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Future Communication Systems: Toward the Intelligent-based Optimization Approaches

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Abstract—The wireless communication systems are expecting to include the high-end service quality for the users and customers. In the last decade, the industry and academia are studying effectively on the sixth generation (6G) systems, since the high performance network connectivity will influence on the number of use cases and also varied applications. For this case, new challenging requirements with key specifications need to be considered deeply for fulfilling the technical drawbacks. In the very recently published papers, it is recognized that researchers focus on solving various problems appeared in the communication systems through advanced optimization methods based on the artificial intelligence (AI). This study devotes to summarize newly and recently published studies where they use optimization and AI-based approaches for tacking their problems related to the communication systems. This review will help readers to discover the suitable AI-based approach for their own challenges.

Index Terms—Artificial intelligence (AI), deep neural network (DNN), fifth generation (5G), machine learning (ML), optimization, sixth generation (6G), wireless.

Fig. 1. AI and subdivision of AI includes machine learning and deep learning presented in [12].

I. INTRODUCTION

The fifth generation (5G) sixth generation (6G) networks include a large number of macro and small base stations, terminals, and so on. In these networks, the designed environment may not be modified [1]. In these complex systems, the transferred/received information is crucial for linking various environments together [2]. From another point of view in 5G/6G networks, there are various specifications as security, privacy protection, efficiency, and so on, that are needed to be optimized.

In [3], two joint beamforming design methods are extracted that are based on the multi-objective optimization problems and will help in: 1) improving the weighted overall performance, and 2) decreasing the total transmit power. The work in [4] presents the beamforming optimization at the dual functional radar communication transmitter. This method leads to enhance the probability of radar detection along with convincing the data rate. For reducing the consumed energy, time, with addition to constant cost of multi-unmanned aerial vehicle, 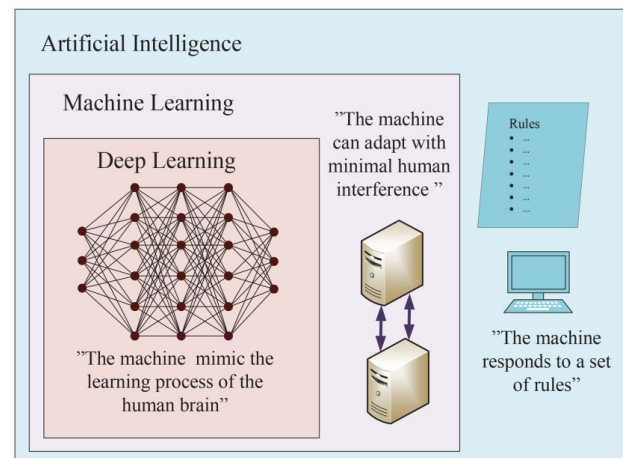a passive beamforming algorithm is presented in [5]. With the help of multiobjective optimization method, the offloading methodology in distributed multi-input multioutput cell-free 6G networks is investigated in [6]. Implementation of this method starts with a nonconvex vector optimization problem, and then transformation into the mixed-integer nonlinear programming is executed. For computing optimal path planning trajectories, in [7] an optimization method is employed for multiple unmanned aerial vehicles. From another aspect, in [8] optimization process is executed for two objectives as end-to-end delay and service relocation for arranging the network slice.

Due to these concepts, advanced optimization methods must be investigated for achieving high performance and advanced networks [9]. In case of multiple specifications, multi-objective optimization algorithms are appreciated to be considered for performing the optimization process in 5G/6G systems [10]. In these complex systems, employing joint optimization can significantly improve the overall performance of systems [11] as well.

Recently, artificial intelligence (AI) has proved its profes-

sional performance in various domains such as image recognition, class-classification, autonomous vehicles, and wireless communication systems [13], [14]. The AI includes machine learning and deep learning as depicted in Fig. 1 where these techniques aim to mimic the behavior of humans. For instance, deep reinforcement learning is employed in [15] leading to achieve the optimal policy in mobile edge computing (MEC) where MEC is the paradigm for delay-sensitive tasks in 5G/6G systems. This paper presents the comprehensively review over the various intelligent-based optimization methods employed for wireless communication systems. Any researcher by reading this paper will get the general information regarding the open challenges, future research directions, and suitable optimization method for the engineer's design problem.

This work is organized as follows: Section II explains the general concept of AI. Section III summarizes the diverse optimization algorithms employed for wireless communication systems with the practical implementation of the AI in various 5G/6G systems where the last section concludes this paper.

II. CONCEPT OF OPTIMIZATION ALGORITHMS WITH AI

Optimization involves the manipulation of datasets to minimize or maximize specific functions. It finds its applications in various scenarios, such as achieving cost efficiency, reducing errors, managing optimal designs, or maximizing profits. The objective of this field is to explore optimization problems, analyze the benefits and drawbacks of optimization, and classify different types of problems [16]. Numerical methods play a key role in providing solutions through iterative computational processes. Hence, improved techniques can be considered to determine their effectiveness. The application and performance of circuits and systems have significantly improved over time. However, meeting constraints poses a challenge, especially due to the complexity of systems, resulting in optimization problems. Recently, diverse optimization approaches have been explored to address design tackles, aiming to obtain compact and cost-effective structures. The effectiveness of different optimization methods is assessed based on their robustness, ease of implementation, and ability to deliver satisfactory optimization performance. Hence, any engineer by evaluating the benefits and deficits of each algorithm, suitable optimization approaches with the necessary tools to tackle electromagnetic design issues are selected. Full-wave and electromagnetic simulations are employed to account for the targeted design parameters. In general, optimization algorithms progressively result in finding the optimal solutions with the aid of evolutionary process [17].

The upcoming 6G technologies will play an important responsibility in shaping the future digital landscape by enabling ultra-wide band data transmission. As we look ahead to 6G technology, it becomes apparent that evolutionary methods will be vital across various communication systems [18]. Therefore, it is imperative to develop algorithms that can enhance the adaptability and versatility of 5G and 6G systems, allowing their deployment in various contexts. Researchers have taken a keen interest in evolutionary algorithms and

neural-based networks due to their ability to approximate solutions effectively for different types of problems, along with their appealing features and strong generalization capabilities. Consequently, these intelligent and evolutionary-based algorithms have found extensive application in domains such as analog, radio frequency, and telecommunication in recent years [19].

AI are machine intelligence methods opposite to the natural intelligence includes animal, human, and any hypothetical alien intelligence. AI approaches are able to solve complicated difficulties without prominent programming [20]. The employed optimization methods along with the AI approach leads to learn and mimic from the experience of humans [21]. The main requirement for employing these methods is the suitable amount of data for modeling the behavior of systems. Additionally, computational systems with advanced codes of algorithms must be prepared for creating the AI-based optimization environment.

Some of the various optimization approaches that can be exploited with the AI method are: Convex optimization [22], stochastic optimization [23], lyapunov optimization [24], and so on for balancing specifications as the overall service performance and security levels [25]–[27].

III. VARIOUS OPTIMIZATION METHODS EMPLOYED IN 5G/6G SYSTEMS

To efficiently address the needs of complex systems, it is crucial to employ adaptable, intelligent, and intuitive algorithms that primarily aim to optimize targeted objectives. Consequently, there is a strong demand for advanced optimization techniques that can effectively meet the specific requirements of these systems. Hence, the implementation of advanced optimization approaches becomes essential to bolster the capabilities of 5G technologies [28], [29].

An optimization method refers to a mathematical representation or defined process utilized to identify the finest components and optimal solutions, ultimately leading to the attainment of desired objectives through the minimization or maximization of objective functions. Optimization essentially aims to reach the highest achievable performance by iteratively pursuing the 'optimal' or most favorable point [30]. Delivering a comprehensive set of optimal solutions that satisfy all specified criteria is a complex task, necessitating the use of multi-objective optimization methods to strike a balance between different desired outcomes [31], [32].

Given the limitations posed by conflicting constraints, there is a deep need for efficient multi-objective optimization techniques. Addressing various drawbacks has become crucial in studying multi-objective optimizations, as well as in preparing for the future with multi-mode terminals and upcoming 6G networks. As communication technologies rapidly evolve, network structures are becoming increasingly complex [33]. In response, many optimization methods are being employed in numerous communication domains to overcome these challenges and attract attention from both academic and industrial sectors. By employing advanced methodologies, these optimization

approaches facilitate progress and provide optimal solutions to optimization problems by striking a balance between targets and restricts. This ensures the delivery of the best and efficient answers [34]. With respect to these challenges, this section devotes to introduce the varied optimization methods used in 5G/6G communication systems. Hence it is categorized into three subparts, each outlining different optimization approaches as follows: (i) strategies inspired by animal, plant, and insect behaviors [35], (ii) techniques influenced by human treatments [36], and (iii) methods based on evolutionary processes [37].

A. Optimization algorithms drawn inspiration from the behaviors of animals, plants, or insects

Particle swarm optimization (PSO): PSO is a stochastic optimization technique used as a computational method. It bears resemblance to the genetic algorithm and improves solutions based on a fitness function. In order to improve the quality of service (QoS) in cellular networks, it is necessary to employ simplified optimization techniques that address both co-channel interference and full-duplex self-interference. A research paper , [38], introduces an algorithm utilizing PSO, which effectively bypasses cooperative coded caching placement. Another variation of PSO known as the bare-bone PSO (BBPSO) algorithm is described in [39]. This approach is specifically applied to optimize the degree distribution of a low-density superposition modulation (LDSM) matrix. The BBPSO algorithm reduces the conventional velocity term of PSO.

Ant colony optimization (ACO): ACO is a statistics approach that draws inspiration from the behavior of actual ants. Its objective is to discover and diminish favorable routes within graphs. This technique falls under the category of swarm intelligence methods and addresses computational problems by evaluating a parameter space that encompasses all potential answers. It specifies the shortest path on a graph with weights. ACO employs a positive feedback mechanism and encompasses different variations. Yet, it suffers from slow convergence rate and speed, as mentioned in [40].

Artificial bee colony algorithm (ABC): In recent times, the ABC method has gained recognition in both the antenna array and wireless sensor network domains. It is utilized for the purpose of designing an optimal array antenna. Additionally, a strategy for path optimization based on a mobile sink is presented in [41], specifically tailored for wireless sensor networks.

Bat algorithm (BA): The BA method is a nature-inspired algorithm that incorporates a frequency-tuning technique to enhance optimal solutions. The primary objective of this process is to strike a balance between exploration and exploitation during the search procedure. The algorithm adopts a global optimization approach and is commonly employed for adjusting loudness and pulse rate. In the context of multi-objective optimization using the BA method, information exchange takes place among different swarms through the utilization of various parameters.

Chicken swarm optimization algorithm (CSO): The CSO, a bio-inspired algorithm, introduces a novel approach to minimize hierarchical order while conducting food search. In the context of optimizing the peak sidelobe level in a distributed random antenna array, the CSO algorithm's application is elaborated upon in [42]. Typically, this method is employed to optimize antenna arrays by addressing beam pattern issues using an analogy of rooster and hens. Another application of the CSO method involves reducing the maximum sidelobe level in the antenna array and generating an optimal solution.

B. Optimization using human interventions

Harmony search (HS) algorithm: The HS algorithm is characterized by its simple application and the balanced integration of exploration and exploitation [43]. It emulates the improvisation process of musicians by incorporating minimal mathematical constraints and aims to identify the desired harmony. The HS algorithm initiates by storing parameters randomly in the harmony memory. In each iteration, individuals are generated by considering the memory, adjusting the pitch, and incorporating random elements for creating new individuals. Before commencing the optimization process, specific factors such as the harmony memory size, pitch adjusting rate, and stop criteria need to be determined [44]. Following that, the initial population's harmonic memory is generated randomly using vectors. Subsequently, a new harmony is improvised by adjusting the pitch. Finally, the harmonic memory is updated iteratively until the desired goals are achieved [45].

C. Use of AI in communication systems

Wireless communication systems gain effectively from AI approaches since they are the milestones for enhancing the overall performance of complex systems [46]. This section devotes to summarize the various AI based methods employed for 5G/6G communication systems.

By evolving the technology, the need for immersing the digital into physical reality is increasing as well. In this case, 'real-time' expression is searching for an appropriate definition where timing is in relation with communication latency [47]. For 6G communication systems, hybrid beamforming is a challenging problem that is targeted to achieve near-optimal performance. Typically, minimal mean square error and alternative manifold optimization are employed for tacking the nominated problems; however, in [48] deep neural network (DNN) is employed recently that is suitable for real-time applications. In this study, DNN is executed for beamforming challenges at the terahertz (THz) band for ultra-massive multiple-input multiple-output designs where it proves its effectiveness in terms of spectral efficiency and computational effort. Figure 2 presents the practical implementation of DNN in beamforming problems.

For 6G networks, in [49] a deep reinforcement learning (DRL) is employed for symbiotic radio Internet of Things (IoT) leading to enhance the total system data rate. The proposed method is divided into two groups: firstly the optimum mode selection of Wi-Fi Network is obtained and afterwards,
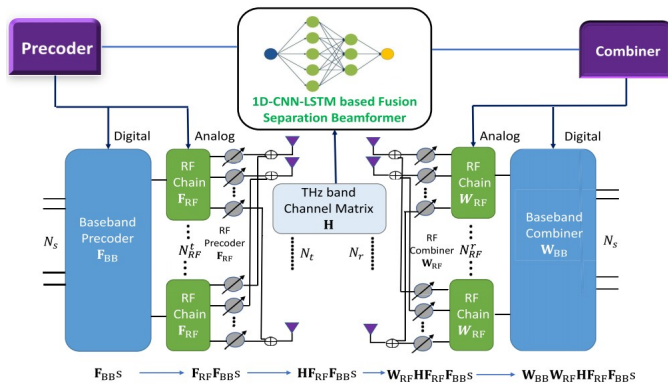
Fig. 2. DNN employed in [48] for beamforming concepts in ultra-massive multiple-input multiple-output designs.

optimum clustering of tags is solved to enhance the overall performance of system.

In [50] for the low earth orbit satellite communication system, the power allocation problem is considered through the DRL technique and proximal policy optimization. This method leads to have better rate-splitting multiple access and low computation complexity. In another study, the DRL is also used in 6G-IoT networks for tackling the problem of security based on the intelligent reflecting surface concept [51]. The effectiveness of DRL method is verified in [52] for adjusting the size of a user-centered virtual cell.

In [53], the meta-material sensors based IoTs are designed with the aid of joint sensing and transmission design method. In this approach, a large number of meta IoT sensors are used for optimizing the sensing accuracy where deep unsupervised learning is executed. The method in [54] is devoted to investigate the involvement of more models in federated Learning systems, and also it considers the approach for the location of wireless resources.

Another appreciated method can be devoted to the quantum computing (QC) leading to solve complex optimization problems. The general flowchart for the data encoding to be used in wireless communication systems is presented in Fig. 3 where H is channel information and it is determined as the input.
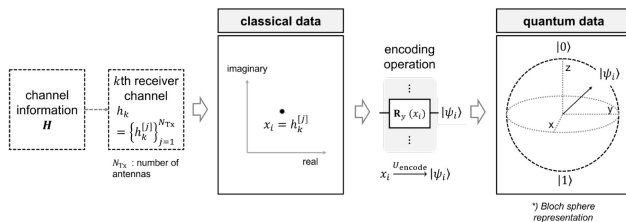

Fig. 3. Data encoding process for 6G systems presented in [55].

In [56], QC with the machine learning (ML) are composed together leading to provide a fast learning process where lately the trained network is employed for 6G systems. The presented methodology is used for investigating various specifications of 6G systems in terms of resource allocation and network security. A general overview regarding the application of QC with ML for 6G systems is presented in Fig. 4. As presented in this figure, there may be some attacks as: authentication, access control, denial of service, and security function exploits.
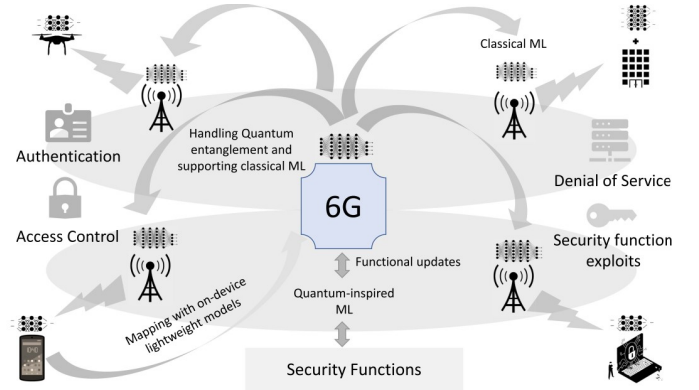

Fig. 4. Explanation for the use of QC and ML in 6G systems [56].

IV. CONCLUSION

The forthcoming 6G networks, as part of the next-generation wireless networks, are anticipated to leverage higher frequency spectrums, leading to enhanced network capacity. However, these networks pose deployment challenges due to their complex nature, involving multiple access networks, frequency bands, and cells. The synthesis of these systems can be approached through two methods: knowledge-based and optimization-based. The knowledge-based technique involves encoding circuit knowledge into programs, which is a time-consuming process. Conversely, optimization-based methods are more fruitful and require less time compared to knowledge-based methods. Optimization methods have proven to be advantageous in addressing the challenges associated with these networks. The advancement of linear and nonlinear optimization techniques has played a significant role in establishing new standards for 5G networks.

This study presents a comprehensive examination of the latest optimization algorithms utilized in current 5G networks, with the aim of informing the design of future 6G networks. It encompasses a wide range of linear and nonlinear optimization methods applicable to the development of 6G mobile communication networks. The incorporation of Machine Learning and Artificial Intelligence in optimization methods will play a crucial role in designing efficient 6G mobile communication systems. Therefore, understanding the theoretical foundations, definitions, and introductions of these various methods is of great significance. To facilitate future research, this article provides a theoretical overview of the optimization methods currently employed in modern communication networks, along with a review of their applications and features in different network contexts. Each method's underlying principles and theories are briefly outlined, and relevant recent papers on these methods are introduced. Lastly, the article discusses

the key challenges associated with the reported optimization methods in a concise manner. By considering the pros and cons of each method, designers can make informed decisions when selecting an appropriate approach for specific problems.

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