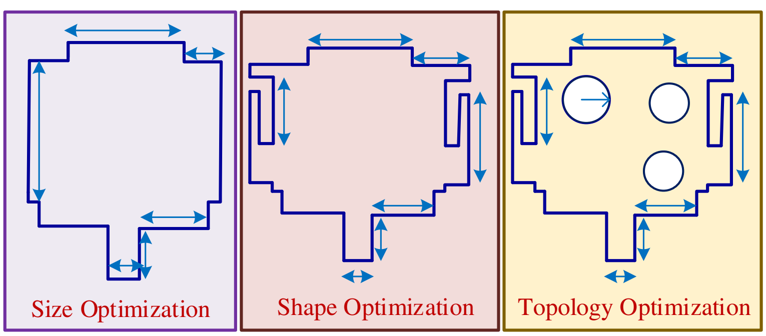

FIGURE 1 Various optimization methods for optimizing a microstrip patch antenna; left to right the parameters are size, shape, and technology[55]

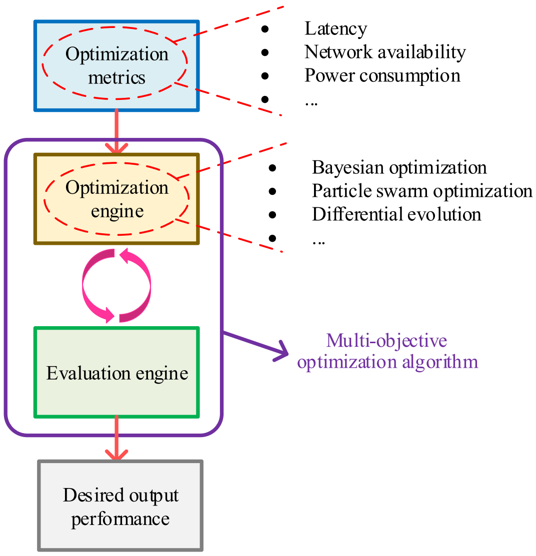

FIGURE 2 Flowchart of multi-objective optimizations[56]

2.3 | Advantages of the optimization process

Optimization methods require either local (typically gradient-based) or global (typically non-gradient based or evolutionary) algorithms by considering the design variables. Optimization processes provide various significant benefits using software tools. The most obvious benefit of the optimization process is improvement in the efficiency of the system designs, that is, improvement in the flow of the overall designs. Efficient and well-organized processes provide opportunities for enhancing the targeted design outputs. In the telecommunication field, special efforts are undertaken to concentrate on techniques that yield optimal solutions. Various optimization methods include some/all of the design variables limited to integer or discrete values. Generally, the algorithms investigate the side constraints that can be efficiently handled by direct implementation.

Unnecessary steps are eliminated in the optimization process. In a short time, the design specifications can be achieved with reduced errors. Using an appropriate optimization algorithm, the design process can efficiently work, in a fast, and flexible manner supported by suitable software tools. Additionally, strictly organized processes facilitate continuous improvements. Optimization processes determine the combination of design variable values that consequently produce the best objective function value.

2.4 | Need for optimization

Wireless technologies became a significant part of our live and science in these current decades. The communication science field experiences up-to-date aspects continuing to wireless systems. These systems require flexible and efficient algorithms for establishing wireless channels, considering that with the development of communication science, more channel conditions with more application requirements have emerged. Therefore, unprecedented and challenging requirements must be optimized to meet high-reliability response.

Linear and nonlinear optimizations have paved the way for new standards by improving the existing services. The implemented optimization methods in the telecommunication filed help address the aforementioned challenges. Optimization methods are developed for various optimization specifications such as ad-hoc networks, seamless ad-hoc networks, and beamforming in MIMO systems. A high data rate for supporting personal and multimedia communications can be obtained by optimizing the whole system-level designs. Optimization methods are required in the future 6G networks because of the following reasons:

1. Speeding-up the process by inactivating unnecessary specifications.
2. Providing solutions for speeding algorithms.
3. Improving various performances using different schemes.

4. Reducing the performance of instructions.
5. Employing the programming constructors to improve high-level designs.
6. Determining the collaboration of device to device communication technology.
7. Efficiently reducing cost and errors with minimum efforts.

3 | OPTIMIZATION METHODS IN COMMUNICATIONS

Figure 3 presents the summarized important blocks that construct communication networks namely as: input/output transducers, transmitter (Tx), channel, and receiver (Rx).[7,57-60] The system-level description of general communication networks comprises assembled sections where Tx and Rx sections includes various sub-blocks, and diverse parameters must be optimized to meet the required design specifications. Some of output specifications that can be optimized for obtaining the optimal solutions are taken from Reference 61. Dealing and challenging with these specifications require substantial effort. Previously some of the optimization methods are employed in practical 4G and 5G networks, where they can lead to the development and implementation of high- performance future 6G networks.[62] For getting deep view regarding the various visions of 5G and 6G, Figure 4 is provided. It demonstrates performance metrics, global coverage, spectrums, and network security of systems. As it is obvious, various specifications are existed that must be optimized concurrently for designing high performance 5G/6G systems. Typically, the planning of CSs with optimization include three important sections as "selection," "crossover," "mutation" lead to minimize the cost of deploying the new network in a fastest way. Figure 5 presents the planning of mobile CSs without and with applying the optimization methods for proving the necessity of optimization methods in the various systems. Hence, for this case multi-objective optimization algorithms are required. The general description of multi-objective is presented in (1).

$$\left\{ \begin{array}{c} \text{minimize } f(x); \quad f(x) \in R^m \\ \text{subject to } g(x) \leq 0; \quad g(x) \in R^k \\ x \in \Omega \end{array} \right\}, \tag{1}$$

where $f(x)$ is a vector with m objective functions, $g(x)$ is a vector with k constraints, and x is a vector with n design variables on the search space Ω. For the case of $m \gneq 1$, multi-objective optimization can be appeared.

Consequently, next-generation networks need the support of optimization methods and technologies to identify, adapt, and predict the functionalities in complex networks. These technologies are used in various applications in the

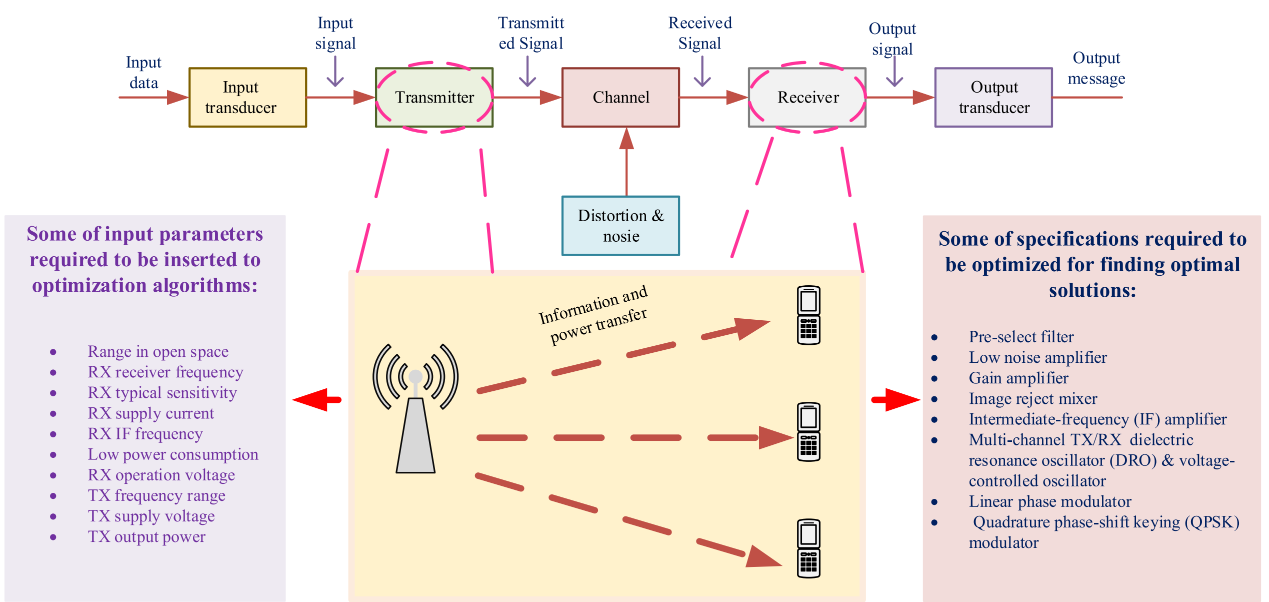

FIGURE 3 Components of communication systems with different specifications for optimization

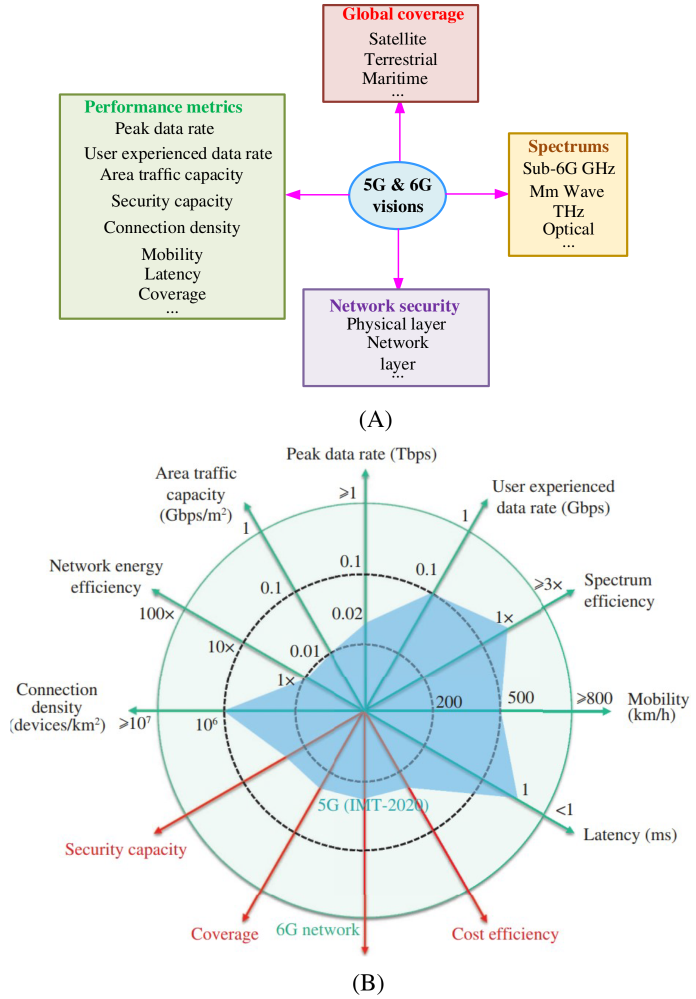

FIGURE 4 (A) Various vision of 5G and 6G networks, and (B) performance of 6G networks[62]

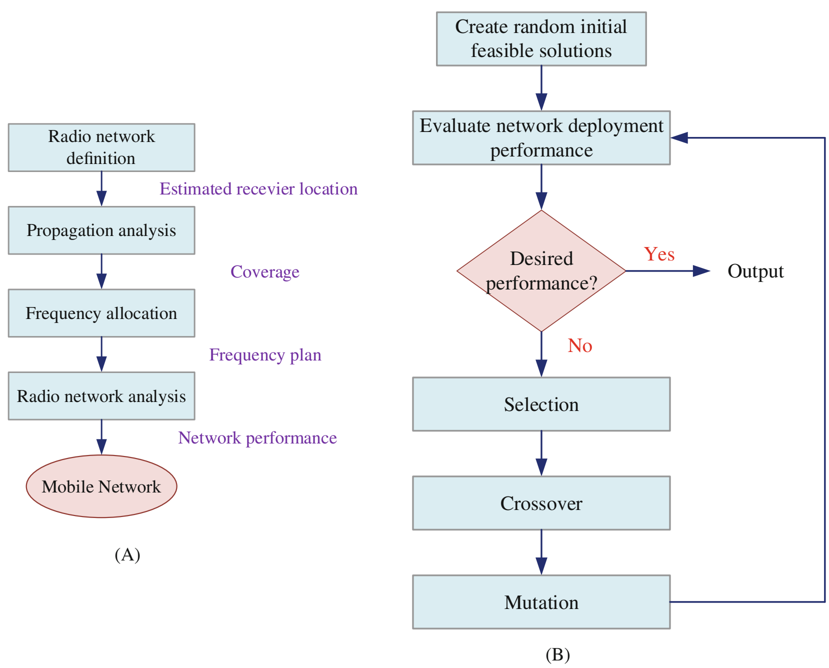

FIGURE 5 Planning of communication system: (A) Without optimization[63] and (B) with optimization[64]

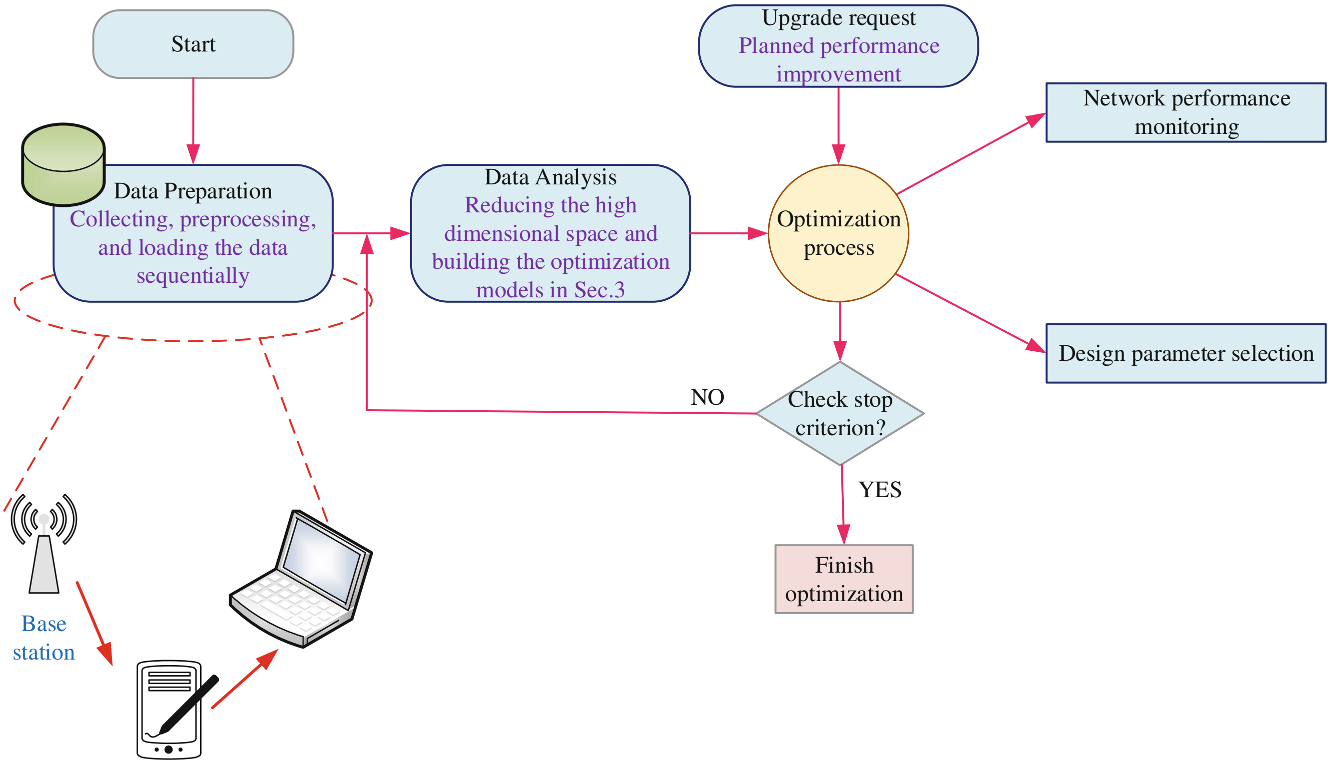

FIGURE 6 General structure of optimization process used for optimizing communication systems

fields of communication network, wireless communication, smart infrastructure, IoT, and image with video communications. Furthermore, these systems are optimized in terms of metrics, such as security, latency, bit error ratio, and power consumption. In this section, we provide a comprehensive explanation of the techniques implemented in different networks as novel optimizations that are required for network management. Employing multi-objective methods with the evolutionary algorithms will strengthen the whole process for finding optimal solutions. In summary, the general structure of optimization methods used for determining optimal solutions for CSs are shown in Figure 6. First, suitable amount of data is collected through the transmitted data from base station, then any described optimization method in Section 3 would become ready for employment, and finally optimization process is applied. Any of the optimization algorithms is selected regarding the advantages and disadvantages provided at the end of this article.[64,65]

3.1 | Intelligent optimization methods

This section is divided into three subsections that describe various optimization methods based on: (i) animal, plant, and insect behaviors, (ii) human treatments, and (iii) evolution processes, respectively.

3.1.1 | Optimization algorithms based on animals, plants, or insect behaviors

Various optimization methods based on animals, plants, or insects include PSO, ACO, ABC, artificial fish swarm algorithm (AFSA), artificial plant optimization algorithm (APOA), chicken swarm optimization algorithm (CSO), bacterial foraging optimization (BFO), firefly algorithm (FA), fruit fly optimization algorithm (FOA), wolf pack algorithm (WPA), shuffled frog leaping algorithm (SFLA), cuckoo search algorithm (CSA), and bat algorithm (BA).[66-71] The use of these optimization methods has been studied in References 72-85. We clarify and report the theory and applications of some methods in this section.

Particle swarm optimization: PSO is a computational method based on the stochastic optimization technique.[86] This method was developed in 1995 by Kennedy and Eberhart.[36] It is similar to the GA[87] method and enhances solutions

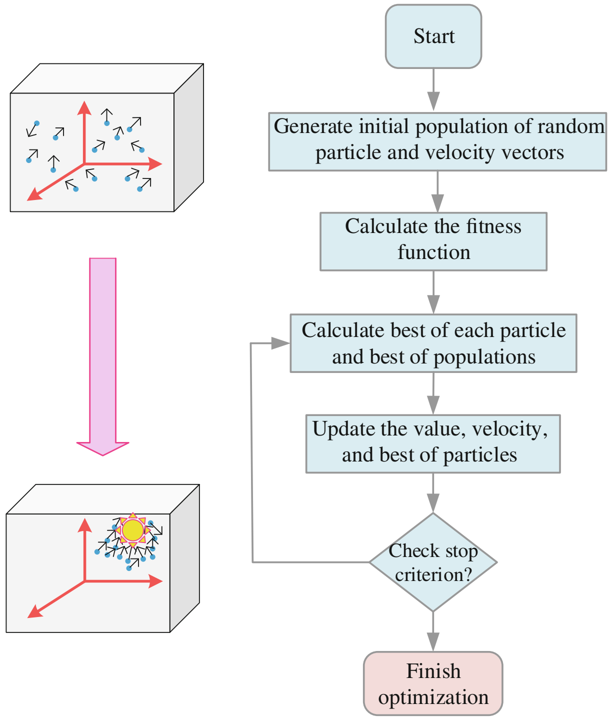

FIGURE 7 PSO method with optimization process[90]

related to a fitness function.[88,89] The general flowchart of PSO method is shown in Figure 7 where it consists of four main steps as following:

1. For each of the population, the best position namely as p_{Best} is determined.
2. In the entire population, the best position is defined namely as g_{Best}.
3. The velocity over time is calculated using the p_{Best} and g_{Best} that is defined as $v_i^{t+1} \approx p_{\text{Best}} + g_{\text{Best}}$.
4. The velocity is updated and continued up to getting the best-position.

As a clear illustration of PSO, Kaur and Grewal[91] presented a new PSO-based dual sink mobility (PSODSM) technique that reduces the energy expenditure of the sensor nodes. This method is a PSO-based cluster head selection approach for optimizing the residual energy, node centrality, node degree, energy consumption rate, cluster head count, and distance factor. In Reference 92, a PSO-based optimization called PSO energy efficient cluster head selection (PSO-ECHS) is presented. This method enhances the fitness function and particle encoding scheme. Figure 8 depicts the functionality of this method where the sink is moving around the environment and various sensor nodes aimed to find the optimal solution as the cluster head. It offers various advantages such as reduced energy, improved network scalability, and conservation of the communication bandwidth. As another example of the PSO method, Figure 9A presents a cluster-based wireless sensor network as a method application where various sensor nodes are employed for finding the optimal solution as a cluster head to be transmitted to the base stations and house/office of people. Also, Figure 9B illustrates the searching of a particle for achieving the optimal solution. For this case, a particle P_i fits the position of $X_{i,d}$ with the velocity of $V_{i,d}$. This occupying is continuing up to achieving the best position namely as $X_{i,d}(s)$.

In cellular networks that are used to improve the quality of service (QoS), low-complexity optimizations are needed to consider both co-channel interference and full-duplex self-interference. In Reference 93, an algorithm based on PSO is reported, which circumvents the cooperative coded caching placement. The bare-bone PSO (BBPSO) algorithm, another version of PSO, is presented in Reference 94. This method is used to optimize the degree distribution of low density superposition modulation (LDSM) matrix. In the BBPSO algorithm, the traditional velocity term of PSO is reduced.

Ant colony optimization: ACO is a probabilistic technique inspired by the behavior of real ants. It attempts to find and reduce the good paths through graphs. This method is a subset of swarm intelligence methods. It solves computational

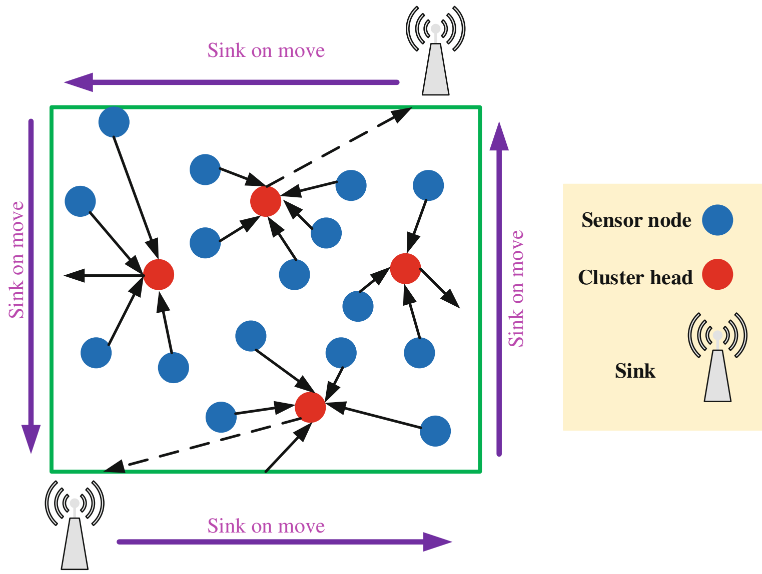

FIGURE 8 Application example of the PSO method illustrates network scenario of PSODSM[91]

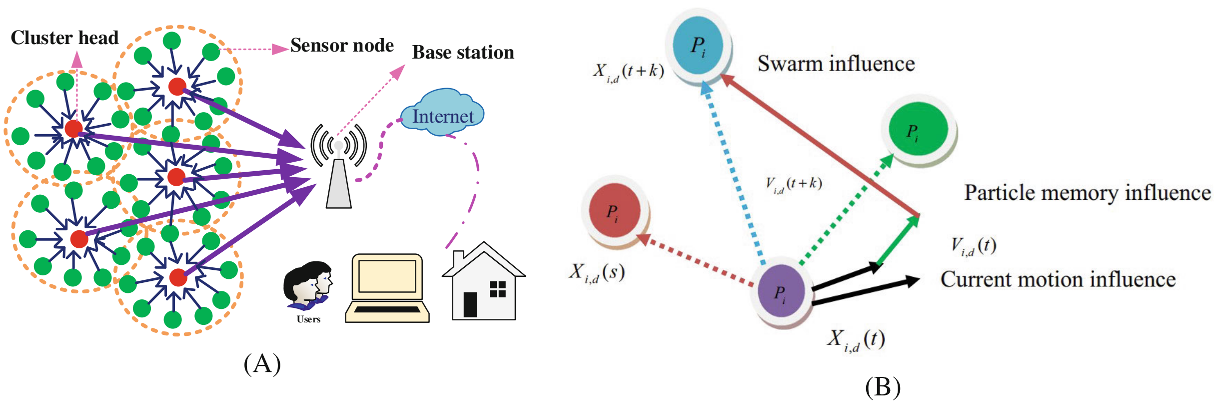

FIGURE 9 (A) A cluster-based wireless sensor network using the PSO method, (B) flying of a particle[92]

problems by determining a parameter space representing all possible solutions, and identifies the shortest path on a weighted graph. It has a positive feedback mechanism and various in types. However, the convergence rate and speed are slow.[95] Figure 10 demonstrates the ACO method, in which the best way (ie, the shortest path) to start moving from points A to B via ball numbers 1 to 4 is determined. The general steps of the ACO method are listed:

1. Each ant stochastically and randomly builds a solution, and guesses the next following edges in the graph.
2. All the paths determined by each ant are compared with each other.
3. The pheromone levels, rates where the increments and decrements influence the algorithm, are updated.
4. If necessary, the iteration from the first step is performed until optimal solutions are found.

Figure 11A depicts the use of this optimization in the wireless networks, where each node includes data packet transmission and ant optimization identifies the shortest path to start transferring data from node A to B by focusing on the critical nodes. There are various base stations where the fastest way for transmitting data is from bubbles number 1 to 4. Figure 11B demonstrates the use of various nodes where high energy node and critical node are being used in transactions. The various behaviors of nodes lead to have operations as transmitting, receiving, or idling. Figure 12 presents another use of the ACO method in wireless sensor networks, in which an aggregation model collects data from regular nodes (ie, node A) and sends them to the destination node (ie, node B). The node “C” is the representation for collecting

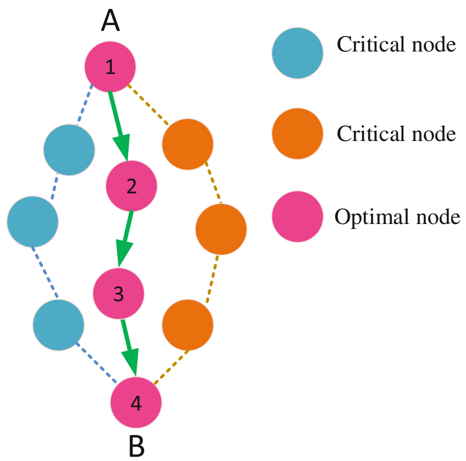

FIGURE 10 Ant colony optimization illustration[96]

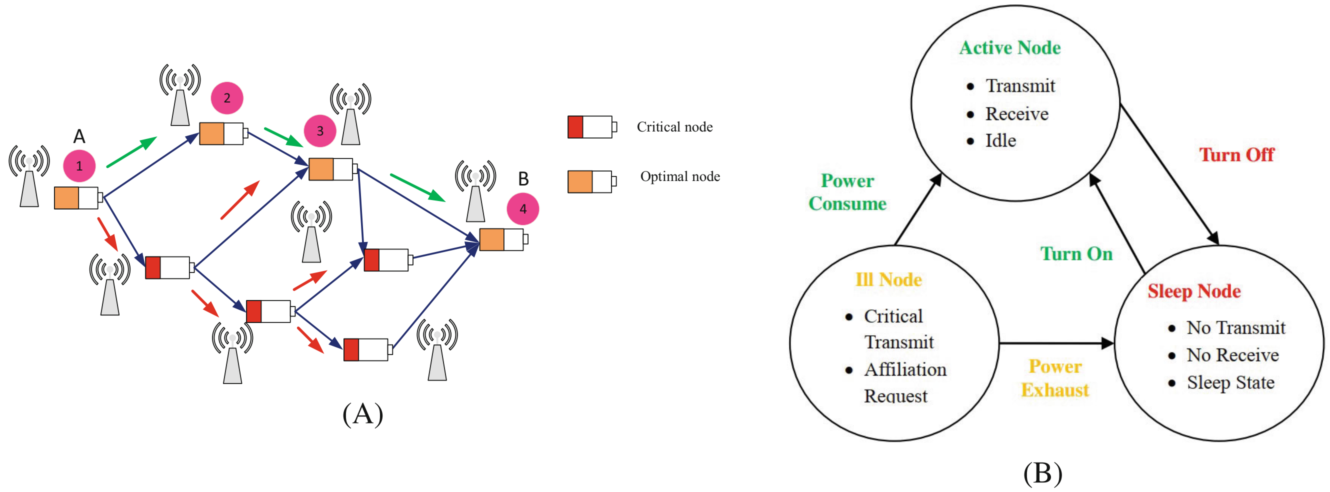

FIGURE 11 Network scenario by using ACO[97]

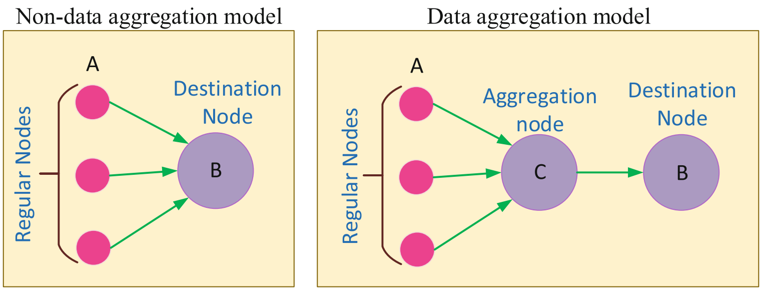

FIGURE 12 Comparison between a non-data aggregation model and a data aggregation model based on ACO[101]

all data and then concurrently sending to the destination node where this performance reduces the energy consumption of whole system.

Various studies that employ the ACO method have recently been reported. A new routing algorithm for wireless sensor networks is presented in Reference 98. This algorithm identifies an optimal path or data transmission. In Reference 99, the ACO method is used to achieve minimum cost and connectivity -guaranteed grid coverage. Moreover, the maximum possible energy efficiency and maximum possible energy balancing are optimized in Reference 100.

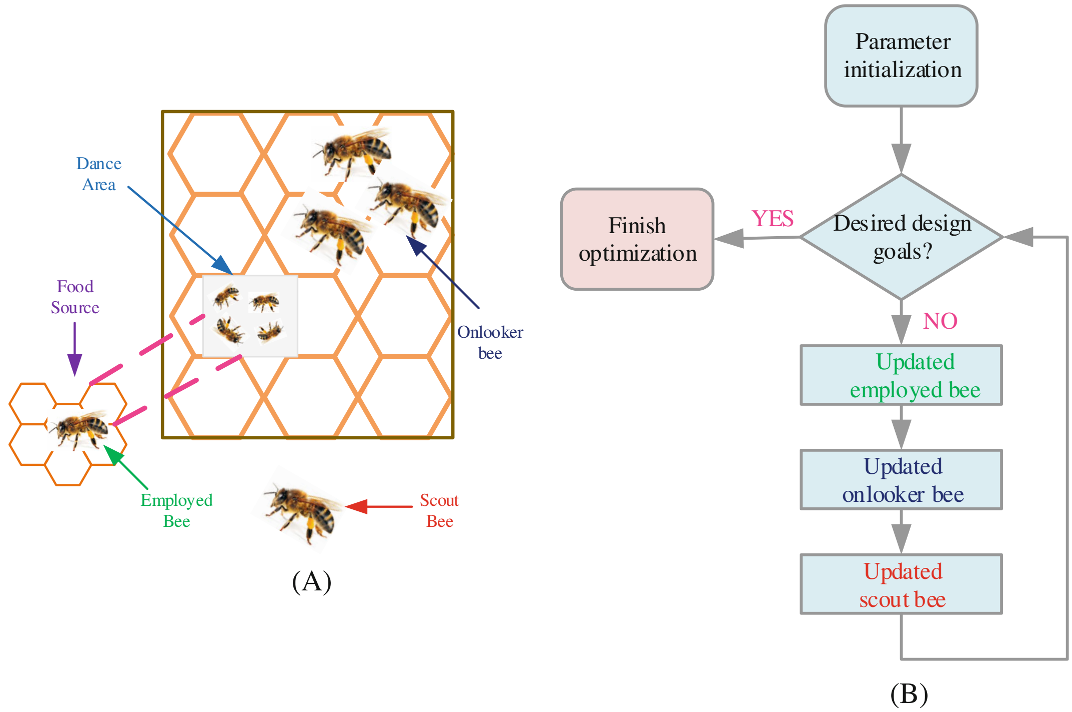

FIGURE 13 ABC optimization: (A) Responsible illustration of different bees, and (B) ABC optimization illustration[103]

Artificial bee colony algorithm: The ABC algorithm is a search procedure method and is a subset of the PSO algorithm. This algorithm explores food places with a high amount of nectar.[102] Figure 13 shows the ABC optimization methodology, and further explanation about this figure is presented in Reference 103. This algorithm solves high dimensional problems at a slow speed.[104,105] The general optimization steps of the ABC method are described:

1. Each employed bee approaches the food source and determines the neighbor source. This bee then dances in the hive and determines the nectar amount.
2. Each onlooker bee considers the dance of the employed bee. Based on the dancing results, the onlooker bee then selects one of the sources and approaches the source. This bee again controls and determines the nectar amount.
3. A scout bee discovers the uncontrolled food sources and replaces these with new food sources.
4. The iteration process is repeated until the requirements are met.

As an example of using the ABC method, Figure 14A shows how the ABC method helps in collecting data for mobile wireless sensor networks.[106] The other use of this method is illustrated in Figure 14B where optimum data transferring route is achieved significantly. This method is employed to solve the bottleneck problem of energy consumption using a mobile sink for data collection. The heuristic ABC algorithm is constructed by considering the selection of the cluster head node, route from nodes to cluster heads, and shortest route of the mobile sink. By using this method, the data collection is enhanced and energy consumption is decreased.

The ABC method has recently been reported in the domain of the antenna array[107] and wireless sensor networks[108] as well. This technique is used for designing an optimal array antenna by solving electromagnetic inverse problems.[109] Accordingly, a mobile sink-based path optimization strategy is reported for wireless sensor networks in Reference 110.

Bat algorithm: The BA method is a bio-inspired algorithm that uses a frequency-tuning method for improving the optimal solutions. This process aim to balance exploration and exploitation in the search process. In this algorithm, the global optimization approach is employed. It is widely used for adjusting loudness and pulse rate.[111] In the multi-objective BA, information is exchanged between various swarms using various parameters.

BAs are stochastically and randomly fly to find the prey with velocity of v_i at the position of x_i with minimum frequency of $f_{\min}$ and wavelength of A_0. The general steps for the BA optimization process is as following:

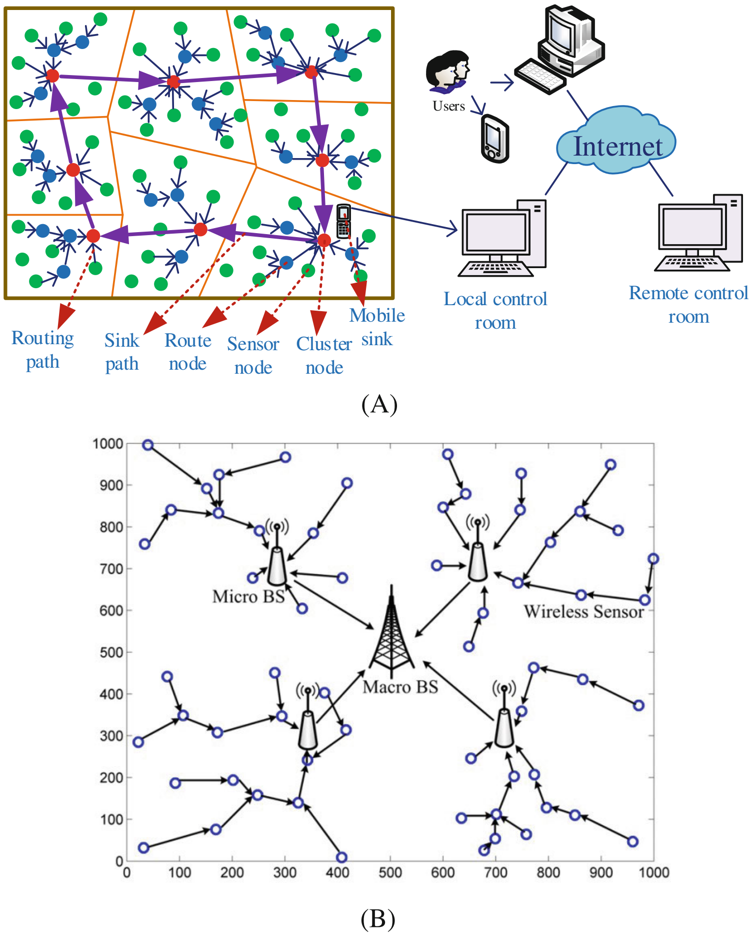

FIGURE 14 (A) Mobile wireless sensor network data collection based on the ABC method,[106] (B) optimal data transferring[103]

1. The initial values of parameters are set to zero.
2. For $v_i, x_i, f_{\min}$, and A_0 parameters, the initial populations are set randomly.
3. The objective function f_i is generated as (2) to (4)

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta, \tag{2}$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x^*)f_i, \tag{3}$$

$$x_i^t = x_i^{t-1} + v_i^t, \tag{4}$$

where $\beta \in [0, 1]$ and is a random vector, x^* is the current global best location, and t is the number of iteration.

4. The local search method is employed.
5. The repetition is applied up to achieving optimal solutions.

Based on the BA algorithm, transmission of redundant information can be effectively reduced in mobile heterogeneous wireless sensor networks.[112] Relay and sensor nodes are developed in a three-dimensional environment using the advanced BA method.[113] Energy consumption consideration for wireless sensor networks has been reported in References 114 and 115 based on the BA method.

Chicken swarm optimization algorithm: The CSO[116] is a recent bio-inspired algorithm that minimizes the hierarchical order during food search. Figure 15A,B presents the basic idea of the CSO method that finds the rooter with the best fitness value. And the Figure 15C,D presents the application of this optimization for beamforming where the optimal solution is achieved in the 46th node with the radius (R) of 2. The typical steps of this method are as following:

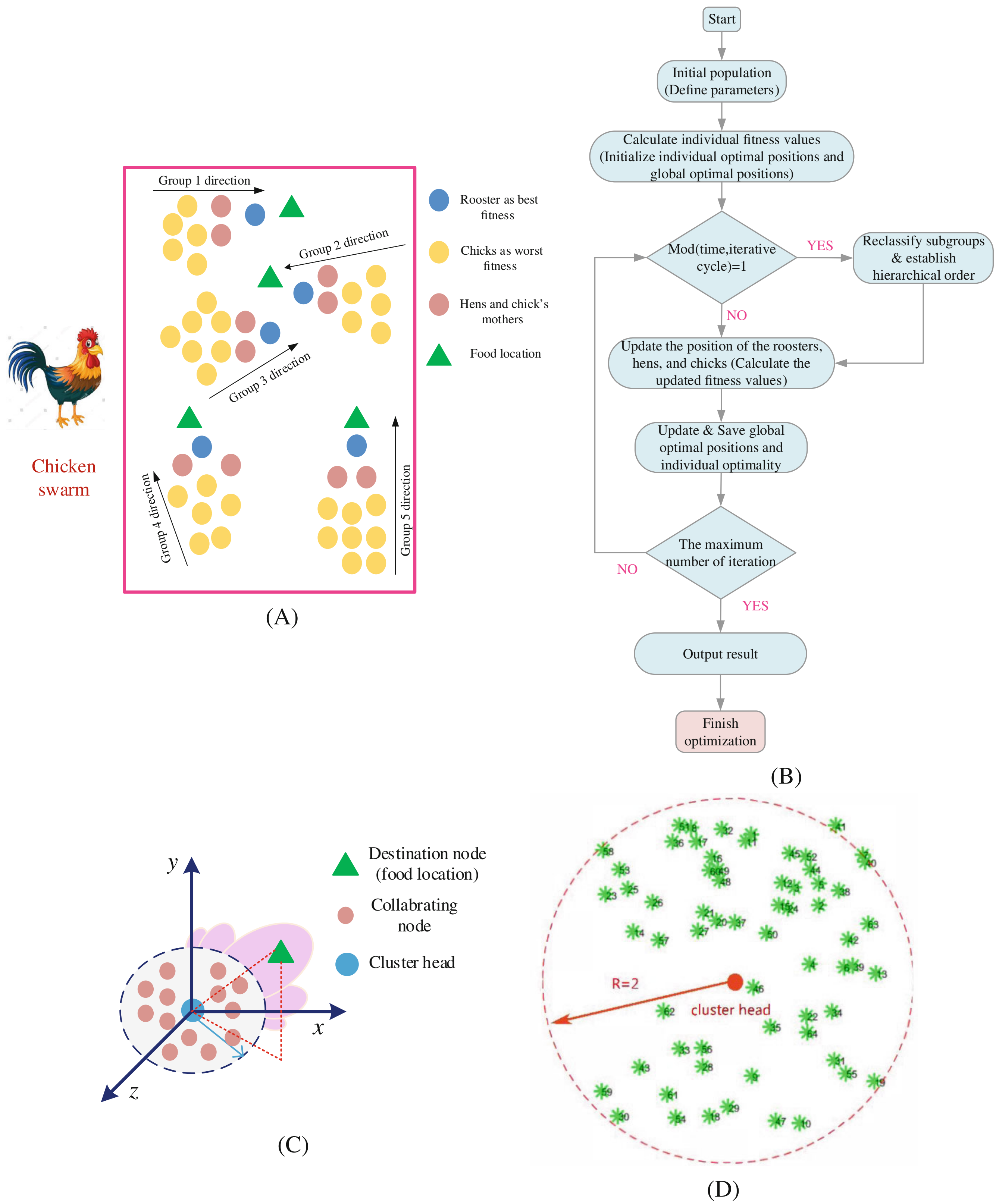

FIGURE 15 Chicken swarm behavior: (A) Basic idea of CSO,[119] (B) optimization process,[120] (C) application of CSO in an antenna array,[117] and (D) node position beamforming

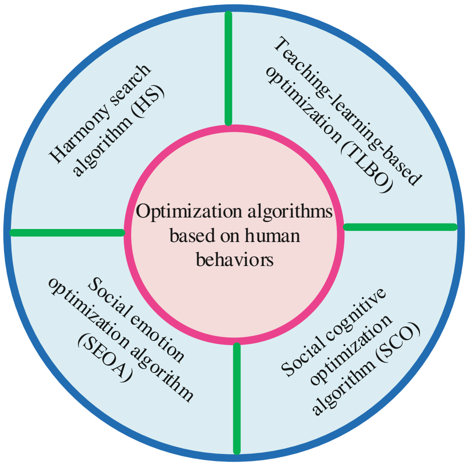

FIGURE 16 Various optimization methods based on human behaviors

1. The chicken swarm is divided into two groups with one rooster and many hens.
2. The hens follow the rooster for searching food.
3. Fitness value outlines swarm hierarchy.
4. The swarm hierarchy will be active only in several time step(s).

The application of this method in the optimization of the peak sidelobe level in a distributed random antenna array is described in Reference 117. This method is generally used to optimize the antenna array by considering the beam pattern problem like the definition of rooster and hens. In another use of the CSO method, the maximum sidelobe level in the antenna array is reduced[118] and optimal solution is generated.

3.1.2 | Optimization based on human treatments

Various optimization methods are based on human behaviors.[121-126] Figure 16 presents a summary of these methods. The theoretical explanations for one of the methods are described below.

Harmony search algorithm: The harmony search (HS) algorithm has a straightforward application and is the combination of exploration and exploitation.[127] The HS algorithm detects the desired harmony and attempts to pattern the improvisation process of musicians[128] by arranging fewer mathematical requirements. The number of iterations is reduced using a stochastic derivative. Figure 17 presents the general description for combining harmonics. The HS algorithm starts with randomly stored parameters in the harmony memory. In each iteration, individuals are then generated by considering memory, adjusting pitch, and regarding the randoms used for preparing new individuals.[129] Before starting the optimization, harmony memory size, pitch adjusting rate, and stop criteria must be determined. Next, the initial population harmonic memory is randomly generated by the vectors. Then, a new harmony is improvised by adjusting pitch. Finally, harmonic memory is updated up to achieving desired goals.

Figure 18 shows the basic idea of the HS method. Accordingly, Lin et al[130] illustrate the application of this method to solve the problem of extending the lifetime of underwater acoustic sensor networks. A detailed description of this method is shown in Figure 18B-D provided from Reference 130. It demonstrates the harmony synchronization at the uniform crossover operation. The number of the covered targets of each sensor is calculated in the first phase, while the uniform crossover operation is performed on A and B in the second phase. The HS method can be useful from the view of energy distribution for the wireless sensor networks.[131]

3.1.3 | Optimization algorithms based on the evolution process

Figure 19 presents the optimization methods based on the evolution process presented in References 132-135. In this section, brief descriptions of some methods are presented with their related applications for the next-generation networks.

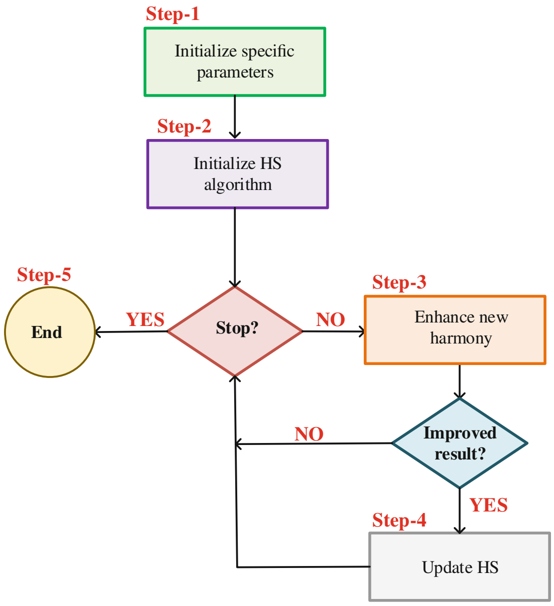

FIGURE 17 Flowchart of the HS algorithm[129]

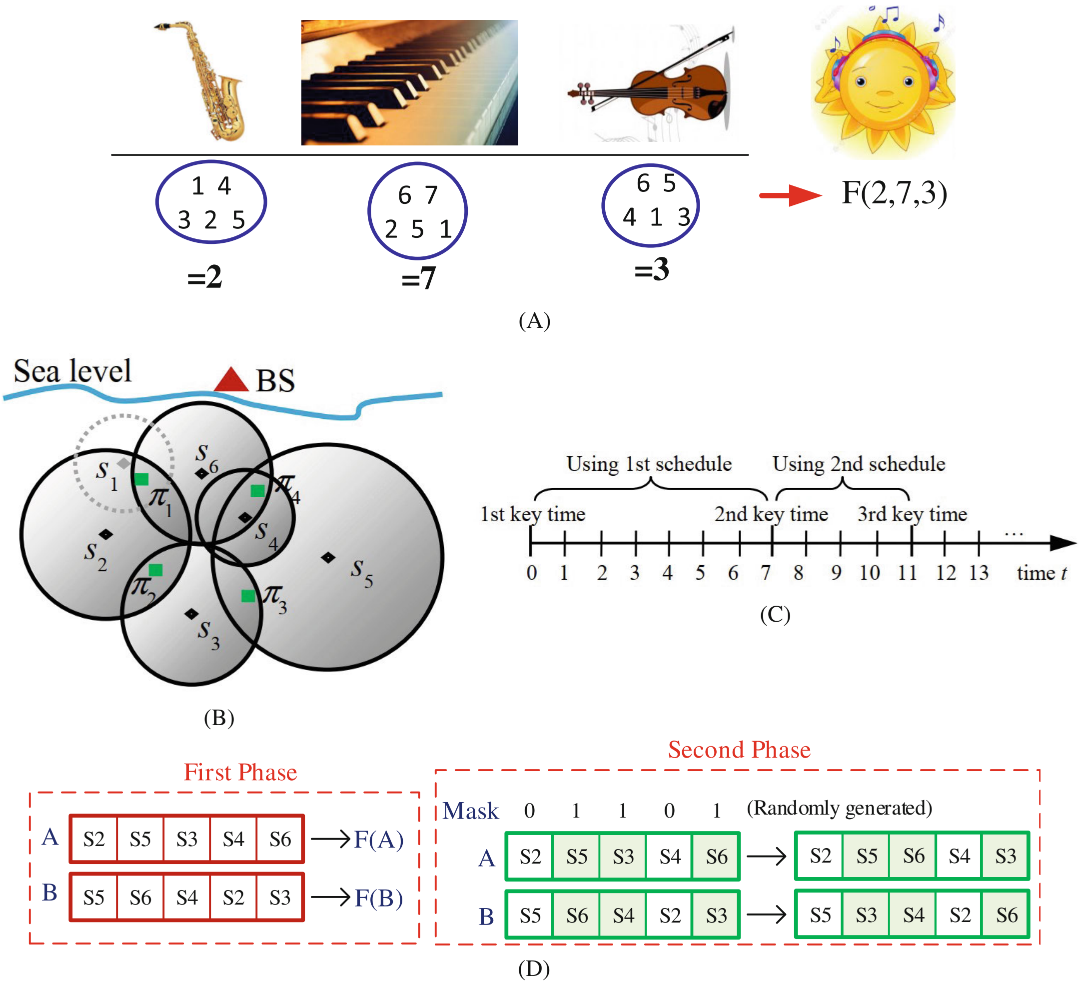

FIGURE 18 Harmonic search algorithm: (A) General explanation of the combination of harmonics in the HS algorithm, (B) underwater acoustic sensor networks with the base station (BS) with sensors (S) from 1 to 6 and targets (π) from 1 to 4,[130] (C) the relationship between times and schedules,[130] and (D) application of the HS method in the uniform crossover operation[130]

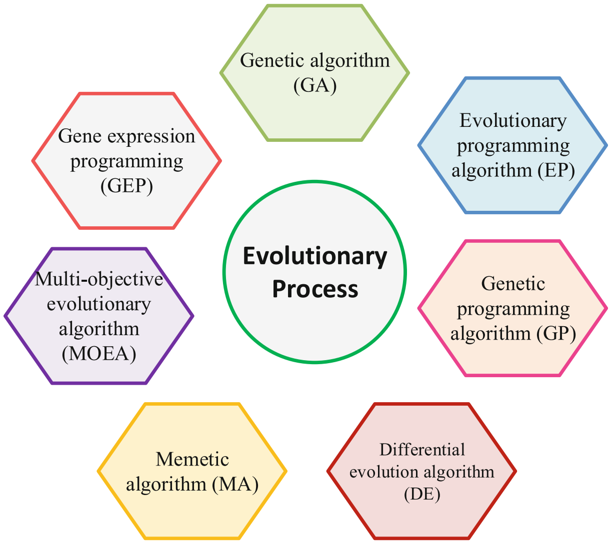

FIGURE 19 Various optimization algorithms based on evolutionary process

Artificial intelligence: The artificial intelligence (AI) can be achieved by using machine learning and multi-objective evolutionary algorithm. Unlike natural intelligence, AI methods are machine intelligence approaches that are considered as a revolutionary feat of computer science. AI techniques that are computational tools, require large amounts of training data to model the general behavior of any systems through programmed simulations. In this approach, algorithms are created and used such that they can learn from experiences and mimic the actions of humans. In other words, AI is the study of computer algorithms that act without being programmed[136,137] and refers to a growing body of computational techniques that can predict outcomes without being explicitly instructed and rationally act like humans. Three key factors must be prepared to create this intelligent environment: computational systems, data generation with data management, and advanced codes of AI algorithms. AI methods are computing computational algorithms that learn the characteristics of a system/network where they exhibit a nonlinear behavior, and extracting an explicit mathematical model which is impossible. They make predictions by absorbing and interpreting complex data groups. These methods are for classification, regression, or interaction of an intelligent agent spanning into three paradigms as supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL)[138] (Figure 20).

A substantial difference exists between supervised and unsupervised algorithms, whereby supervised learning needs prior knowledge of outputs for related inputs. Alternatively, reinforcement learning provides a feedback loop between the learning system and related experiences and does not need accurate inputs and outputs.[139] Based on the unsupervised learning algorithm, in Reference 140, optimization is performed to identify the optimal small cells by adjusting their position. Different AIs can be classified as follows:

1. Type 1

   - Artificial narrow intelligence
   - Artificial general intelligence
   - Artificial super intelligence

2. Type 2 (based on functionalities)

   - Reactive machines
   - Limited memory
   - Theory of mind
   - Self-awareness
   - Reasoning in AI

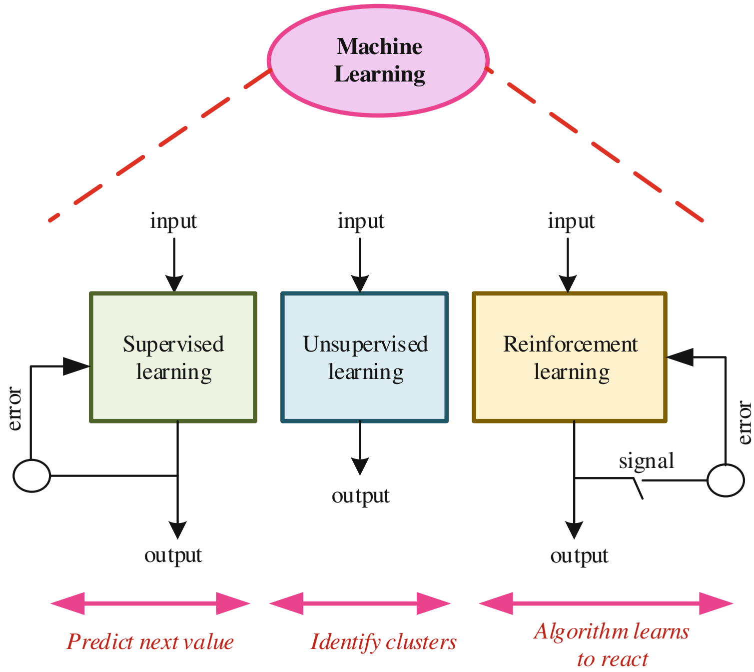

FIGURE 20 Types of ML used in communication systems[55]

- Common sense reasoning
- Deductive reasoning
- Inductive reasoning
- Abductive reasoning
- Non-monotonic reasoning
- Monotonic reasoning

Each AI type is briefly described.

Artificial narrow intelligence: Artificial narrow intelligence (ANI), known as a weak AI, is programmed to solve a single-objective function that performs on only one task. The performance of the ANI method is based on a specific data-set and it can join the task in real-time. It is called a weak and unconscious method because it operates within a predetermined range; hence, these methods cannot think and operate by themselves.[141] Google Translate and Siri are two explicit applications of ANI methods. For instance, we ask Siri to call a person from our telephone contact, and Siri does this accurately because the contact number is within the range of intelligence and, not more than this. Although, it is called a weak method, it offers benefits such as providing responses promptly, even quicker than any human reaction.

Artificial general intelligence: Artificial general intelligence (AGI), known as a strong AI that performs intellectual tasks, even better than human intelligence. As, opposed to ANI, AGI is smart and driven by self-awareness. Under uncertainty, AGI can decide, innovate, and make a decision but cannot be realized.[142]

Artificial super intelligence: Artificial super intelligence (ASI), which is known as a smart AI, surpasses human intelligence and can make smart decisions. It can even build emotional relationships. Nowadays, researchers are worried that ASI will pave the way for the human race. Advanced robotics use ASI and have incredible human-level intelligence. They use clustering and association for data processing.[143]

Machine learning (ML) and deep learning (DL) are sequentially developed over time (Figure 21) and learn from experience to improve performances. These methods are significant optimization approaches for communication networks and RF systems. They provide robust algorithms, thereby improving design specifications, such as band frequency, spectrum monitoring, figure of merit (FoM), and antenna. In these techniques, a suitable amount of data is generally trained first. Subsequently, end-to-end system modeling and learning are performed to create optimal networks. Figure 22 presents ML/AI as a service offered to end users by providing suitable data, knowledge, and results.

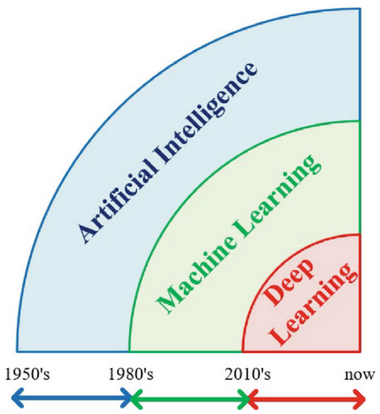

FIGURE 21 Visualization of AI over time[144]

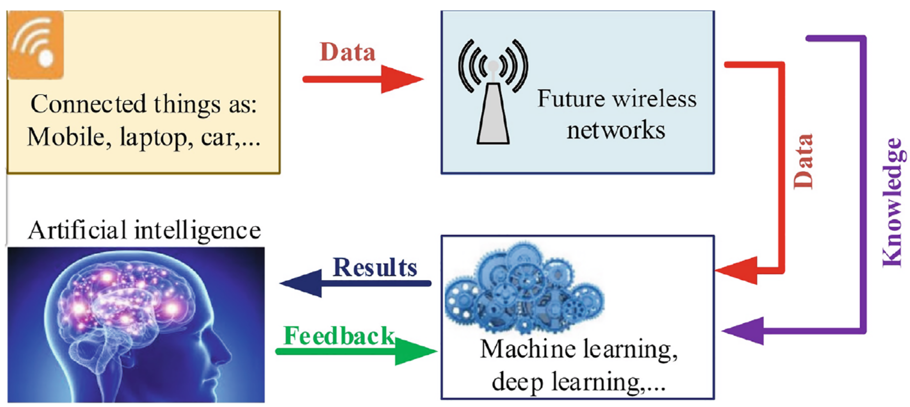

FIGURE 22 Service offered to users based on AI[145]

The traditional design and optimization of systems are based on iterative algorithmic search and depend on the engineers' experience. These traditional methods may require huge process time (eg, maybe some months), however, AI methods perform the optimization process in a few hours.[146] Hence, the computational cost and power consumption can be reduced, and designers can prioritize the key design parameters during the optimization process. The technology development of AI for wireless communication and RF systems has become an important challenge in the academic, and in industrial communities. Additionally, AI addresses major challenges in communication networks by optimizing parameters in terms of specifications, such as latency and flexibility of efficiency.[147] Figure 23 depicts branches of AI include machine learning and deep learning with explanation of the related subsets, where it is used to characterize communication channels in the digital domain.

ML and DL methods have recently gained popularity. Current networks have become more popular than the previous communication networks. Furthermore, DL can handle massive amounts of data compared with ML. These techniques can use data from Tx and Rx and optimize wireless channels (Figure 24). In the field of machine intelligence, various multi-objective functions can be used for optimizing determined specifications.[149] Recently, researchers are benefiting from "learning to optimize" solutions[139,150,151] in their optimization process[152] and are replacing traditional optimization methods with neural network solutions considering that this method can:

1. Handle a large and complex amount of data by reducing a mismatch between the real and approximated models.
2. Increase connectivity with MIMO and mmWave.
3. Facilitate autonomous adaptability for networks.
4. Provide monitoring and predicting fault.
5. Improve reliability and modularity of future 6G networks.
6. Increase the quality of service, and provide an automated optimization method by reducing the computational time.

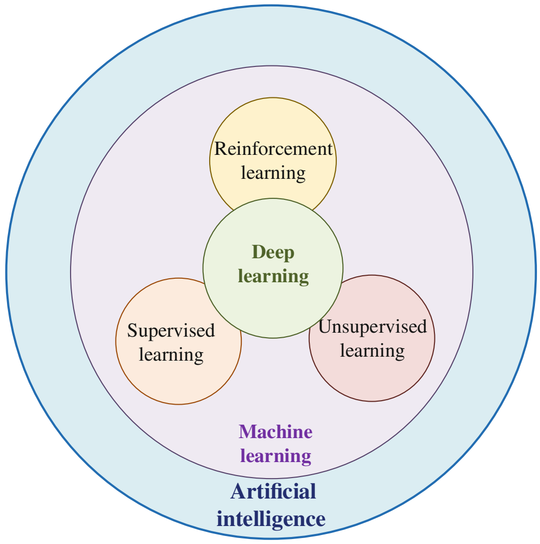

FIGURE 23 Artificial intelligence and related branches[148]

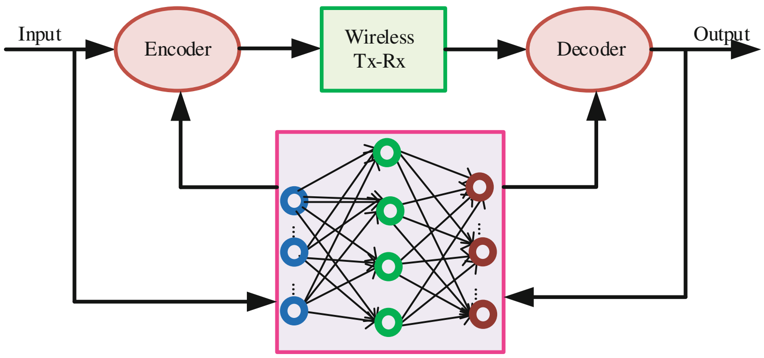

FIGURE 24 ML as optimizer for wireless communication systems[149]

The 5G and 6G networks can significantly benefit from AI solutions because AIs are the key drivers for enhancing performances and predicting output results when making decisions. Instead of simplifying the systems, AIs are embracing complexity and learning optimal solutions. An artificial neural network (ANN) is one of the main tools in this method. A detail tutorial for employing and constructing an ANN is reported in Reference 153.

To construct any neural network, the required parameters include the number of hidden layers, the number of hidden layer nodes, learning rate, and the number of iterations for improved optimization. Deep neural networks (DNNs) are multilayer fully connected neural networks comprising an input layer, multiple hidden layers, and an output layer. Therefore, an accurate construction of ANN/DNN is essential for employing the optimization method.[154] An acceptable ANN/DNN is the one that can predict information with less error[155] and can exploit information fast with convergence guarantees and less power.[156] An ANN can be used to estimate and predict optimization metrics by eliminating the simulation environment (Figure 25). In other words, 6G networks can exploit an ANN/DNN solution that provides an automated environment and enhance the output performances by determining an optimal solution.

As a solution for 5G network management, the benefits of ML are surveyed in Reference 152. One of the main tasks of ML is handling a huge amount of data and learning from these data by developing the performance. ML is an important tool for solving complex problems because it can efficiently address problems to high-dimensional data with many variables. A self-organizing network (SON) is an important factor for improving the management and operation in communication networks, and it comprises three self-organizations.[157] Figure 26 shows an AI-based SON comprising three sections (ie, self-configuration, self-healing, and self optimization) in the cycle of planning, deployment, optimization, and maintenance.

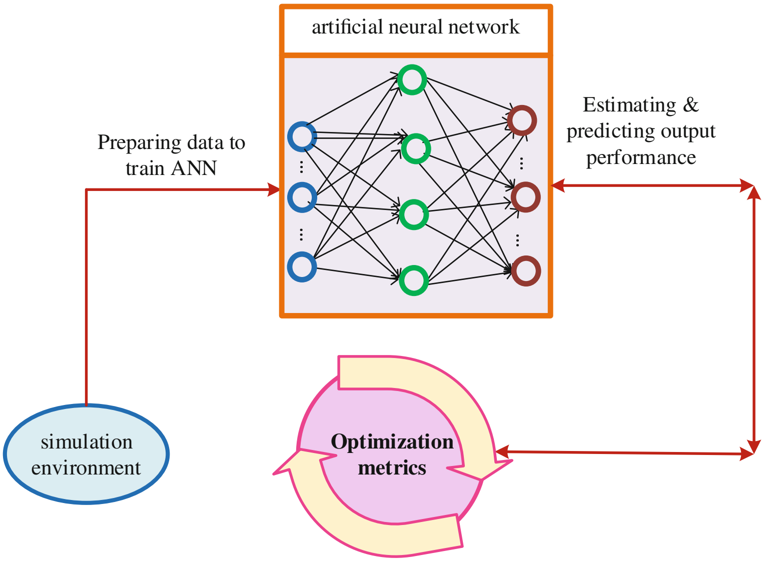

FIGURE 25 General flow of optimizing a system using ANN[156]

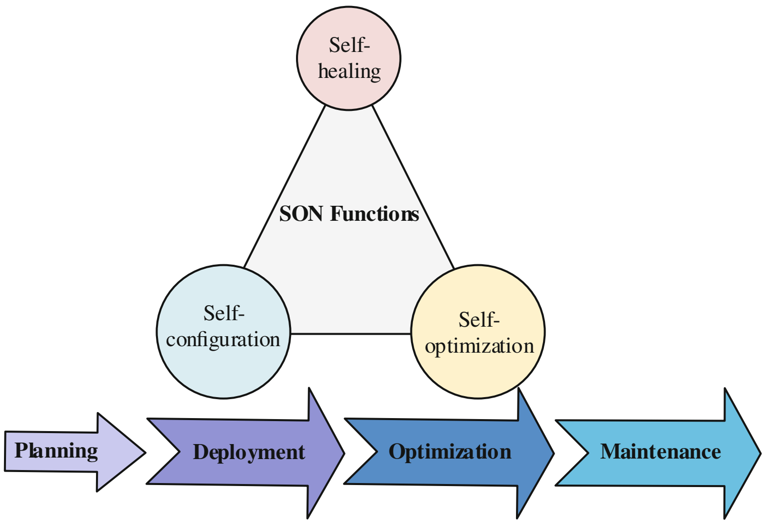

FIGURE 26 General flow of AI-based self-organization networks that starts from planning to maintenance and is divided into three sections: Self-healing, self-configuration, and self-optimization[157]

Network slicing is a newly agreed-upon concept that will provide a foundation for next generation networks.[158,159] In network slicing, the number of network slice classes is high, with an exponential increase in variables. The ML approach is reported in Reference 160 to maximize the monetization of the 5G infrastructure and determine an optimal solution. Accordingly, the ML method generates a practical solution for trading-off with sophisticated unknown systems. To employ the 5G infrastructure market optimization, a suitable model is first presented along with the formulation of the optimal revenue obstacle. An algorithm based on the ANN is then designed[160] with a low computational complexity. This algorithm is called network-slicing neural network admission control.

Proactive network optimization is another important method for maximizing the network potential and effectively enhancing RAN engineering.[161] A survey based on proactive network optimization, which is a useful method for transforming a 5G network with a large amount of data, is reported in Reference 47. This ML-solution-based optimization can provide a model-free optimization environment for decreasing real-time complexity[162] and improving the SON decision time.[163] ML methods use online data for modeling and attempt to determine suitable parameters that fit well with the desired output performance using Bayesian optimization (BO).[164-168]

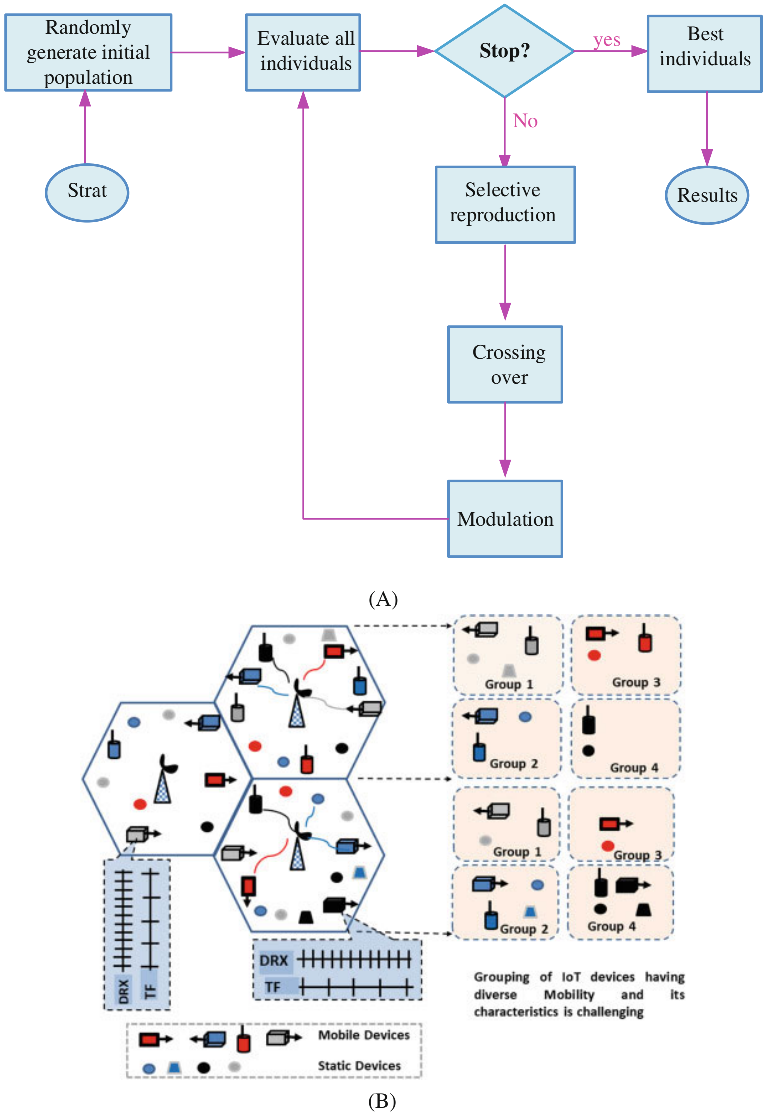

FIGURE 27 (A) Fundamentals of the genetic algorithm,[184] and (B) energy efficient group paging approach for IoT over 5G using the GA algorithm[190]

Heterogeneous network orchestration is another substantial issue to be considered in information networks. In Reference 33, BO is applied to a heterogeneous network to optimize multi-model heterogeneous networks for the next generation by generating a surrogate model. BO is a global model-free optimization method that predicts optimal design parameters using the Gaussian process (GP) and probability framework. It is preferred among surrogate models because it delivers an improved fine-grained uncertainty expression.

In Reference 169, the traffic issue in next generation networks is investigated using the ML solution that can predict forthcoming high traffic demands. Traffic is unpredictable, requiring a solution that can estimate and adjust cell margins. For this case, proactive load-balancing procedures[170] based on ML have been reported. The presented methods determine the solution for self-optimizing and proactive schemes using the ML method for traffic prediction.

Significant efforts in distributed nonconvex optimizations are undertaken for designing wireless networks.[171,172] A DL framework (ie, DNN)[173] is reported in Reference 174 for correctly approximating unknown computations. A novel stochastic binarization technique is developed in the described method for the output layer of the DL network. As a nonconvex optimization problem in Reference 172, the joint design of beamforming, power control, and interference coordination is optimized and solved using deep reinforcement learning.[175] In terms of speed, fast ML (ie, online learning algorithm) is presented in Reference 176 to solve the beam selection problem at mmWave base stations.

Genetic algorithm: GA is a member of the heuristic search strategy.[177] This method is an evolutionary algorithm for solving feature selection problems.[178] Figure 27A presents the fundamentals of the GA method, which is briefly explained

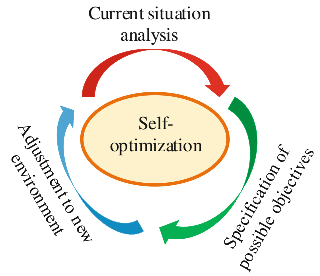

FIGURE 28 Self-optimization cycle[191]

in References 179-183. The application of the GA method is employed for the 5G systems in Figure 27B for considering traffic patterns, delay requirements, and mobility patterns. It is a stochastic search algorithm that is commonly used in engineering for solving complex nonlinear and nonconvex problems. The loop cycle of this method is as following: initialization of population, fitness function, selection, reproduction, and convergences.[184] The performance of the heterogeneous network improved in Reference 185 for 5G mobile networks using the GA method. Some other specifications that showed improvements using the GA technique include the crossover ratio, mutation ratio, and chromosome length, which are explained in References 186-189.

3.2 | Self-optimization

Self-optimization or auto-tuning, is a branch of SON as shown in Figure 26. A network is self-optimized if it can evaluate the current situation, specify the possible objectives, and finally adapt to newly modified parameters that is illustrated in Figure 28. Self-optimization is a method in which wireless networks continuously adapt to the targeted and desired network environment in terms of power and topology. The system itself changes and adapts to attain its objectives, and truly behaves according to the altering and evolving technology.

A joint self-optimization method for optimizing coverage and maximizing system throughput is reported in Reference 191 for 5G heterogeneous ultradense networks. This method is useful for determining the optimal base station.

A self-optimization algorithm based on adjusting handovers (HOs) is reported in Reference 192 for improving heterogeneous networks. This algorithm uses the speed and received signal reference power to arrange HO margins with time-to-trigger. HO performance is improved in this case and can be efficient for mobility management.[193-195] The HO topic[196-198] and the number of used HOs[199,200] in mobile communication are described in References 46,201-209. Determining an optimal HO is significant because they can be useless when users are far from the serving cell. The optimal prediction times for macrocell user equipment (UEs) are briefly explained in Reference 210. The IPv6-based HOs[211] and fast HOs for FMIPv6 protocol have improved advancements for HOs and have been comprehensively reviewed in in Reference 45. A dual-link soft HO scheme for the C/U network[212-214] is described in Reference 215 where this scheme manages HOs and decreases the communication interruption time by setting up two antennas and applying bi-casting.

3.3 | Markov approximation

Markov approximation equation is a numerical solution for stochastic differential equations,[216] which can find a suitable approximation for the determined cost function.[217] Brief explanations about the Markov optimization for combinational networks are described in Reference 218 and the general flowchart of Markov approximation is depicted in Figure 29 where transition edge-pairs between two states are added/removed. This figure demonstrates the time-reversible condition where the “sparse” Markov chains are modified and all the chains are in the same stationary distribution.

The error patterns that provide information about the behavior of data transmissions are studied in Reference 217 based on a two-state Markov error model. The modeling error obtained using Markov approximation provides fast simulation results with less computational problems. Figure 30 shows a three-state Markov chain model that represents the probability between nets[219] that is supposed the users in a radio access technologies (RAT) can handover to other RAT. Using this method, the user dynamics in multi-RATs are investigated and formulated to determine a solution for high computational complexity.

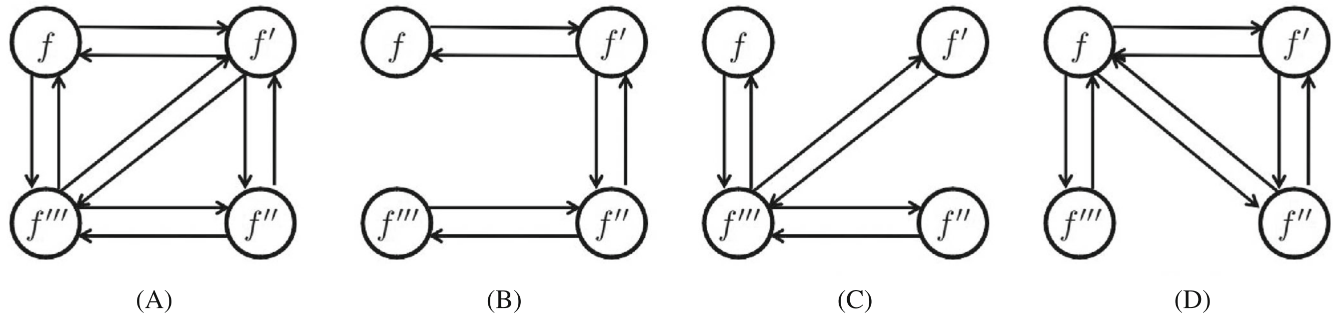

FIGURE 29 Flowchart of Markov chain for communication networks:[218] (A) The initial situation and (B-D) states that are removed/added by Markov optimization

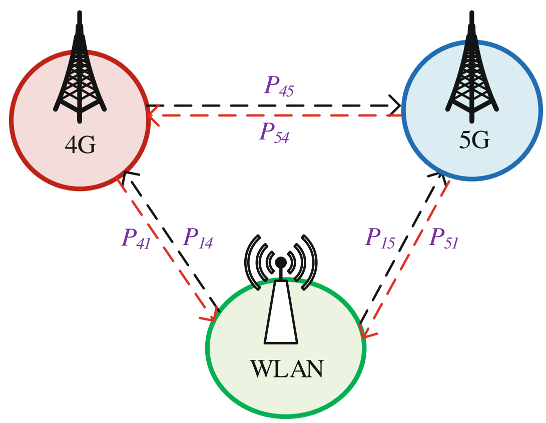

FIGURE 30 Markov chain for communication networks[219] where P_{ij} denotes the probability from RAT i to RAT j

3.4 Joint optimization

In the MEC domain,[220] to address various parameters, including delay and efficiency, the joint optimization of radio resources is reported in Reference 221, and stochastic-based joint management is discussed in Reference 222. Further, the joint optimization of infrastructure resources for transferring big data over a 5G network is reported in Reference 223. The optimization is based on ACO to effectively transfer data in terms of the performance parameters of data transmission, such as delay and energy consumption. Achieving high speed and stable mobile computing is a big challenge in MEC technology. Accordingly, MEC has become a significant issue in 5G communication. In Reference 224, joint optimization is used by combining MEC with simultaneous wireless information and power transfer (SWIPT), resulting in less energy consumption. The main problem is divided into two sub-problems. A group iterative optimization algorithm is then used to improve the latency and energy consumption of the system. The general structure of this kind of optimization is presented in Figure 31 where parameter and construction optimizations are performed concurrently for optimizing the structure of belief-rule-base (BRB). The BRB system is the successful branch of decision support systems.

3.5 Closed-loop optimization

Opposite to open loop optimization (OLO), the CLO methods include feedback performance during the process, where the inputs are updated according to the output performance.[226,227] Systems are efficiently optimized using the CLO method by addressing large parameter spaces and maintaining the prescribed relationship between the input and output by performing a comparison. Figure 32 shows the CLO method with a feedback controller. The system performance is updated based on the output performance, where the feedback is compared with the input signal.[228]

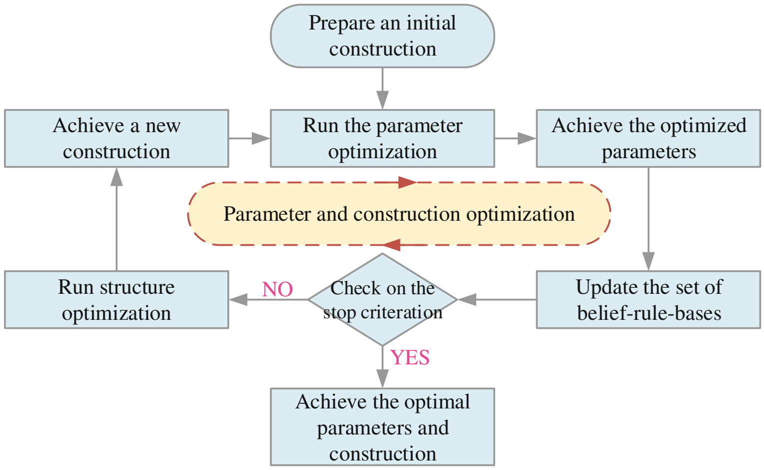

FIGURE 31 Joint optimization process where parameter and structure are optimized to be used in belief-rule-based systems[225]

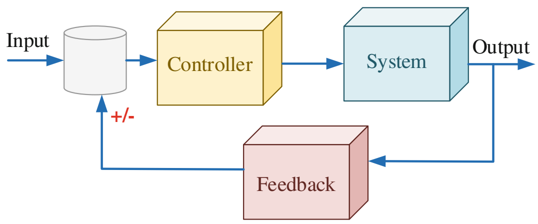

FIGURE 32 Block diagram of closed-loop optimization[228]

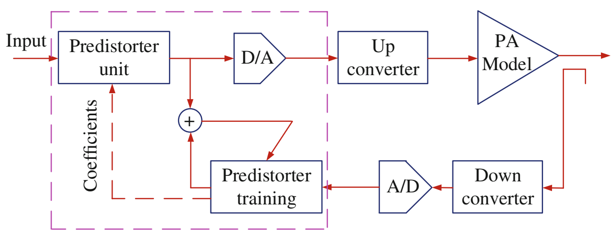

FIGURE 33 Block diagram of the DPD process[239]

Various studies have reported the use of the CLO method for MIMO systems.[229-233] In the field of power amplifiers, the CLO method is used for linearizing digital predistortion (DPD).[234,235] Figure 33 presents the block diagram of the DPD processing stages. This diagram clearly shows that the DPD design uses the look-up table (LUT) to predict suitable coefficients of the predistorter. The CLO methods are also used for HO optimization,[236] fault detection,[237] and cell outage management.[238]

3.6 | Convex optimization

Convex optimization is generally used in designing and analyzing wireless networks and refers to the minimization of the convex objective function subject to convex constraints. This optimization is important because in convex problems, a local optimum is a global optimum. The method is flexible and powerful numerical algorithm that can solve problems more efficiently.[240]

The main objective of this optimization is to find a waveform that reduces the spectral performance of the communication outline. Convex optimization has been successfully used for pulse shaping filter designs, transmitting beamforming,

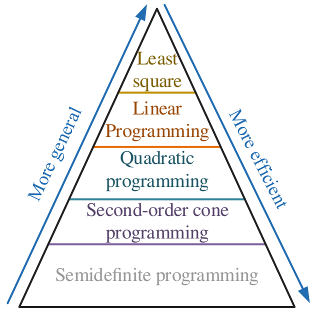

FIGURE 34 Hierarchy of convex optimization[242]

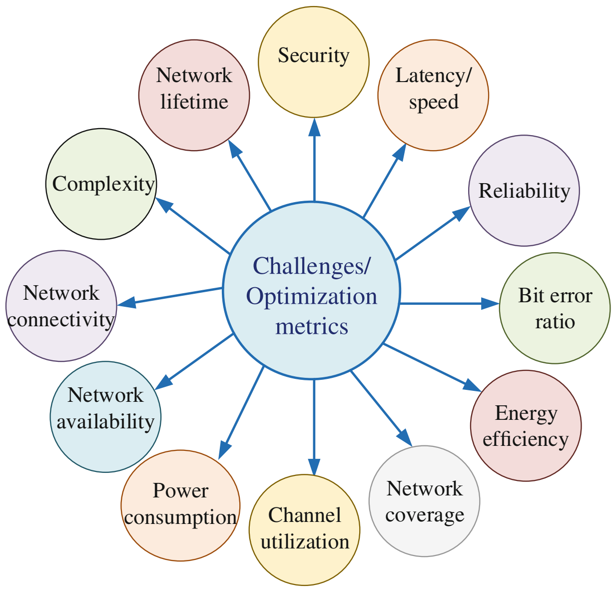

FIGURE 35 Potential optimization metrics and challenges reported in various studies for 5G networks

achieving robust beamforming, and allocating network resource.[241] Figure 34 depicts the sub-classes and hierarchy of convex optimization. These methods are very powerful algorithms that can efficiently solve large convex problems.[242]

4 | CHALLENGES AND FUTURE TRENDS

Future 6G networks including next-generation wireless networks, will benefit from a higher frequency spectrum with improved network capacity. However, these networks consist of multiple access networks and frequency bands and cells, representing deployment challenges. System synthesis is divided into knowledge-based and optimization-based approaches. The knowledge-based technique includes transcribing circuit knowledge into programs, which is time consuming. On the contrary, optimization-based methods are quite efficient, and the time cost is less than that required by knowledge-based methods.[258,259] Optimization methods have been identified to be beneficial for addressing the aforementioned challenges. New standards for 4G and 5G networks have been introduced by the advanced progress of linear and nonlinear optimization techniques. Various optimization metrics and challenges recently published in studies focus on the specifications summarized in Figure 35.

For the next generation networks (ie, 6G technology), there are several open issues that must be considered by the researchers. These open trends can be massive connectivity, data consumption, and device resource restrictions.[260] Some of the other challenges for 5G systems and technologies are summarized, discussed, and explained in this section. We summarized the specifications of each method in Table 2 to clarify the advantages and disadvantages

TABLE 2 Advantages, disadvantages, and authors' outlook of various optimization methods that can be suitable for the future 6G networks

Ref.	Methods	Advantages	Disadvantages	Authors' outlook
91,243	PSO	1. Fast convergence 2. Easy to implement owing to a parallel computing process	1. Poor ability in searching for an optimal solution 2. Cannot optimize the cluster head selection	1. Easy implementation 2. Low quality solution
101	ACO	1. Acceptable convergence rate with energy consumption 2. Satisfied network life 3. Includes a positive feedback	Moderate convergence rate	1. Simple method 2. Low efficiency
72	ABC	Intelligent algorithm that can handle a large amount of data	Drawback in determining the convergence rate	1. Self-organizing 2. Poor local search ability
82	AFSA	Fast convergence	Low optimization accuracy	1. Good robustness 2. Long search time
78	APOA	Improved profitability	Low convergence rate	1. Powerful and better handling 2. Slow
111,112	BA	1. Very quick convergence at a very initial stage by switching from experience to exploitation 2. Applied for classification problems	No guarantee optimality	1. Strong global search 2. Long running time
77	BFO	Optimizing multi-objective functions	Large computing with a slow convergence speed	1. Strong parallel search 2. Low speed
84	CSO	Minimizing the hierarchical order	Single-objective optimization	Time consuming process
74	CSA	1. Maintaining balance between local and global random walks 2. Suitable for global optimization	Slow convergence rate	1. Simple 2. Iterative process
244	FA	1. Light intensity encoding 2. Can efficiently handle nonlinear, multi-model optimization problems efficiently	Slow convergence rate	1. Simple implementation 2. Slow convergence
245	FOA	Simple realization structure	1. Low convergence precision 2. Easily trapped in a local optimum value at the later stage	1. Group collaboration 2. Low local optimum
246	SFLA	Solving combinational optimization problems	Slow convergence	1. Single-objective optimization 2. Slow convergence

(Continues)

TABLE 2 (Continued)

Ref.	Methods	Advantages	Disadvantages	Authors' outlook
247	WPA	1. Better prediction accuracy 2. Acceptable stability	Low solving accuracy	Self-organizing
248	HS	Quick convergence at a very initial stage	Weaknesses relaxed convergence	1. Complex implementation 2. Consumes a lot memory
249	EA	1. Robust to noise 2. Dealing professional with attribute iteration	1. Long optimization time 2. Require external processes	Self-adaption
250	GA	1. Find good quality solutions in a short computation time 2. Useful for nonbinary decisions	1. Cannot guarantee an optimal solution 2. Can take a long time to find an optimal solution or may not even find one	1. Complex 2. Fast convergence
251	DE	Finding the true global minimum of a multi-model search space	1. Time consuming for convergence 2. Incomprehensible solutions	Multi-objective optimization
252	SL	Can predict the relationship between input and output data for linear and logistic regression	Need training and testing data	1. Requires a training process 2. Performs classification and regression tasks
253	USL	Iteratively updates the algorithm	1. Cannot predict new input data 2. Can be used for the classification process	Performs just classification
172,254	RL	1. Smart method that can achieve global optimal after iteration 2. Independent to the designer's experience 3. Highly accurate system modeling	1. Time consuming and requires high power 2. Fairly late response time	Non-depreciable
43,139	ANN	1. Modeling and approximating objective functions for modeling communication systems 2. Fast modeling	1. Not highly accurate in modeling as deep learning 2. Huge training complexity	1. Powerful in predicting parameters 2. Consuming time

(Continues)

TABLE 2 (Continued)

Ref.	Methods	Advantages	Disadvantages	Authors' outlook
255	DL	1. Predicting and coordinating of complex nonlinear multi-objective functions 2. Highly accurate modeling	Time consuming	1. High accurate 2. Low speed 3. Multi-objective optimization
148	AI	1. Safety, comfort, and efficient 2. Secure and more reliable	Low speed	Slow convergence
152,256	SO	1. Can predict network traffic 2. Includes operator and online data 3. Faster than the centralized optimization method	Associated with high cost and long delay	1. Statistical techniques 2. Fast convergence
257	MA	Obtaining relationships among various user behaviors with satisfied accuracy	1. Low response time 2. Fairly convergence reliability	Good robustness
229,230	CLO	Computationally feasible	Scalability problems	1. Less instability 2. Good accuracy
241	CO	Ensuring about not generating infeasible solutions	Limited parallelism	Single-objective optimization

of various optimization methods reported in the previous section. Hereby, any researchers by considering the features of each method can select the suitable algorithm for their future system's needs. Employing the presented methods with the AI based science can improve the full-dimensional wireless coverage with enhancing computation and caching.[261] Additionally, the nominated methods can be used in each of the block circuits and designs that construct the 5G/6G systems such as antennas, filters, high power amplifiers, digital-to-analog and analog-to-digital converters.

4.1 | Trading off between accuracy and speed

Two important factors, namely, *accuracy* and *speed* must be considered carefully in system optimization and design. The trade-off between these two specifications must also be determined by designers. In other words, as the two main factors, the development cost and production time must be efficiently determined and evaluated.

Accuracy: Several methods are used in the domain of functional surrogate modeling techniques:[262-264] support vector machine,[265] kriging,[266] polynomial-based surrogate modeling,[267] and shape-preserving response.[268] Among these methods, AI methods including ANN and DNN[269] have become the most successful optimization techniques in communications and signal processing, according to the studied literature. Neural networks have become an acceptable interference for algorithm designs and have attracted considerable research attention. The success of DNN is attributed to their following unique features:

1. These networks are under the category of functional surrogate modeling. They are fast modeling methods because they implement high-level circuit designs.
2. They can provide an automated environment that becomes less dependent on designer experience.
3. Modeling and optimization are performed with high accuracy because the number of hidden layers is more than two.[270]

AI, ML, and DNN can help communication operators overcome various drawbacks by considering and analyzing geographic data and engineering parameters. The 5G and 6G networks can be an important enabler for driving AI integration into networks.

Speed: Technology is developing. Thus, significant design time should be allocated and the designing time must be reduced by managing time-consuming procedures in simulations and optimizations. Any optimization framework must be aware of time-consuming simulation outcomes. Four parameters must be considered to emphasize the importance of speed in 4G and 5G networks and to realize high-speed wireless networks. The parameters are network deployments, signal processing, channel estimation, and mobility management.[46]

The number of simulations must be decreased to reduce time to market.[271] Bayesian optimization, space mapping,[272,273] combination of the evolutionary optimization approaches with deep learning methods,[274] and combination of coarse and fine models[275] are some of the methods that can accelerate the optimization process. These optimization methods can substantially reduce the computational design time and provide faster optimization duration than direct optimizations. Implicit space mapping is a simple method for combining "coarse" model with "fine" model, which is a circuit-theory-based model with an electromagnetic simulator and leads to an average of 16× faster design in Reference 275.

Hence, any optimization designer must focus on speed and accuracy specifications and must select a suitable optimization technique with respect to the required design specifications. As the reported studies have shown, there is still room for research and advanced multi-objective optimizations that should be developed for accomplishing the required outcomes.

4.2 | Backscatter communications

The field of backscatter communications open research topics that have not been optimized for large-scale low -power networks. Some of these open research topics are: security,[276] resource allocation,[277] and channel modeling with estimation.[278] Hence, advanced optimization methods are required to improve network efficiency.

4.3 | Self organizing network

Although new SON solutions affect 5G network management, some open challenges remain unsolved. The drawbacks include SON functions in which multiobjective function optimizations are required. Moreover, smart solutions between centralized and distributed SON implementations become significant. As a future plan to outperform the network complexity, AI and ML algorithms for big data technologies can be established to leverage the nominated problems in SON systems.[152,163,279] Additionally, for auto-tuning HO margins, advanced SON methods must be developed to exploit fuzzy logic controllers.

4.4 | Wireless physical layer security

The physical layer security for the future 6G networks has attracted attention from academia and industry. Owing to the importance of security designs, various optimizations have been reported for maximizing the secrecy rate with secure energy efficiency and minimizing the secrecy outrage probability with power consumption. However, additional efforts and significant progress are needed to optimize secure designs at a physical layer. Some of the parameters that must be studied in-depth are: the effects of wireless channels and hardware impairments, and advanced optimization methods for determining security with reliability in wireless systems.[280]

4.5 | Mobile edge computing

Substantial efforts have been undertaken for MEC services; however, there are still emerging research directions and existing open challenges. In the future, researchers can develop MEC systems by developing advanced architectures, scheduling mobility-aware servers, and enhancing privacy issues with networking security. Some of the technical challenges in the MEC service are presented and summarized below:

1. Network integration
2. Application portability
3. Security
4. Performance
5. Resilience
6. Operation
7. Regulatory and legal considerations

Optimization methods are extremely useful methods in wireless networks for addressing design problems. Considering the rapid development of 5G and 6G networks, there is a large scope for research. Hence, the reported methods must be considered from different features when developing and implementing systems that welcome optimal solution structures.

Overall, future next-generation systems include 6G networks are experiencing an unprecedented growth of computation demands because of increased storage resources in networks. Therefore, new design challenges for facilitating highly-efficient network operations in complex communication environments must be solved. In this survey, we report a theoretical view of various linear and nonlinear optimization methods and provide a practical application of these methods in the telecommunication field by considering recently published studies.

5 | AUTHORS' OUTLOOK

Optimization methods are typically employed for solving the complex drawbacks and for finding optimal solutions for the defined problems. In the last decade, AI, ML, and DL techniques have successfully used in various engineering fields.[281] Generally, these methods can be employed in free of charge programming languages and can provide automatic design methodologies.[282]

As Table 2 presents each of the reported methods has both advantages and disadvantages. Any engineer with respect to the need of 6G systems, can select the appropriate algorithms. With respect to the authors' experience, AI methods can be used as platforms for constructing reported optimization methods and optimizing system's output specifications in an efficient way. Kouhalvandi et al in various research papers have proved this idea where ANNs and deep neural networks (DNNs) are used as platforms for optimizing power amplifiers (PAs) and antennas' output specifications using diverse multi-objective optimization methods.[56,261,283] This idea leads to optimize complex systems in an automated environment without depending to any human's experience.

6 | CONCLUSION

This article presents a comprehensive study on the most recently published optimization algorithms employed for the present 4G and 5G networks that will lead to design the future 6G networks. That included various kinds of linear and nonlinear optimization methods which can be used to design 6G mobile communication networks. Optimization methods with Machine Learning and Artificial Intelligent will play an important role in designing 6G mobile CSs; hence, the theoretical knowledge, definition, and introduction of various methods are significant. To pave the way for future studies, this article provided a theoretical view of the various applied optimization methods in today's communication networks, and review the applications and features of the algorithms in various networks. The basic idea and theory of each method are briefly described. The recently published papers related to these methods are then introduced. Finally, a compressed challenge for the reported various optimization methods is discussed. By considering the advantages and disadvantages of each method, any designer can select a suitable method for the determined problems.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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Research data are not shared.

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REFERENCES

1. Maskooki A, Sabatino G, Mitton N. Ch. 21 - Analysis and performance evaluation of the next generation wireless networks. In: Obaidat MS, Nicopolitidis P, Zarai F, eds. *Modeling and Simulation of Computer Networks and Systems*. Boston, MA: Morgan Kaufmann; 2015:601-627.
2. Cokyasar T. Optimization of battery swapping infrastructure for e-commerce drone delivery. *Comput Commun*. 2021;168:146-154. doi:10.1016/j.comcom.2020.12.015
3. Adedoyin MA, Falowo OE. Combination of ultra-dense networks and other 5G enabling technologies: a survey. *IEEE Access*. 2020;8:22893-22932.
4. Shayea I, Azmi MH, Rahman TA, Ergen M, Han CT, Arsad A. Spectrum gap analysis with practical solutions for future mobile data traffic growth in Malaysia. *IEEE Access*. 2019;7:24910-24933.
5. Chowdhury MZ, Shahjalal M, Ahmed S, Jang YM. 6G wireless communication systems: applications, requirements, technologies, challenges, and research directions. *IEEE Open J Commun Soc*. 2020;1:957-975.
6. Shayea I, Ergen M, Azmi MH, Çolak SA, Nordin R, Daradkeh YI. Key challenges, drivers and solutions for mobility management in 5g networks: a survey. *IEEE Access*. 2020;8:172534-172552.
7. Shayea I, Ergen M, Azizan A, Ismail M, Daradkeh YI. Individualistic dynamic handover parameter self-optimization algorithm for 5G networks based on automatic weight function. *IEEE Access*. 2020;8:214392-214412. doi:10.1109/ACCESS.2020.3037048

8. Dash L, Khuntia M. Energy efficient techniques for 5G mobile networks in WSN: a survey; 2020:1-5; IEEE.
9. Ai N, Wu B, Li B, Zhao Z. 5G heterogeneous network selection and resource allocation optimization based on cuckoo search algorithm. *Comput Commun*. 2021;168:170-177. doi:10.1016/j.comcom.2020.12.026
10. Zhao S, Feng Y, Yu G. D2D communication channel allocation and resource optimization in 5G network based on game theory. *Comput Commun*. 2021;169:26-32. doi:10.1016/j.comcom.2021.01.016
11. Mezzavilla M, Zhang M, Polese M, et al. End-to-end simulation of 5G mmWave networks. *IEEE Commun Surv Tutor*. 2018;20(3):2237-2263.
12. Morattab A, Dziong Z, Sohraby K. Mode selection map-based vertical handover in D2D enabled 5G networks. *IET Commun*. 2019;13(14):2173-2185.
13. Fang D, Qian Y, Hu RQ. Security for 5G mobile wireless networks. *IEEE Access*. 2018;6:4850-4874.
14. Akyildiz IF, Kak A, Nie S. 6G and beyond: the future of wireless communications systems. *IEEE Access*. 2020;8:133995-134030.
15. Bariah L, Mohjazi L, Muhaidat S, et al. A prospective look: key enabling technologies, applications and open research topics in 6G networks; 2020.
16. Mahmoud HHH, Amer AA, Ismail T. 6G: a comprehensive survey on technologies, applications, challenges, and research problems. *Trans Emerg Telecommun Technol*. 2021;32(4):e4233. doi:10.1002/ett.4233
17. Fakih MA, Diallo A, Le Thuc P, Staraj R, Mourad O, Rachid EA. Optimization of efficient dual band PIFA system for MIMO half-duplex 4G/LTE and full-duplex 5G communications. *IEEE Access*. 2019;7:128881-128895.
18. Moghadami S, Hajilou F, Agrawal P, Ardalan S. A 210 GHz fully-integrated OOK transceiver for short-range wireless chip-to-chip communication in 40 nm CMOS technology. *IEEE Trans Terahertz Sci Technol*. 2015;5(5):737-741.
19. Han C, Bicen AO, Akyildiz IF. Multi-ray channel modeling and wideband characterization for wireless communications in the Terahertz band. *IEEE Trans Wirel Commun*. 2015;14(5):2402-2412.
20. Cui FJ, Xia H, Zhang R, Hu XB, Cheng GX. Optimization scheme for intrusion detection scheme GBDT in edge computing center. *Comput Commun*. 2021;168:136-145. doi:10.1016/j.comcom.2020.12.007
21. Wong VWS, Schober R, Ng DWK, Wang LC. *Overview of New Technologies for 5G Systems*. Cambridge: Cambridge University Press; 2017:1-9624.
22. Kwon G, Park J, Kim D, Hwang KC. Optimization of a shared-aperture dual-band transmitting/receiving array antenna for radar applications. *IEEE Trans Antennas Propag*. 2017;65(12):7038-7051.
23. Getting to 5G. http://qorvo.com. Accessed November 11, 2021.
24. Li H, Dong M, Ota K. Control plane optimization in software-defined vehicular ad hoc networks. *IEEE Trans Veh Technol*. 2016;65(10):7895-7904.
25. Erel-Özçevik M, Canberk B. Road to 5G reduced-latency: a software defined handover model for eMBB services. *IEEE Trans Veh Technol*. 2019;68(8):8133-8144.
26. Verma S, Kawamoto Y, Kato N. Energy-efficient group paging mechanism for QoS constrained mobile IoT devices over LTE-A pro networks under 5G. *IEEE Internet Things J*. 2019;6(5):9187-9199.
27. Qiang L, Li J, Touati C. A user centered multi-objective handoff scheme for hybrid 5G environments. *IEEE Trans Emerg Top Comput*. 2017;5(3):380-390.
28. Zhang J, Chen T, Zhong S, et al. Aeronautical ad hoc networking for the internet-above-the-clouds. *Proc IEEE*. 2019;107(5):868-911.
29. Hussain AA, Al-Turjman F. Artificial intelligence and blockchain: a review. *Trans Emerg Telecommun Technol*. 2021;32(9):e4268. doi:10.1002/ett.4268
30. Liu J, Bentley ES. Hybrid-beamforming-based millimeter-wave cellular network optimization. *IEEE J Select Areas Commun*. 2019;37(12):2799-2813.
31. Malandrino F, Chiasserini CF, Casetti C, Landi G, Capitani M. An optimization-enhanced MANO for energy-efficient 5G networks. *IEEE/ACM Trans Netw*. 2019;27(4):1756-1769.
32. Liu J, Bentley E. Hybrid-beamforming-based millimeter-wave cellular network optimization; 2017:1-8.
33. Wang H, Zhang G, Jiang H, Wu J, Yang X, Zhou M. Bayesian optimization for multimodal heterogeneous network orchestration via hybrid probability process. *IEEE Access*. 2019;7:117954-117967.
34. Goudos S. Evolutionary algorithms for wireless communications: a review of the state-of-the art; 2014
35. Mirjalili S, Hashim SZM, Sardroudi HM. Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm. *Appl Math Comput*. 2012;218(22):11125-11137. doi:10.1016/j.amc.2012.04.069
36. Kennedy J, Eberhart R. Particle swarm optimization; Vol. 4, 1995:1942-1948.
37. Nadipally M. Ch. 2 - Optimization of methods for image-texture segmentation using ant colony optimization. In: Hemanth DJ, Gupta D, Balas VE, eds. *Intelligent Data Analysis for Biomedical Applications Intelligent Data-Centric Systems*. Science Direct: Academic Press; 2019:21-47.
38. Karaboga D, Basturk B. Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems. In: Melin P, Castillo O, Aguilar LT, Kacprzyk J, Pedrycz W, eds. *Foundations of Fuzzy Logic and Soft Computing*. Berlin, Heidelberg: Springer; 2007:789-798.
39. Zhang L, Xu X, Zhou C, Ma M, Yu Z. An improved differential evolution algorithm for optimization problems. In: Jin D, Lin S, eds. *Advances in Computer Science, Intelligent System and Environment*. Berlin, Heidelberg: Springer; 2011:233-238.
40. Reeves C. *Genetic Algorithms*. Boston: Springer; 2003:55-82.
41. Wu J, Fan P. A survey on high mobility wireless communications: challenges opportunities and solutions. *IEEE Access*. 2016;4:450-476.

42. Rappaport TS, Xing Y, MacCartney GR, Molisch AF, Mellios E, Zhang J. Overview of millimeter wave communications for fifth-generation (5G) wireless networks—With a focus on propagation models. *IEEE Trans Antennas Propag*. 2017;65(12):6213-6230.
43. Zhang H, Dai L. Mobility prediction: a survey on state-of-the-art schemes and future applications. *IEEE Access*. 2019;7:802-822.
44. Wang D, Bai B, Zhao W, Han Z. A survey of optimization approaches for wireless physical layer security. *IEEE Commun Surv Tutor*. 2019;21(2):1878-1911.
45. Sajjad MM, Jayalath D, Bernardos CJ. A comprehensive review of enhancements and prospects of fast handovers for mobile IPv6 protocol. *IEEE Access*. 2019;7:4948-4978.
46. Tayyab M, Gelabert X, Jäntti R. A survey on handover management: from LTE to NR. *IEEE Access*. 2019;7:118907-118930.
47. Ma B, Guo W, Zhang J. A survey of online data-driven proactive 5G network optimisation using machine learning. *IEEE Access*. 2020;8:35606-35637.
48. Ojijo MO, Falowo OE. A survey on slice admission control strategies and optimization schemes in 5G network. *IEEE Access*. 2020;8:14977-14990.
49. Abrol A. Power optimization in 5G networks: a step towards GrEEn communication. *IEEE Access*. 2016;4:1. doi:10.1109/ACCESS.2016.2549641
50. Deniz A, Angin M, Angin P. Evolutionary multiobjective feature selection for sentiment analysis. *IEEE Access*. 2021;9:142982-142996. doi:10.1109/ACCESS.2021.3118961
51. Jimánez F, Lucena-Sánchez E, Sánchez G, Sciavicco G. Multi-objective evolutionary simultaneous feature selection and outlier detection for regression. *IEEE Access*. 2021;9:135675-135688. doi:10.1109/ACCESS.2021.3115848
52. Doevenspeck J, Degraeve R, Fantini A, et al. OxRRAM-based analog in-memory computing for deep neural network inference: a conductance variability study. *IEEE Trans Electron Dev*. 2021;68(5):2301-2305. doi:10.1109/TED.2021.3068696
53. Haensch W, Gokmen T, Puri R. The next generation of deep learning hardware: analog computing. *Proc IEEE*. 2019;107(1):108-122. doi:10.1109/JPROC.2018.2871057
54. Amri MM, Tran NM, Choi KW. Reconfigurable intelligent surface-aided wireless communications: adaptive beamforming and experimental validations. *IEEE Access*. 2021;9:147442-147457. doi:10.1109/ACCESS.2021.3124319
55. Kouhalvandi L, Ceylan O, Ozoguz S. Optimization techniques for analog and RF circuit designs: an overview. *Analog Integr Circ Sig Process*. 2021;106(3):511-524. doi:10.1007/s10470‐020‐01733‐7
56. Kouhalvandi L, Ceylan O, Ozoguz S. Multi-objective efficiency and phase distortion optimizations for automated design of power amplifiers through deep neural networks; 2021:233-236.
57. Aslan Y, Puskely J, Roederer A, Yarovoy A. Multiple beam synthesis of passively cooled 5G planar arrays using convex optimization. *IEEE Trans Antennas Propag*. 2020;68(5):3557-3566. doi:10.1109/TAP.2019.2955885
58. Hoffmann M, Kryszkiewicz P. Reinforcement learning for energy-efficient 5G massive MIMO: intelligent antenna switching. *IEEE Access*. 2021;9:130329-130339. doi:10.1109/ACCESS.2021.3113461
59. Giannopoulos A, Spantideas S, Kapsalis N, Karkazis P, Trakadas P. Deep reinforcement learning for energy-efficient multi-channel transmissions in 5G cognitive hetnets: centralized, decentralized and transfer learning based solutions. *IEEE Access*. 2021;9:129358-129374. doi:10.1109/ACCESS.2021.3113501
60. Ppallan JM, Arunachalam K, Gantha SS, Jaiswal S, Song S, Nigam A. A method for enabling context-awareness at transport layer for improved quality-of-service control. *IEEE Access*. 2021;9:123987-123998. doi:10.1109/ACCESS.2021.3110266
61. Cavalcanti F, Andersson S. *Optimizing Wireless Communication Systems*. New York, NY: Springer Link; 2009.
62. Zhu X, Yang Y, Liu Z, et al. Towards 6G wireless communication networks: vision, enabling technologies, and new paradigm shifts; 2020.
63. Tutschku K, Gerlich N, Tran-Gia P. An integrated approach to cellular network planning; 1998.
64. Moysen J, Giupponi L, Mangues-Bafalluy J. A mobile network planning tool based on data analytics. *Mob Inf Syst*. 2017;2017:6740585. doi:10.1155/2017/6740585
65. Chimmanee K, Jantavongso S. Practical mobile network planning and optimization for Thai smart cities: towards a more inclusive globalization. *Res Global*. 2021;3:100062. doi:10.1016/j.resglo.2021.100062
66. Bonabeau E, Dorigo M, Theraulaz G. *Swarm Intelligence: From Natural to Artificial Systems*. New York, NY: Oxford University Press; 1999.
67. Dorigo M, Maniezzo V, Colorni A. Ant system: optimization by a colony of cooperating agents. *IEEE Trans Syst Man Cybern B Cybern*. 1996;26(1):29-41.
68. Karaboga D, Gorkemli B, Ozturk C, Karaboga N. A comprehensive survey: artificial bee colony (ABC) algorithm and applications. *Artif Intell Rev*. 2014;42(1):21-57. doi:10.1007/s10462-012-9328-0
69. García-Martínez C, Rodriguez FJ, Lozano M. Genetic Algorithms. In: Martí R, Pardalos P, Resende M, eds. *Handbook of Heuristics*. Springer, Cham; 2018. doi:10.1007/978-3-319-07124-4_28
70. Smith K, Zielinksi S. The startling intelligence of the common chicken. *Sci Am*. 2014;310(2):60-65.
71. Han WH, Shen XH, Xu J, Yang P, Yang XH, He GDX. An efficient adaptive wolf pack search algorithm. *Applied Mechanics and Materials*. Vol 590. Ukraine: Trans Tech Publications Ltd; 2014:702-709.
72. Akay B, Karaboga D. A survey on the applications of artificial bee colony in signal, image, and video processing. *Signal Image Video Process*. 2015;9(4):967-990. doi:10.1007/s11760‐015‐0758‐4
73. Wang H, Wang W, Zhou X, et al. Firefly algorithm with neighborhood attraction. *Inf Sci*. 2017;382:374-387. doi:10.1016/j.ins.2016.12.024
74. Shehab M, Khader AT, Al-Betar MA. A survey on applications and variants of the cuckoo search algorithm. *Appl Soft Comput*. 2017;61:1041-1059. doi:10.1016/j.asoc.2017.02.034

75. Hasanien HM. Shuffled frog leaping algorithm for photovoltaic model identification. *IEEE Trans Sustain Energy*. 2015;6(2):509-515.
76. Wang L, Zheng X. A knowledge-guided multi-objective fruit fly optimization algorithm for the multi-skill resource constrained project scheduling problem. *Swarm Evol Comput*. 2017;38:54-63. doi:10.1016/j.swevo.2017.06.001
77. Chen YP, Li Y, Wang G, et al. A novel bacterial foraging optimization algorithm for feature selection. *Expert Syst Appl*. 2017;83:1-17. doi:10.1016/j.eswa.2017.04.019
78. Akyol S, Alatas B. Plant intelligence based metaheuristic optimization algorithms. *Artif Intell Rev*. 2016;47(4):417-4662. doi:10.1007/s10462‐016‐9486‐6
79. YongBo C, YueSong M, JianQiao Y, XiaoLong S, Nuo X. Three-dimensional unmanned aerial vehicle path planning using modified wolf pack search algorithm. *Neurocomputing*. 2017;266:445-457. doi:10.1016/j.neucom.2017.05.059
80. Chawla M, Duhan M. Bat algorithm: a survey of the state-of-the-art. *Appl Artif Intell*. 2015;29(6):617-634. doi:10.1080/08839514.2015.1038434
81. AlRashidi MR, El-Hawary ME. A survey of particle swarm optimization applications in electric power systems. *IEEE Trans Evol Comput*. 2009;13(4):913-918.
82. Che J, Zhou K, Zhang X, et al. Application of hybrid artificial fish swarm algorithm based on similar fragments in VRP. *Proceeding SPIE 10611, MIPPR 2017: Remote Sensing Image Processing, Geographic Information Systems, and Other Applications.* 106111L. 2018.
83. Zhang H, Wang X, Memarmoshrefi P, Hogrefe D. A survey of ant colony optimization based routing protocols for mobile ad hoc networks. *IEEE Access*. 2017;5:24139-24161.
84. Wu D, Xu S, Kong F. Convergence analysis and improvement of the chicken swarm optimization algorithm. *IEEE Access*. 2016;4:9400-9412.
85. Darvish A, Ebrahimzadeh A. Improved fruit-fly optimization algorithm and its applications in antenna arrays synthesis. *IEEE Trans Antennas Propag*. 2018;66(4):1756-1766.
86. Reynolds CW. Flocks, herds and schools: a distributed behavioral model. *SIGGRAPH '87. Association for Computing Machinery*. New York, NY: Springer; 1987:25-34.
87. Xu M, Feng G, Ren Y, Zhang X. On cloud storage optimization of blockchain with a clustering-based genetic algorithm. *IEEE Internet Things J*. 2020;7(9):8547-8558.
88. Jin N, Rahmat-Samii Y. Advances in particle swarm optimization for antenna designs: real-number, binary, single-objective and multiobjective implementations. *IEEE Trans Antennas Propag*. 2007;55(3):556-567.
89. Goudos SK, Zaharis ZD, Kampitaki DG, Rekanos IT, Hilas CS. Pareto optimal design of dual-band base station antenna arrays using multi-objective particle swarm optimization with fitness sharing. *IEEE Trans Magn*. 2009;45(3):1522-1525.
90. Walha C, Bezine H, Alimi AM. Towards a particle swarm optimization approach for grasp planning problem; 2012:1692-1697.
91. Kaur S, Grewal V. A novel approach for particle swarm optimization-based clustering with dual sink mobility in wireless sensor network. *Int J Commun Syst*. 2020;33(16):e4553. doi:10.1002/dac.4553
92. Srinivasa Rao PC, Jana P, Banka H. A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks. *Wirel Netw*. 2017;23(7):2005-2020. doi:10.1007/s11276‐016‐1270‐7
93. Tan LT, Hu RQ, Hanzo L. Heterogeneous networks relying on full-duplex relays and mobility-aware probabilistic caching. *IEEE Trans Commun*. 2019;67(7):5037-5052.
94. Lu K, Jiang C. Optimized low density superposition modulation for 5G mobile multimedia wireless networks. *IEEE Access*. 2019;7:174227-174235.
95. Yang Q, Chen W, Yu Z, et al. Adaptive multimodal continuous ant colony optimization. *IEEE Trans Evol Comput*. 2017;21(2):191-205.
96. Dorigo M, Birattari M, Stützle T. Ant colony optimization. *IEEE Comput Intell Mag*. 2006;1:28-39. doi:10.1109/MCI.2006.329691
97. Umadevi M, Devapriya M. An enhanced ant colony based approach to optimize the usage of critical node in wireless sensor networks. *Proc Comput Sci*. 2015;47:452-459. Graph Algorithms, High Performance Implementations and Its Applications (ICGHIA 2014). doi:10.1016/j.procs.2015.03.229
98. Sun Y, Dong W, Chen Y. An improved routing algorithm based on ant colony optimization in wireless sensor networks. *IEEE Commun Lett*. 2017;21(6):1317-1320.
99. Liu X. Sensor deployment of wireless sensor networks based on ant colony optimization with three classes of ant transitions. *IEEE Commun Lett*. 2012;16(10):1604-1607.
100. Liu X. A transmission scheme for wireless sensor networks using ant colony optimization with unconventional characteristics. *IEEE Commun Lett*. 2014;18(7):1214-1217.
101. Jamal Abdul Nasir H, Ku-Mahamud K, Kamioka E. Ant colony optimization approaches in wireless sensor network: performance evaluation. *J Comput Sci*. 2017;13:153-164. doi:10.3844/jcssp.2017.153.164
102. Aderhold A, Diwold K, Scheidler A, Middendorf M. *Artificial Bee Colony Optimization: A New Selection Scheme and Its Performance*. Berlin, Heidelberg: Springer; 2010:283-294.
103. Zhang X, Zhang X, Han L. An energy efficient internet of things network using restart artificial bee colony and wireless power transfer. *IEEE Access*. 2019;7:12686-12695.
104. Karaboga D, Kaya E. An adaptive and hybrid artificial bee colony algorithm (aABC) for ANFIS training. *Appl Soft Comput*. 2016;49:423-436. doi:10.1016/j.asoc.2016.07.039
105. Kumar R, Kumar D. Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network. *Wirel Netw*. 2015;22(5):1461-1474. doi:10.1007/s11276‐015‐1039‐4

106. Yue Y, Li J, Fan H, Qin Q. Optimization-based artificial bee colony algorithm for data collection in large-scale mobile wireless sensor networks. *J Sens*. 2016;2016:1-12. doi:10.1155/2016/7057490
107. Wang L, Zhang X, Zhang X. Antenna array design by artificial bee colony algorithm with similarity induced search method. *IEEE Trans Magn*. 2019;55(6):1-4.
108. Wang Z, Ding H, Li B, Bao L, Yang Z. An energy efficient routing protocol based on improved artificial bee colony algorithm for wireless sensor networks. *IEEE Access*. 2020;8:133577-133596.
109. Zhang X, Zhang X, Wang L. Antenna design by an adaptive variable differential artificial bee colony algorithm. *IEEE Trans Magn*. 2018;54(3):1-4.
110. Lu Y, Sun N, Pan X. Mobile sink-based path optimization strategy in wireless sensor networks using artificial bee colony algorithm. *IEEE Access*. 2019;7:11668-11678.
111. Yílmaz S, Küçüksille EU. A new modification approach on bat algorithm for solving optimization problems. *Appl Soft Comput*. 2015;28:259-275. doi:10.1016/j.asoc.2014.11.029
112. Cao L, Cai Y, Yue Y, Cai S, Hang B. A novel data fusion strategy based on extreme learning machine optimized by bat algorithm for mobile heterogeneous wireless sensor networks. *IEEE Access*. 2020;8:16057-16072.
113. Ng CK, Wu CH, Ip WH, Yung KL. A smart bat algorithm for wireless sensor network deployment in 3-D environment. *IEEE Commun Lett*. 2018;22(10):2120-2123.
114. Sangaiah AK, Sadeghilalimi M, Hosseinabadi AAR, Zhang W. Energy consumption in point-coverage wireless sensor networks via bat algorithm. *IEEE Access*. 2019;7:180258-180269.
115. Zhao X, Cui Y, Gao C, Guo Z, Gao Q. Energy-efficient coverage enhancement strategy for 3-D wireless sensor networks based on a vampire bat optimizer. *IEEE Internet Things J*. 2020;7(1):325-338.
116. Zouache D, Ould Arby Y, Nouioua F, Ben Abdelaziz F. Multi-objective chicken swarm optimization: a novel algorithm for solving multi-objective optimization problems. *Comput Ind Eng*. 2019;129:377-391. doi:10.1016/j.cie.2019.01.055
117. Shuang L, Tie F, Sun G, Zhang J, Zhang H. Transmission power optimization for reducing sidelobe via bat-chicken swarm optimization in distributed collaborative beamforming; 2016:2164-2168.
118. Liang S, Fang Z, Sun G, Liu Y, Qu G, Zhang Y. Sidelobe reductions of antenna arrays via an improved chicken swarm optimization approach. *IEEE Access*. 2020;8:37664-37683.
119. Ahmed K, Hassanien AE, Ezzat E, Tsai PW. An adaptive approach for community detection based on chicken swarm optimization algorithm. In: Pan JS, Lin JCW, Wang CH, Jiang XH, eds. *Genetic and Evolutionary Computing*. Cham: Springer International Publishing; 2017:281-288.
120. Liu J, Feng J, Gao X. Fault diagnosis of rod pumping wells based on support vector machine optimized by improved chicken swarm optimization. *IEEE Access*. 2019;7:171598-171608. doi:10.1109/ACCESS.2019.2956221
121. Wang S, Wang L. An estimation of distribution algorithm-based memetic algorithm for the distributed assembly permutation flow-shop scheduling problem. *IEEE Trans Syst Man Cybern Syst*. 2016;46(1):139-149.
122. Qu B, Zhu Y, Jiao Y, Wu M, Suganthan P, Liang J. A survey on multi-objective evolutionary algorithms for the solution of the environmental/economic dispatch problems. *Swarm Evol Comput*. 2018;38:1-11. doi:10.1016/j.swevo.2017.06.002
123. Zhong J, Feng L, Ong Y. Gene expression programming: a survey [review article]. *IEEE Comput Intell Mag*. 2017;12(3):54-72.
124. Gong YJ, Chen WN, Zhan ZH, et al. Distributed evolutionary algorithms and their models: a survey of the state-of-the-art. *Appl Soft Comput*. 2015;34:286-300. doi:10.1016/j.asoc.2015.04.061
125. Das S, Mullick SS, Suganthan P. Recent advances in differential evolution – An updated survey. *Swarm Evol Comput*. 2016;27:1-30. doi:10.1016/j.swevo.2016.01.004
126. Cano A, Luna JM, Zafra A, Ventura S. A classification module for genetic programming algorithms. *J Mach Learn Res*. 2015;16(15):491-494.
127. Kim JH. Harmony search algorithm: a unique music-inspired algorithm. *Proc Eng*. 2016;154:1401-1405. doi:10.1016/j.proeng.2016.07.510
128. Askarzadeh A, Rashedi E. Harmony search algorithm; 2017.
129. Geem ZW, Yang XS, Tseng CL. Harmony search and nature-inspired algorithms for engineering optimization. *J Appl Math*. 2013;2013:1-2. doi:10.1155/2013/438158
130. Lin C, Deng D, Wang S. Extending the lifetime of dynamic underwater acoustic sensor networks using multi-population harmony search algorithm. *IEEE Sens J*. 2016;16(11):4034-4042.
131. Hoang DC, Yadav P, Kumar R, Panda SK. Real-time implementation of a harmony search algorithm-based clustering protocol for energy-efficient wireless sensor networks. *IEEE Trans Ind Inform*. 2014;10(1):774-783.
132. Patel VK, Savsani VJ. A multi-objective improved teaching–learning based optimization algorithm (MO-ITLBO). *Inf Sci*. 2016;357:182-200. doi:10.1016/j.ins.2014.05.049
133. Guo Z, Yue X, Yang H, Liu K, Liu X. Enhancing social emotional optimization algorithm using local search. *Soft Comput*. 2016;21(24):7393-7404. doi:10.1007/s00500‐016‐2282‐z
134. Niknam T, Kavousi-Fard A. Optimal energy management of smart renewable micro-grids in the reconfigurable systems using adaptive harmony search algorithm. *Int J Bio Inspired Comput*. 2016;8:184-194.
135. Liu ZZ, Chu DH, Song C, Xue X, Lu BY. Social learning optimization (SLO) algorithm paradigm and its application in QoS-aware cloud service composition. *Inf Sci*. 2015;326:315-333. doi:10.1016/j.ins.2015.08.004
136. Bishop CM. *Pattern Recognition and Machine Learning*. New York, NY: Springer; 2006.
137. Ma H, Li S, Zhang E, Lv Z, Hu J, Wei X. Cooperative autonomous driving oriented MEC-aided 5G-V2X: prototype system design, field tests and AI-based optimization tools. *IEEE Access*. 2020;8:54288-54302.

138. Berry M, Mohamed A. Supervised and unsupervised learning for data science; 2020.
139. Morocho-Cayamcela ME, Lee H, Lim W. Machine learning for 5G/B5G mobile and wireless communications: potential, limitations, and future directions. *IEEE Access*. 2019;7:137184-137206.
140. Gazda J, ŠLapak E, Bugár G, Horváth D, Maksymyuk T, Jo M. Unsupervised learning algorithm for intelligent coverage planning and performance optimization of multitier heterogeneous network. *IEEE Access*. 2018;6:39807-39819.
141. Page J, Bain M, Mukhlish F. The risks of low level narrow artificial intelligence; 2018:1-6.
142. Fjelland R. Why general artificial intelligence will not be realized. *Palgrave Commun*. 2020;7(1):1-9. doi:10.1057/s41599‐020‐0494‐4
143. Zhu W, Wang X, Gao W. Multimedia intelligence: when multimedia meets artificial intelligence. *IEEE Trans Multimed*. 2020;22(7):1823-1835.
144. Wu A, Wang Y, Shu X, et al. Survey on artificial intelligence approaches for visualization data; 2021.
145. Chen T, Guo W, Gao X, Liang Z. AI-based self-service technology in public service delivery: user experience and influencing factors. *Gov Inf Q*. 2020;38:101520. doi:10.1016/j.giq.2020.101520
146. Luo F. *Machine Learning for Future Wireless Communications*. Wiley – IEEE, Wiley; 2019.
147. Gilabert PL, López-Bueno D, Quynh Anh Pham T, Montoro G. Machine Learning for Digital Front-End. In: Luo F-L, ed. *In Machine Learning for Future Wireless Communications*. Wiley; 2020.
148. Tong W, Hussain A, Bo WX, Maharjan S. Artificial intelligence for vehicle-to-everything: a survey. *IEEE Access*. 2019;7:10823-10843.
149. Al-Tashi Q, Abdulkadir SJ, Rais HM, Mirjalili S, Alhussian H. Approaches to multi-objective feature selection: a systematic literature review. *IEEE Access*. 2020;8:125076-125096.
150. Sun H, Chen X, Shi Q, Hong M, Fu X, Sidiropoulos ND. Learning to optimize: training deep neural networks for interference management. *IEEE Trans Signal Process*. 2018;66(20):5438-5453.
151. Kim M, de Kerret P, Gesbert D. Learning to cooperate in decentralized wireless networks; 2018:281-185.
152. Moysen J, Giupponi L. From 4G to 5G: self-organized network management meets machine learning. *Comput Commun*. 2018;129:248-268. doi:10.1016/j.comcom.2018.07.015
153. Chen M, Challita U, Saad W, Yin C, Debbah M. Artificial neural networks-based machine learning for wireless networks: a tutorial; 2017.
154. Shanmuganathan S, Samarasinghe S. *Artificial Neural Network Modelling*. 1st ed. Springer: Springer Publishing Company, Incorporated; 2016.
155. Han Z, Liang J. The analysis of node planning and control logic optimization of 5G wireless networks under deep mapping learning algorithms. *IEEE Access*. 2019;7:156489-156499.
156. Pelekanou A, Anastasopoulos M, Tzanakaki A, Simeonidou D. Provisioning of 5G services employing machine learning techniques; 2018:200-205.
157. Muñoz P, Barco R, de la Bandera I. On the potential of handover parameter optimization for self-organizing networks. *IEEE Trans Veh Technol*. 2013;62(5):1895-1905.
158. Giordani M, Mezzavilla M, Rangan S, Zorzi M. An efficient uplink multi-connectivity scheme for 5G millimeter-wave control plane applications. *IEEE Trans Wirel Commun*. 2018;17(10):6806-6821.
159. Sciancalepore V, Samdanis K, Costa-Perez X, Bega D, Gramaglia M, Banchs A. Mobile traffic forecasting for maximizing 5G network slicing resource utilization; 2017:1-9.
160. Bega D, Gramaglia M, Banchs A, Sciancalepore V, Costa-Pérez X. A machine learning approach to 5G infrastructure market optimization. *IEEE Trans Mob Comput*. 2020;19(3):498-512.
161. Chen T, Ling Q, Giannakis GB. An online convex optimization approach to proactive network resource allocation. *IEEE Trans Signal Process*. 2017;65(24):6350-6364.
162. Liao RF, Wen H, Wu J, Song H, Pan F, Dong L. The Rayleigh fading channel prediction via deep learning. *Wirel Commun Mob Comput*. 2018;2018:1-11. doi:10.1155/2018/6497340
163. Klaine PV, Imran MA, Onireti O, Souza RD. A survey of machine learning techniques applied to self-organizing cellular networks. *IEEE Commun Surv Tutor*. 2017;19(4):2392-2431.
164. Snoek J, Larochelle H, Adams RP. Practical Bayesian optimization of machine learning algorithms; 2012.
165. Shahriari B, Swersky K, Wang Z, Adams RP, de Freitas N. Taking the human out of the loop: a review of bayesian optimization. *Proc IEEE*. 2016;104(1):148-175.
166. Wang Z, Shakibi B, Jin L, de Freitas N. Bayesian multi-scale optimistic optimization ArXiv 2014; abs/1402.7005.
167. Xia Y, Liu C, Li Y, Liu N. A boosted decision tree approach using Bayesian hyper-parameter optimization for credit scoring. *Expert Syst Appl*. 2017;78:225-241. doi:10.1016/j.eswa.2017.02.017
168. Klein A, Falkner S, Bartels S, Hennig P, Hutter F. Fast Bayesian optimization of machine learning hyperparameters on large datasets; 2016.
169. Ma B, Yang B, Zhu Y, Zhang J. Context-aware proactive 5G load balancing and optimization for urban areas. *IEEE Access*. 2020;8:8405-8417.
170. Franco CAS, de Marca JRB. Load balancing in self-organized heterogeneous LTE networks: a statistical learning approach; 2015:1-5.
171. Sun Y, Babu P, Palomar DP. Majorization-minimization algorithms in signal processing, communications, and machine learning. *IEEE Trans Signal Process*. 2017;65(3):794-816.
172. Mismar FB, Evans BL, Alkhateeb A. Deep reinforcement learning for 5G networks: joint beamforming, power control, and interference coordination. *IEEE Trans Commun*. 2020;68(3):1581-1592.

173. Huang H, Guo S, Gui G, et al. Deep learning for physical-layer 5G wireless techniques: opportunities, challenges and solutions. *IEEE Wirel Commun*. 2019;27(1):214-222.
174. Lee H, Lee SH, Quek TQS. Deep learning for distributed optimization: applications to wireless resource management. *IEEE J Select Areas Commun*. 2019;37(10):2251-2266.
175. Zhang T, Mao S. Smart power control for quality-driven multi-user video transmissions: a deep reinforcement learning approach. *IEEE Access*. 2020;8:611-622.
176. Asadi A, Müller S, Sim GH, Klein A, Hollick M. FML: fast machine learning for 5G mmWave vehicular communications; 2018:1961-1969.
177. Hamdani TM, Won JM, Alimi AM, Karray F. Hierarchical genetic algorithm with new evaluation function and bi-coded representation for the selection of features considering their confidence rate. *Appl Soft Comput*. 2011;11(2):2501-2509. The Impact of Soft Computing for the Progress of Artificial Intelligence. doi:10.1016/j.asoc.2010.08.020
178. Li S, Zhang K, Chen Q, Wang S, Zhang S. Feature selection for high dimensional data using weighted K-nearest neighbors and genetic algorithm. *IEEE Access*. 2020;8:139512-139528.
179. Rayno J, Iskander MF, Kobayashi MH. Hybrid genetic programming with accelerating genetic algorithm optimizer for 3-D metamaterial design. *IEEE Antennas Wirel Propag Lett*. 2016;15:1743-1746.
180. Silva ER, Guardieiro PR. An efficient genetic algorithm for anycast routing in delay/disruption tolerant networks. *IEEE Commun Lett*. 2010;14(4):315-317.
181. Jiang Y, Zhang S, Guo Q, Luan X. A hybrid strategy based on weighting density and genetic algorithm for the synthesis of uniformly weighted concentric ring arrays. *IEEE Antennas Wirel Propag Lett*. 2017;16:186-189.
182. Koganei Y, Yofune M, Li C, Hoshida T, Amezawa Y. SC-LDPC code with nonuniform degree distribution optimized by using genetic algorithm. *IEEE Commun Lett*. 2016;20(5):874-877.
183. Xiong J, Wang W, Shao H, Chen H. Frequency diverse array transmit beampattern optimization with genetic algorithm. *IEEE Antennas Wirel Propag Lett*. 2017;16:469-472.
184. Mehboob U, Qadir J, Ali S, Vasilakos A. Genetic algorithms in wireless networking: techniques, applications, and issues. *Soft Comput*. 2016;20(6):2467-2501. doi:10.1007/s00500‐016‐2070‐9
185. Kao SJ, Hsiao KC, Chang FM. Radio resource allocation using genetic algorithm in heterogeneous networks. *Int J Commun Syst*. 2019;32:e4089. doi:10.1002/dac.4089
186. Jiao Y, Joe I. Energy-efficient resource allocation for heterogeneous cognitive radio network based on two-tier crossover genetic algorithm. *J Commun Netw*. 2016;18(1):112-122.
187. Chakraborty G. Genetic algorithm to solve optimum TDMA transmission schedule in broadcast packet radio networks. *IEEE Trans Commun*. 2004;52(5):765-777.
188. Khan M, Fakhri ZH, Al-Raweshidy HS. Semistatic cell differentiation and integration with dynamic BBU-RRH mapping in cloud radio access network. *IEEE Trans Netw Serv Manag*. 2018;15(1):289-303.
189. Li WT, Shi XW, Hei YQ, Liu SF, Zhu J. A hybrid optimization algorithm and its application for conformal array pattern synthesis. *IEEE Trans Antennas Propag*. 2010;58(10):3401-3406.
190. Pradhan B, Vijayakumar V, Pratihar S, Kumar D, Reddy KHK, Roy DS. A genetic algorithm based energy efficient group paging approach for IoT over 5G. *J Syst Archit*. 2021;113:101878. doi:10.1016/j.sysarc.2020.101878
191. Jo Y, Kim H, Lim J, Hong D. Self-optimization of coverage and system throughput in 5G heterogeneous ultra-dense networks. *IEEE Wirel Commun Lett*. 2020;9(3):285-288.
192. Alhammadi A, Roslee M, Alias MY, Shayea I, Alraih S, Mohamed KS. Auto tuning self-optimization algorithm for mobility management in LTE-A and 5G HetNets. *IEEE Access*. 2020;8:294-304.
193. Alhammadi A, Mardeni R, Alias M, Ibraheem S, Alraih S. Self-optimization of handover control parameters for mobility management in 4G/5G heterogeneous networks. *Autom Control Comput Sci*. 2019;53:441-451. doi:10.3103/S014641161905002X
194. Cia M, Mason F, Peron D, et al. Using smart city data in 5G self-organizing networks. *IEEE Internet Things J*. 2017;5(2):645-654. doi:10.1109/JIOT.2017.2752761
195. Jain A, Lopez-Aguilera E, Demirkol I. Evolutionary 4G/5G network architecture assisted efficient handover signaling. *IEEE Access*. 2019;7:256-283.
196. Yang B, Yang X, Ge X, Li Q. Coverage and handover analysis of ultra-dense millimeter-wave networks with control and user plane separation architecture. *IEEE Access*. 2018;6:54739-54750.
197. Ray SK, Pawlikowski K, Sirisena H. Handover in mobile WiMAX networks: the state of art and research issues. *IEEE Commun Surv Tutor*. 2010;12(3):376-399.
198. Alhabo M, Zhang L. Multi-criteria handover using modified weighted TOPSIS methods for heterogeneous networks. *IEEE Access*. 2018;6:40547-40558.
199. Choi J, Shin D. Generalized RACH-less handover for seamless mobility in 5G and beyond mobile networks. *IEEE Wireless Communications Letters*. 2019;8(4):1264-1267.
200. Chopra G, Jain S, Jha RK. Possible security attack modeling in ultradense networks using high-speed handover management. *IEEE Trans Veh Technol*. 2018;67(3):2178-2192.
201. Yang J, Ji X, Huang K, Chen Y, Xu X, Yi M. Unified and fast handover authentication based on link signatures in 5G SDN-based HetNet. *IET Commun*. 2019;13(2):144-152.
202. Balakrishnan R, Akyildiz I. Local anchor schemes for seamless and low-cost handover in coordinated small cells. *IEEE Trans Mob Comput*. 2016;15(5):1182-1196.

203. Jin M, Wu EH, Chang C. An intelligent handover scheme for the next generation personal communication systems. *J Commun Netw*. 2004;6(3):245-257.
204. Gupta H, Sharma M, Franklin AA, Tamma BR. Apt-RAN: a flexible split-based 5G RAN to minimize energy consumption and handovers. *IEEE Trans Netw Serv Manag*. 2020;17(1):473-487.
205. Zhang H, Huang W, Liu Y. Handover probability analysis of anchor-based multi-connectivity in 5G user-centric network. *IEEE Wirel Commun Lett*. 2019;8(2):396-399.
206. Polese M, Giordani M, Mezzavilla M, Rangan S, Zorzi M. Improved handover through dual connectivity in 5G mmWave mobile networks. *IEEE J Select Areas Commun*. 2017;35(9):2069-2084.
207. Luo H, Zhang H, Qiao C. Optimal cache timeout for identifier-to-locator mappings with handovers. *IEEE Trans Netw Serv Manag*. 2013;10(2):204-217.
208. Yaseen FA, Al-Raweshidy HS. Smart virtualization packets forwarding during handover for beyond 5G networks. *IEEE Access*. 2019;7:65766-65780.
209. Lu Y, Xiong K, Fan P, Zhong Z, Ai B. The effect of power adjustment on handover in high-speed railway communication networks. *IEEE Access*. 2017;5:26237-26250.
210. Suarez-Rodriguez C, He Y, Dutkiewicz E. Theoretical analysis of REM-based handover algorithm for heterogeneous networks. *IEEE Access*. 2019;7:96719-96731.
211. Fathi H, Chakraborty SS, Prasad R. Optimization of mobile IPv6-based handovers to support VoIP services in wireless heterogeneous networks. *IEEE Trans Veh Technol*. 2007;56(1):260-270.
212. Yan L, Fang X, Fang Y. A novel network architecture for C/U-plane staggered handover in 5G decoupled heterogeneous railway wireless systems. *IEEE Trans Intell Transp Syst*. 2017;18(12):3350-3362.
213. Zhang Z, Junhui Z, Ni S, Gong Y. A seamless handover scheme with assisted eNB for 5G C/U plane split heterogeneous network. *IEEE Access*. 2019;7:164256-164264.
214. Song H, Fang X, Yan L. Handover scheme for 5G C/U plane split heterogeneous network in high-speed railway. *IEEE Trans Veh Technol*. 2014;63(9):4633-4646.
215. Zhao J, Liu Y, Gong Y, Wang C, Fan L. A dual-link soft handover scheme for C/U plane split network in high-speed railway. *IEEE Access*. 2018;6:12473-12482.
216. Kushner HJ, Dupuis P. *The Markov Chain Approximation Method: Introduction*. New York: Springer; 2001:67-88.
217. Myint SH, Yu K, Sato T. Modeling and analysis of error process in 5G wireless communication using two-state Markov chain. *IEEE Access*. 2019;7:26391-26401.
218. Chen M, Liew SC, Shao Z, Kai C. Markov approximation for combinatorial network optimization. *IEEE Trans Inf Theory*. 2013;59(10):6301-6327.
219. Chen S, Gan X, Feng X, Tian X, Wu W, Liu J. Markov approximation for Multi-RAT selection; 2015:3045-3050.
220. Wang C, Yu FR, Liang C, Chen Q, Tang L. Joint computation offloading and interference management in wireless cellular networks with mobile edge computing. *IEEE Trans Veh Technol*. 2017;66(8):7432-7445.
221. Sardellitti S, Scutari G, Barbarossa S. Joint optimization of radio and computational resources for multicell mobile-edge computing. *IEEE Trans Signal Inf Process Netw*. 2015;1(2):89-103.
222. Mao Y, Zhang J, Song SH, Letaief KB. Stochastic joint radio and computational resource management for multi-user mobile-edge computing systems. *IEEE Trans Wirel Commun*. 2017;16(9):5994-6009.
223. Siddavaatam R, Woungang I, Anpalagan A. Joint optimisation of radio and infrastructure resources for energy-efficient massive data storage in the mobile cloud over 5G HetNet. *IET Wirel Sens Syst*. 2019;9(5):323-332.
224. Chen F, Fu J, Wang Z, Zhou Y, Qiu W. Joint communication and computation resource optimization in FD-MEC cellular networks. *IEEE Access*. 2019;7:168444-168454.
225. Yang LH, Wang YM, Liu J, Martínez L. A joint optimization method on parameter and structure for belief-rule-based systems. *Knowl-Based Syst*. 2018;142:220-240. doi:10.1016/j.knosys.2017.11.039
226. Kouvaritakis B, Cannon M. Closed-loop optimization strategies for additive uncertainty; 2016:121-174.
227. Eisenberg BBR, Sage AP. Closed loop optimization of fixed configuration systems. *Int J Control*. 1966;3(2):183-194. doi:10.1080/00207176608921377
228. Attia PM, Grover A, Jin N, et al. Closed-loop optimization of fast-charging protocols for batteries with machine learning. *Nature*. 2020;578(7795):397-402. doi:10.1038/s41586‐020‐1994‐5
229. Zhou Z, Zhang S. A perturbation approach to the beam tracing in the line-of-sight massive MIMO systems. *IEEE Wirel Commun Lett*. 2020;9(9):1529-1532.
230. Duly AJ, Kim T, Love DJ, Krogmeier JV. Closed-loop beam alignment for massive MIMO channel estimation. *IEEE Commun Lett*. 2014;18(8):1439-1442.
231. Choi J, Love DJ, Bidigare P. Downlink training techniques for FDD massive MIMO systems: open-loop and closed-loop training with memory. *IEEE J Select Top Signal Process*. 2014;8(5):802-814.
232. Liu A, Zhu F, Lau VKN. Closed-loop autonomous pilot and compressive CSIT feedback resource adaptation in multi-user FDD massive MIMO systems. *IEEE Trans Signal Process*. 2017;65(1):173-183.
233. Lau VKN, Cai S, Liu A. Closed-loop compressive CSIT estimation in FDD massive MIMO systems with 1 bit feedback. *IEEE Trans Signal Process*. 2016;64(8):2146-2155.
234. Liu Y, Pan W, Shao S, Tang Y. A new digital predistortion using indirect learning with constrained feedback bandwidth for wideband power amplifiers; 2014:1-3.

235. Liu Z, Hu X, Liu T, Li X, Wang W, Ghannouchi FM. Attention-based deep neural network behavioral model for wideband wireless power amplifiers. *IEEE Microw Wirel Compon Lett*. 2020;30(1):82-85.
236. Lee CL, Su WS, Tang KA, Chao WI. Design of handover self-optimization using big data analytics; 2014:1-5.
237. Tcholtchev N, Chaparadza R. Autonomic fault-management and resilience from the perspective of the network operation personnel; 2011:469-474.
238. Onireti O, Imran A, Imran M, Tafazolli R. Cell outage detection in heterogeneous networks with separated control and data plane; 2014.
239. Yu C, Lu Q, Sun H, Wu X, Zhu XW. Digital predistortion of ultra-broadband mmwave power amplifiers with limited TX/feedback loop/baseband bandwidth. *Wirel Commun Mob Comput*. 2018;2018:4510243. doi:10.1155/2018/4510243
240. Zhi-Quan L, Wei Y. An introduction to convex optimization for communications and signal processing. *IEEE J Select Areas Commun*. 2006;24(8):1426-1438.
241. Yang SJ, Kim YD, Yun DJ, Yi DW, Myung NH. Antenna modeling using sparse infinitesimal dipoles based on recursive convex optimization. *IEEE Antennas Wirel Propag Lett*. 2018;17(4):662-665.
242. Boyd S, Vandenberghe L. *Convex Optimization*. Cambridge: Cambridge University Press; 2004.
243. Cao L, Cai Y, Yue Y. Swarm intelligence-based performance optimization for mobile wireless sensor networks: survey, challenges, and future directions. *IEEE Access*. 2019;7:161524-161553.
244. Hung H, Huang Y, Wei C, Chen R. Performance of PTS-based firefly algorithm scheme for PAPR reduction in SFBC MIMO-OFDM communication systems; 2016:854-857.
245. Iscan H, Gündüz M. Parameter analysis on fruit fly optimization algorithm. *J Comput Commun*. 2014;02:137-141. doi:10.4236/jcc.2014.24018
246. Jabeena A, Jayabarathi T, Gupta P, Hazarika G, Bhawsinka N. Optimization of wireless optical communication system with placement of relay using shuffled frog leaping algorithm. *ARPN J Eng Appl Sci*. 2013;8:534-538.
247. Zhu J, Wei Z, Li T. Research of wolf pack algorithm; 2018:695-698.
248. Nazari-Heris M, Mohammadi-Ivatloo B, Asadi S, Kim JH, Geem ZW. Harmony search algorithm for energy system applications: an updated review and analysis. *J Exp Theor Artif Intell*. 2019;31(5):723-749. doi:10.1080/0952813X.2018.1550814
249. Greiner D, Periaux J, Quagliarella D, Magalhaes-Mendes J, Galván B. Evolutionary algorithms and metaheuristics: applications in engineering design and optimization. *Math Probl Eng*. 2018;2018:2793762. doi:10.1155/2018/2793762
250. Campos R, Lovisolo L. Wireless communication systems optimization using genetic algorithms; 2016.
251. Shilaja C. Implementation of differential evolution algorithm and its variants for optimal scheduling of distributed generations. *Int J Commun Syst*. 2021;34(6):e4318. doi:10.1002/dac.4318
252. Sampedro C, Martinez C, Chauhan A, Campoy P. A supervised approach to electric tower detection and classification for power line inspection; 2014:1970-1977.
253. Gijón C, Toril M, Solera M, Luna-Ramírez S, Jiménez LR. Encrypted traffic classification based on unsupervised learning in cellular radio access networks. *IEEE Access*. 2020;8:167252-167263.
254. Li R, Zhao Z, Sun Q, et al. Deep reinforcement learning for resource management in network slicing. *IEEE Access*. 2018;6:74429-74441.
255. Jiang W, Schotten HD. Deep learning for fading channel prediction. *IEEE Open J Commun Soc*. 2020;1:320-332.
256. Moradi M, Lin Y, Mao ZM, Sen S, Spatscheck O. SoftBox: a customizable, low-latency, and scalable 5G core network architecture. *IEEE J Select Areas Commun*. 2018;36(3):438-456.
257. Hadachi A, Batrashev O, Lind A, Singer G, Vainikko E. Cell phone subscribers mobility prediction using enhanced Markov Chain algorithm; 2014:1049-1054.
258. Settaluri K, Haj-Ali A, Huang Q, Hakhamaneshi K, Nikolic B. AutoCkt: deep reinforcement learning of analog circuit designs; 2020:490-495.
259. Na WC, Zhang QJ. Automated knowledge-based neural network modeling for microwave applications. *IEEE Microw Wirel Compon Lett*. 2014;24(7):499-501.
260. Hewa T, Gür G, Kalla A, Ylianttila M, Bracken A, Liyanage M. The role of blockchain in 6G: challenges, opportunities and research directions; 2020:1-5.
261. Kouhalvandi L, Ceylan O, Ozoguz S. Automated deep neural learning-based optimization for high performance high power amplifier designs. *IEEE Trans Circuits Syst I Regul Pap*. 2020;67(2):4420-4433.
262. Feng F, Na W, Liu W, et al. Multifeature-assisted neuro-transfer function surrogate-based EM optimization exploiting trust-region algorithms for microwave filter design. *IEEE Trans Microw Theory Techn*. 2020;68(2):531-542.
263. Koziel S, Ogurtsov S, Zieniutycz W, Sorokosz L. Expedited design of microstrip antenna subarrays using surrogate-based optimization. *IEEE Antennas Wirel Propag Lett*. 2014;13:635-638.
264. Koziel S, Ogurtsov S. Simulation-based design of microstrip linear antenna arrays using fast radiation response surrogates. *IEEE Antennas Wirel Propag Lett*. 2015;14:759-762.
265. Angiulli G, Cacciola M, Versaci M. Microwave devices and antennas modelling by support vector regression machines. *IEEE Trans Magn*. 2007;43(4):1589-1592.
266. Koziel S, Couckuyt I, Dhaene T. Variable-fidelity optimization of microwave filters using co-kriging and trust regions; 2012:242-245.
267. Chávez-Hurtado JL, Rayas-Sánchez JE. Polynomial-based surrogate modeling of RF and microwave circuits in frequency domain exploiting the multinomial theorem. *IEEE Trans Microw Theory Techn*. 2016;64(12):4371-4381.
268. Koziel S. Shape-preserving response prediction for microwave circuit modeling; 2010:1660-1663.
269. Jin J, Zhang C, Feng F, Na W, Ma J, Zhang Q. Deep neural network technique for high-dimensional microwave modeling and applications to parameter extraction of microwave filters. *IEEE Trans Microw Theory Techn*. 2019;67(10):4140-4155.

270. Telgarsky M. *Benefits of Depth in Neural Networks*. Newyork: Columbia University; 2016.
271. Zhang W, Li L, Li F. Reducing the number of elements in linear and planar antenna arrays with sparseness constrained optimization. *IEEE Trans Antennas Propag*. 2011;59(8):3106-3111.
272. Bandler JW, Cheng QS, Dakroury SA, et al. Space mapping: the state of the art. *IEEE Trans Microw Theory Techn*. 2004;52(1):337-361.
273. Kouhalvandi L, Ceylan O, Ozoguz S. A review on optimization methods for designing RF power amplifiers; 2019:375-378.
274. Hakhamaneshi K, Werblun N, Abbeel P, Stojanovi V. BagNet: Berkeley analog generator with layout optimizer boosted with deep neural networks; 2019:1-8.
275. Cheng QS, Bandler JW, Koziel S. Combining coarse and fine models for optimal design. *IEEE Microw Mag*. 2008;9(1):79-88.
276. Zhang Y, Gao F, Fan L, Lei X, Karagiannidis G. Secure communications for multi-tag backscatter systems. *IEEE Wirel Commun Lett*. 2019;8(4):1146-1149. doi:10.1109/LWC.2019.2909199
277. Xiao S, Guo H, Liang YC. Resource allocation for full-duplex-enabled cognitive backscatter networks. *IEEE Trans Wirel Commun*. 2019;18(6):3222-3235. doi:10.1109/TWC.2019.2912203
278. Zhang Y, Gao F, Fan L, Lei X, Karagiannidis G. Backscatter communications over correlated Nakagami-*m* fading channels. *IEEE Trans Commun*. 2018;67(2):1693-1704. doi:10.1109/TCOMM.2018.2879611
279. Imran A, Zoha A, Abu-Dayya A. Challenges in 5G: how to empower SON with big data for enabling 5G. *IEEE Netw*. 2014;28:27-33. doi:10.1109/MNET.2014.6963801
280. Guvenkaya E, Hamamreh J, Arslan H. On physical-layer concepts and metrics in secure signal transmission. *Phys Commun*. 2017;25:14-25. doi:10.1016/j.phycom.2017.08.011
281. Simsek E. Machine learning exercises on 1-D electromagnetic inversion. *IEEE Trans Antennas Propag*. 2021;69(10):6797-6805. doi:10.1109/TAP.2021.3069519
282. Canelas A, Passos F, Lourenço N, et al. Hierarchical yield-aware synthesis methodology covering device-, circuit-, and system-level for radiofrequency ICs. *IEEE Access*. 2021;9:124152-124164. doi:10.1109/ACCESS.2021.3110758
283. Mir F, Kouhalvandi L, Matekovits L, Gunes EO. Automated optimization for broadband flat-gain antenna designs with artificial neural network. *IET Microw Antennas Propag*. 2021;15(12):1537-1544. doi:10.1049/mia2.12137

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APPENDIX

For easy access to the abbreviations used in different phrases, we prepare a table listing the abbreviations and their definitions as shown in Table A1.

TABLE A1 List of abbreviations

Abbreviation	Definition
ABC	Artificial bee colony
ACO	Ant colony optimization
AFSA	Artificial fish swarm algorithm
APOA	Artificial plant optimization algorithm
AI	Artificial intelligence
ANN	Artificial neural network
ANI	Artificial narrow intelligence
AGI	Artificial general intelligence
ASI	Artificial Super Intelligence
BRB	Belief-rule-base
BO	Bayesian optimization
BA	Bat algorithm

(Continues)

TABLE A1 (Continued)

Abbreviation	Definition
BFO	Bacterial foraging optimization
BBPSO	Bare-bone particle swarm optimization
CLO	Close loop optimization
CO	Convex optimization
C-RAN	Centralized RAN
CSO	Chicken swarm optimization algorithm
CSA	Cuckoo search algorithm
CS	Communication systems
DE	Differential evolution algorithm
DL	Deep learning
DNN	Deep neural network
DPD	Digital predistortion
EA	Evolutionary algorithm
EM	Electromagnetic
5G	Fifth generation
FMIPv6	Fast handovers for mobile IPv6
FA	Firefly algorithm
FOA	Fruit fly optimization algorithm
GA	Genetic algorithm
GP	Gaussian process
GEP	Gene expression programming
HS	Harmony search
HUDN	Heterogeneous ultra-dense networks
HetNet	Heterogeneous network
HO	Handover
IoT	Internet of Things
JO	Joint optimization
LDSM	Low density superposition modulation
LUT	Look-up table
mmWave	Millimeter wave communication
MAA	Markov approximation algorithm
MIMO	Multi-input-multi-output
MCC	Mobile cloud computing
MEC	Mobile edge computing
ML	Machine learning
Multi-RAT	Multi-radio access technology
MA	Memetic algorithm
MOEA	Multi-objective evolutionary algorithm
N3AC	Network-slicing neural network admission control
OLO	Open loop optimization

(Continues)

TABLE A1 (Continued)

Abbreviation	Definition
PA	Power amplifier
PSO	Particle swarm optimization
PSTN	Public switched telephone network
PSO-ECHS	Particle swarm optimization energy efficient cluster head selection
QoS	Quality of service
Rx	Receiver
RAN	Radio access network
RAT	Radio access technology
RNC	Radio network controller
RL	Reinforcement learning
SON	Self-organizing network
SWIPT	Simultaneous wireless information and power transfer
SFLA	Shuffled frog leaping algorithm
6G	Sixth generation
SCO	Social cognitive optimization algorithm
SEOA	Social emotion optimization algorithm
SL	Supervised learning
SO	Self-optimization
Tx	Transceiver
THz	TeraHertz
UE	User equipment
USL	Unsupervised learning