Journal of Engineering Sciences and Information Technology (JESIT) • Vol 7, Issue 4 (2023) • P: 48 - 33
https://journals.ajsrp.com/index.php/jesit
ISSN: 2522-3321(Online) • ISSN: 2522-3321(Print)

An Efficient Energy Optimization Method for 5G Networks using Integrated Optimization Algorithm

Eng. Wesam Ahmad Jaradat

College of Computer Science and Informatics | Amman Arab University | Jordan

Received: 28/05/2023

Revised: 09/06/2023

Accepted: 07/09/2023

Published: 30/12/2023

* Corresponding author: wisamjr@gmail.com

Citation: Jaradat, W. A. (2023). An Efficient Energy Optimization Method for 5G Networks using Integrated Optimization Algorithm. *Journal of engineering sciences and information technology, 7*(4), 33 – 48. https://doi.org/10.26389/AJSRP.D280523

Abstract: The 5G network technology is a promising technology that can successfully meet the demand for network capacity growth, due to its high-speed, low-latency, and wide connectivity capabilities. Adapting 5G will increase the energy consumption and CO2 emissions caused by this high consumption. Base stations (BSs) consume the most power in mobile networks accounting for approximately 57% of total energy consumption. This study proposes an integrated meta-heuristic optimization algorithm that combines the Arithmetic Optimization Algorithm (AOA) and the Particle Swarm Optimization (PSO) method. This combination aims to leverage the strengths of both approaches improving the speed and accuracy of the optimization process, to achieve better energy efficiency (EE) in 5G network technology. The proposed algorithm performance is evaluated based on a set of benchmarks functions and compared with other optimization methods. And to demonstrate the applicability of the proposed algorithm in terms of network energy efficiency problem, it was tested against a real-world case study involving power allocation in 5G, the results showed that the proposed algorithm outperforms more recent meta-heuristics state-of-the-art methods in solving a wide range of benchmark functions and obtaining a fair power allocation for multiple users in 5G network. Moreover, it maximizes energy efficiency while maintaining users service quality and availability and reducing total network energy consumption.

Keywords: Energy Efficiency,5G, Optimization, AOA, PSO.

تحسين استهلاك الطاقة لشبكات الهاتف الخلوي ذات الجيل الخامس باستخدام خوارزمية تحسين مدمجة

م. وسام أحمد جرادات

كلية علم الحاسوب والمعلوماتية | جامعة عمان العربية | الأردن

المستخلص: تعد تقنية شبكات الجيل الخامس للاتصالات المتنقلة تقنية واعدة وقادرة على تلبية الطلبات المتزايدة للتواصل واتساع الشبكات لما تتميز به من سرعات اتصال بيانات عالية، وزمن انتقال منخفض للغاية. سيؤدي تشغيل شبكة الجيل الخامس إلى زيادة استهلاك الطاقة وانبعاثات ثاني أكسيد الكربون. تستهلك المحطات القاعدية حوالي 57٪ من إجمالي استهلاك طاقة الشبكة. تقترح هذه الدراسة خوارزمية تحسين تجمع بين خوارزمية التحسين الحسابي وخوارزمية تحسين حشد الجسيمات، هذا الدمج يستغل قوة كلا الخوارزميتين ويزيد سرعة ودقة التنفيذ وذلك لغايات تحسين كفاءة استخدام الطاقة ضمن شبكات الجيل الخامس.

تم تقييم أداء الخوارزمية المقترحة من خلال تطبيق اختبار المحاكاة لمجموعة من المهام والمؤشرات المعتمدة ومن ثم مقارنتها مع خوارزميات اخرى ضمن نفس المعايير. ولإثبات قدرة الخوارزمية المقترحة في تحسين كفاءة الطاقة لشبكات الجيل الخامس، تم تطبيق اختبار المحاكاة على حالة واقعية تتعلق بتخصيص الطاقة في شبكات الجيل الخامس. أظهرت مقارنة النتائج مع مجموعة النتائج مع خوارزميات تحسين أخرى تفوق الخوارزمية المقترحة من حيث الأداء، والقدرة على ضمان استقرار معدل التقارب مع تغيير قيم المتغيرات وعددها، مما يؤدي إلى زيادة كفاءة الطاقة مع الحفاظ على جودة الخدمة وتوافرها وبالتالي تقليل استهلاك طاقة الشبكة.

الكلمات المفتاحية: شبكات الجيل الخامس، خوارزمية التحسين الحسابي، خوارزمية تحسين حشد الجسيمات، كفاءة الطاقة.

1. Introduction

Every ten years or so, a new generation of mobile technology emerges, bringing significant advancements to mobile network capabilities and modifications to spectrum management strategies. In the past three decades, the wireless communication industry has experienced fast expansion, as it makes the transition from 1G to 4G evolutions. With each evolution, new issues have arisen, which next-generation mobile networks have been able to address. Figure1 shows that from 1G to 5G, mobile networks have undergone five generations. Mobile networks that allowed voice calls were first introduced with 1G. With the advent of 2G, SMS text messaging became practical.

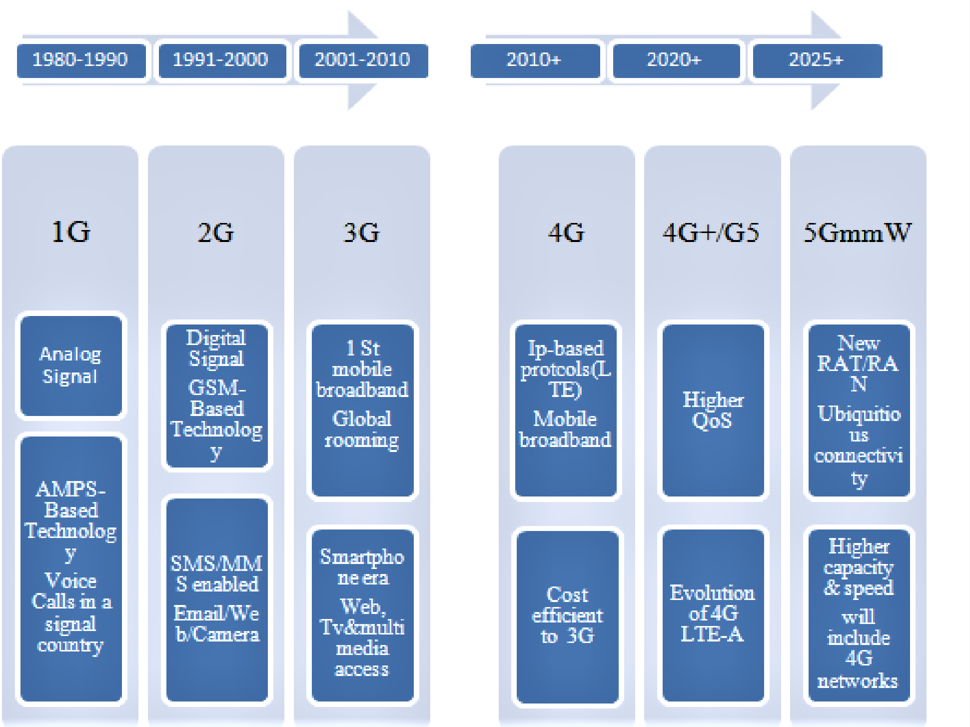

Figure 1: A timeline of mobile network evolution (Mobile Data Growth Forecast, 2017)

Mobile web browsing started with 3G, and when 4G was introduced, data speed and capacity significantly increased, which then made it possible for video streaming on mobile devices (Y. Zhao et al., 2020). It enables new use case opportunities and more connected devices, which were previously impossible. The most recently developed wireless standard communication, 5G, outperforms 4G/LTE in terms of reliability and speed. Some of the remote mining is one of the most prominent applications of 5G communications, Vehicle communications, military, and health care are just a few examples. Based on their performance requirements, 5G applications can be divided into three main categories: The first is called Enhanced Mobile Broadband (eMBB): This technology connects traditional cell phones to 5G networks, and it is anticipated that this will be its most popular use. Massive machine type communications make up the second category. Finally, ultra-reliable low latency communications (URLLC), which is developed for important applications where dependability is crucial, is intended for the enormous internet of things.

Even though the number of nations that have introduced 5G services for commercial use is increasing, the 5G era in the mobile industry is still in its early phases. Operators require access to a significant portion of harmonized spectrum in order to build a 5G network that performs as well as possible. This needs to be brand-new spectrum that is not being used by the GSM, UMTS, or LTE networks that are already in place. A few of the applications that 5G is anticipated to enable include enhanced Mobile Broad Band service (eMBB), Ultra-Reliable and Low-Latency Communications (URLLC), and large machine type communications. Spectrum in the low, mid, and high spectrum ranges is required to ensure that 5G networks can meet all performance requirements.

For the purpose of providing 5G coverage in urban, suburban, and rural areas as well as to enable IoT services, low-band spectrum (below 1 GHz) is ideal. The 3.5 GHz frequency of mid-band spectrum provides an excellent mix between capability and coverage. The GSMA advises authorities to aim for contiguous spectrum availability in this band of 80-100 MHz per operator. Applications needing low latency over short distances and at ultrahigh speeds are ideally suited to high-band spectrum. The GSMA advises each operator to have about 1 GHz of contiguous spectrum in this band (Ning et al., 2019).

This study addresses many issues associated with 5G networks in terms of energy efficiency. The introduction of 5G may increase the overall energy consumption of the network, the introduction of new services and increased traffic demands may also contribute to an increase in network energy consumption, which raises Co2 levels. Therefore, it is crucial to find proper solutions that might decrease energy consumption. Furthermore, during the optimization process, the network's energy constraints and performance requirements must be considered. It is critical to ensure that all users' demands are met in an energy-efficient EE manner. This effort's goal is to improve energy usage and address the issue. Moreover, in order to reduce RAN energy consumption, we intend to create an integrated meta-heuristic optimization algorithm. The objective would be to maximize the advantages without sacrificing the users' experience of service availability and quality.

Premature convergence is a common problem for single-solution meta-heuristics optimization algorithms. Due to single solution trapping, the method fails to solve the provided optimization problem and fails to find the global optima. Every iteration of a multi-solution-based meta-heuristic like AOA employs a population of solutions. Premature convergence can be avoided by exchanging information and collaborating among those solutions (Abualigah et al., 2021). Despite this benefit, they are more computationally expensive because the objective function must be called for all solutions in each iteration, resulting in a slower convergence speed. This is one of the most active research areas in computational intelligence. The existence of such promising chances in reaching a solution represented by a computationally cost-effective optimization algorithm capable of equitably and efficiently discovering the optimal solution prompted the development of an upgraded version of the AOA algorithm.

2. Research Methodology

- A comprehensive review and study of the related works in the 5G technology field.
- Study and review the underlined optimization algorithms (AOA and PSO).
- Study and review different optimization algorithms and then identify their major features.
- Integrate the two different meta-heuristic optimization algorithms; AOA and PSO into the AOAPSO algorithm and identify its major features.
- Numerical and simulation using MATLAB.
- Investigation between different optimization algorithms and the AOAPSO Optimization algorithm in terms of energy-efficiency.

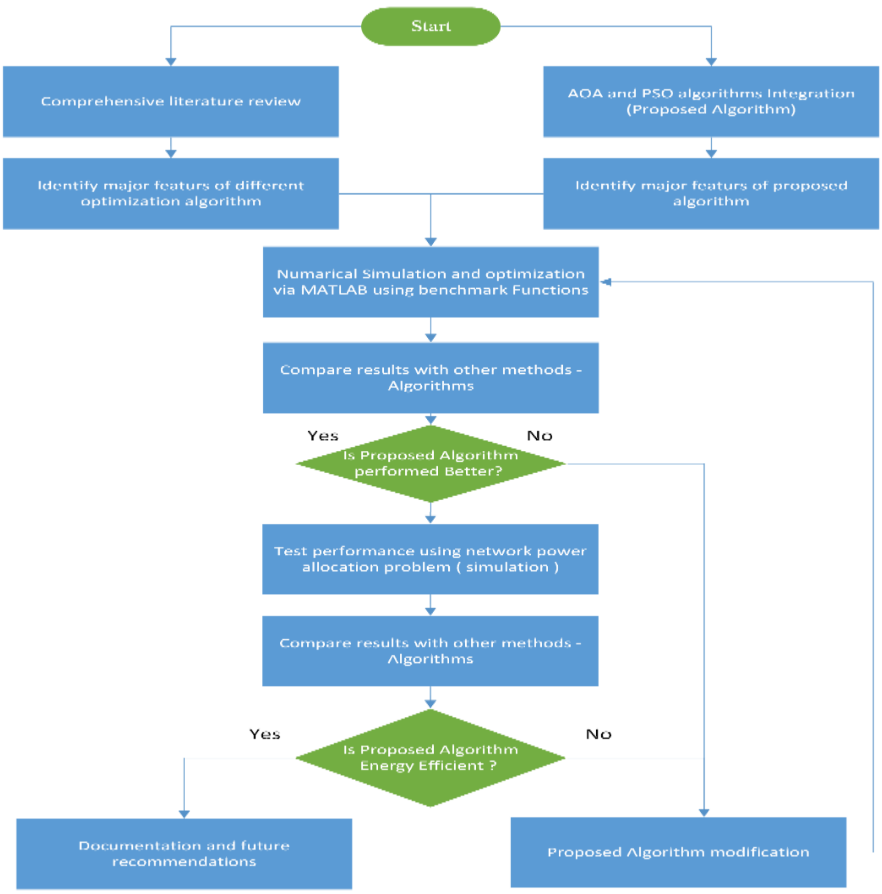

Figure 2: Research Methodology

3. Literature Review

Recently, huge research has been done to enhance the PE of the latest communication networks, for example satellite and global networks massive MIMO systems (Lin et.al, 2022). SC on/off switching is a promising approach to reduce the power consumption and increase the PE of the system (Tang et.al,2019). The authors in (Xiao et.al,2015) explored the increased energy consumption of WLAN. And suggested the approach of base stations on/off switching and power tuning.

The authors in (Manssour et.al,2015) suggested a load-aware approach, where small cells in HetNets are turned to sleep mode corresponding to cells load amount. In (Rathore et.al,2017), each small cell separately switches off based on the drop in the number of users equipment's (UEs) and initiates using one of three methods. The first method is the sleeping SC maintains detecting the interference and noise levels. If new UE is detected in its coverage zone it switches on. The second method is that when number of UEs is increased the MC sends a wake-up request to all SCs, and any SCs has no active UEs will be turned off. The third method defines the nearest SC to the UEs to be switched on. According to (Tang et al,2019), a sleeping cluster is formed by the pre-sleeping SCs in the same area. Then SCs are randomly picked to be turned off, allowing only one functioning SC to guarantee coverage. The authors in (Tao et.al ,2019) presented switching off the SCs and passing on the UEs to the MC. Therefore, unscheduled SC off switching may result in more unwanted handovers and underutilization of the SCs. Hence, innovative SC on/off switching approaches are necessary to improve the performance of 5G HetNets while reducing system power consumption.

The authors of (AL-Samarrie et al,2016) recommended using the BPSO algorithm to select the optimal sites for the MCs to achieve least overlap and to ensure enough coverage for the UEs. In (Venkateswararao,2022) authors improved system performance by using the PSO algorithm to switch SC and suggested an effective cell modeling (ECM) approach for establishing the first connection between the UEs and the SCs by picking the strongest received signals. Alternatively, a combined optimal frequency and power allocation (COFPA) method is suggested in (Alyasiri et.al ,2016).

Multiplication, division, addition, and subtraction are the four basic arithmetic operators that novice mathematicians use to analyze how they behave in terms of distribution. A meta-heuristic tool is the arithmetic optimization algorithm. The mathematical model and implementation were used to carry out the optimization procedure of AOA in a variety of research areas to demonstrate AOA's applicability; its Performance was measured against 29 benchmark functions as well as a number of actual functions. issues with engineering design When compared to eleven few other well-known optimization techniques Algorithms such as GWO, BAT, GSA, and others, performance analysis, AOA's convergence behaviors and computation complexity were extremely promising as a result of dealing with difficult optimization problems (Abualigah et al., 2021).

(Agushaka & Ezugwu, 2021) demonstrated how to produce Using the natural logarithm and the exponential operator, high-density numbers, which were then incorporated into the nAOA algorithm, a suggested upgrade to the AOA. To kick start the potential solutions, the beta distribution was used. The method employed random variables and adoptions with a beta distribution. The performance of nAOA algorithms is evaluated using 30 benchmark functions (20 classical functions, 10 composite functions), as well as 3 engineering design benchmarks. nAOA's effectiveness was compared to that of the original AOA and other cutting-edge algorithms. The GWO (PVD) design was the only one that outperformed the nAOA for the modeled beam design (MBD), compression spring designs (CSD), and design of pressure vessels. The nAOA displayed effective performance for the benchmark functions.

(Bhatt & KV, 2022) proposed a method for localizing and deploying the AOA optimization algorithm. A deployment model was created using the findings of the localization method, which used an arithmetic optimization technique, to produce a fully connected network. This algorithm has been tested in a variety of fields. The method could precisely localize nodes and 14 locate the coverage hole with an error rate of less than 0.27% when the average localization error (ALE) was within 5 m. They had reported a localization strategy in order to assist the end user in finding coverage gaps and unconnected networks in a dispersed manner. The AOA was used in the reported approach to pinpoint the locations of the nodes. The missing convergence region was then determined by the localized nodes using neighbor data gathered for localization purposes.

When compared to other approaches, AOA improved ALE by 24% to 45%. It was also discovered that by lowering the average localization errors from 10 m to 5 m, the average deployment mistakes were reduced from 5% to 0.04%. (Abd Elaziz et al., 2021) proposed an innovation method based on a hybrid integration of the AOA optimization algorithm and the electric fish optimization algorithm (EFO). It was necessary to accelerate the EFO's exploitation stage, in order to solve high-dimensional problems with rapid convergence. To evaluate the proposed EFAOA for various real-world applications, eighteen datasets were used. The EFOAOA findings were compared to those of a recent set of state-of-the-art optimizers using a variety of statistical 15 indicators and the Friedman test. The results of the analysis demonstrated the value of combining the two algorithms, EFO and AOA. The proposed EFOAOA can efficiently and accurately identify the most important properties with the fewest ones and in accuracy of 50% and 67% of the used datasets, respectively. An optimal placement of EV charging stations (EVCS) and DGs in IEEE 33 bus systems was provided using the loss sensitivity factor (LSF) technique, and AOA optimally scheduled DGs based on their 24-hour load profiles. Because EV load demand and DGs in the distribution system are stochastic, this hybrid model method seeks to plan both EVs and DGs for power loss reduction and provides an improved voltage profile. Several analyses were performed to determine whether the proposed methodology would survive.

Finally, the optimal DG scheduling for an IEEE33 bus system is presented. To find the best scheduling of the home appliance, (Bahmanyar et al., 2022) proposed the multi-objective arithmetic optimization method (MOAOA), a newly introduced meta-heuristic AOA (MOAOA). The Rasp Berry Pi and a minicomputer outfitted with Node-RED and Node-MCU modules were also used to program the HEMS architecture. HEMC used the MOAOA algorithm to determine the best scheduling pattern in order to reduce daily electricity expenditures, lower the peak to average ratio (PAR), and increase customer comfort. The multi-objective Antlion optimization technique (MOAOA) results are compared to those of the multi-objective particle swarm optimization method (MOPSO), multi-objective gray wolf optimizer method (MOGWO), and multi-objective wolf optimizer method (MOWO) (MOALO). The findings demonstrated that the proposed 16 method significantly reduces the cost of power consumption and PAR while also integrating MOAOA with RES, which significantly improved user comfort. (Purushothaman & Nagarajan, 2021) developed a new method for multiple-objective self-organizing particle swarm optimization. This was used to solve a variety of objectives for 5G wireless networks, including average area ratio, user data rate, energy efficiency, spectral efficiency, and a fuzzy decision maker was also used to select a solution vector to achieve the best possible compromise.

This algorithm is an energy-efficient approach to resolving the multiple objective issues in a 5G network. Base station energy conservation measures were proposed, with the number of users requesting high data rate traffic and the number of users present within the overlapped areas commonly covered by the coverage of the BS and the neighbors defining the base station's state. The particle swarm optimization technique was used to formulate and solve the proposed energy-saving plan. The findings demonstrated that the proposed plan uses less energy and has less aggregate delay (Choubey et al., 2017). Mobile edge computing (MEC) macro base stations and small base stations were used to calculate the data more efficiently. To select low-energy devices for edge networks, the particle swarm optimization approach was used (Xiao et al., 2018). Data processing in 5G networks is greatly accelerated by the proposed offloading system. The workload energy is presented by the multilevel offloading mechanism employed in the IoT and MEC 5G networks to speed up execution and save energy.

The system's complexity was optimized using PSO, an energy optimization technique. The results show that 17 mobile edge servers use 11 J for the set of 500 tasks, whereas the core cloud uses 15 J for each work. (Taheri et al., 2021) proposed a method for identifying proton exchange fuel cells (PEMFCs) for use in a variety of applications. For identifying purposes, the technique introduced a modified version of the extreme learning machine (ELM) model. The update was founded on the suggestion and development of the evolved AOA (dAOA) approach, a new and improved meta-heuristic optimization method. This method was validated to demonstrate its effectiveness before being used to optimize the ELM configuration in order to minimize the sum of square errors between the real PEMFC data output voltage and the network output voltage. The proposed dAOA with the highest training errors, which provided far more precise parameters for the PEMFC stack system, was found to be 0.0 and 0.0584, respectively.

(Sadiq et al., 2022) proposed a low-cost approach in the NOMA-VLCB5G systems. The search patterns of the Marine Predator algorithm (MPA) were altered using a set of non-linear functions (MPA). A set of benchmark functions was used to put the proposed non-linear MPA algorithm (NMPA) to the test. It resolved a real-world case study on power allocation for beyond 5G networks using non-orthogonal multiple access (NOMA) and visible light communication (VLC) to demonstrate the applicability of the NMPA and to obtain equitable power distribution for multiple users in NOMA-VLCB5G systems rather than the MPA algorithm (AlQerm & Shihada, 2017).

4. Proposed Algorithm (AOAPSO)

Because of its mathematical formulation and implementation, AOA is an optimization method that can perform optimization operations in a variety of meta-heuristic algorithms. Its effectiveness in tackling difficult optimization problems has been demonstrated to be superior to eleven existing current optimization algorithms. Unlike the majority of popular optimization algorithms, AOA has a simple and clear implementation, as well as the benefits of a straightforward structure, straightforward application, and a powerful search capability, according to its mathematical description. It has been used successfully in a variety of industries since its introduction (Abualigah et al., 2021).

Exploration and exploitation are two crucial search strategies used by meta-heuristic optimization algorithms. Exploration is the capacity to conduct worldwide information searches. This skill is concerned with avoiding local optimal and escaping from local optimal entrapment. Based on two primary search techniques, in order to discover a better solution, AOA's exploration operation analyzes the search at random on various regions and methodologies. It must decide between the two search phases before it can start working. After numerous cycles, the exploitation search discovers a nearly ideal answer.

At this step of the optimization process, the exploitation operators (subtraction and addition) are being employed to enhance communication between them and support the exploration stage. On the other hand, the ability to research nearby optimal solutions in order to raise the quality of those solutions locally is referred to as exploitation. How effectively these two tactics are balanced determines how well an algorithm performs. The ideal potential response obtained in each iteration is considered the most effective response, the most effective response or roughly the optimum thus far. The optimization process begins with a set of candidate solutions (X) generated at random.

Although AOA has outperformed well-known meta-heuristic algorithms in terms of performance, it still has drawbacks like poor exploitation, a tendency to enter local optima, and slow convergence speed and accuracy in large-scale applications. No optimization technique, according to the No Free Lunch theorem, can solve every optimization issue, which is why academics don't utilize a single optimization algorithm. We must either alter existing algorithms or suggest brand-new ones in order to more effectively solve the current problem or offer answers to fresh difficulties. It can be integrated with other stochastic components to enhance AOA performance, such as search methods used in optimization.

The particle swarm optimization algorithm is the most well-known and oldest swarm intelligence algorithm. It is a simple bio-inspired algorithm that searches the solution space for the optimal solution. PSO is distinct from other optimization methods in that it simply needs the objective function and does not require the gradient or any differential forms of the objective (Z. Liu et al., 2019). The PSO algorithm takes several particles into account when determining the best particle position. Then, at random, each person's circumstance is altered. in accordance with the best global position that any one person can obtain as well as the best position of the individuals. The movement of a particle considers both its own optimal solution and the population's optimal solution. Although the particle swarm optimization approach has a fast convergence rate, its control parameters are more delicate, and it is prone to -in some high-dimensional scenarios-local optimization. This is what motivates us to present a new optimization algorithm that combines the two distinct algorithms: AOA and (PSO).

4.1 How do Proposed Algorithm (AOAPSO) work

We illustrate the discovery and exploitation methods in the proposed AOAPSO in the ensuing subsections. These operations are accomplished via the mathematical operator's multiplication (M), division (D), subtraction (S), and addition (A). This meta-heuristic technique without knowing the derivatives solves optimization problems using population data.

Algorithm 1 Pseudo Code of the AOAPSO Algorithm

1. **Initialize the AOA parameters.**
2. **Initialize the candidate solutions.**
3. **AOA is working**
4. **Initialize the PSO parameters**
5. **Initialize the positions of solution**
6. **Calculate the fitness values of solution**
7. **While (C_Iter < M_Iter+1)**
8. **Calculate the probability ratio**
9. **Calculate the accelerated function**
10. **IF (each LB && UB has a just value)**

11. **IF (r_1 <MOA)**
12. **IF(r_2 > 0.5)**
13. **Utilize the Division Operator**
14. **Else**
15. **Utilize the Multiplication Operator**
16. **Else**
17. **IF (r_3 > 0.5)**
18. **Utilize the Subtraction Operator**
19. **Else**
20. **Utilize the Addition Operator**
21. **Else**
22. **IF(r_1 <MOA)**
23. **IF(r_2 > 0.5)**
24. **Utilize the Multiplication Operator**
25. **Utilize the Division Operator**
26. **Else**
27. **Utilize the Multiplication Operator**
28. **Utilize the Multiplication Operator**
29. **Else**
30. **IF(r_3 > 0.5)**
31. **Utilize the Subtraction Operator**
32. **Utilize the Multiplication Operator**
33. **Else**
34. **Utilize the Addition Operator**
35. **Utilize the Multiplication Operator**
36. **Update the positions of solution**
37. **Calculate the Fitness function**
38. **Update the Coverage Curve**
39. **C_Iter = C_Iter+1**
40. **IF (C_Iter %50 ==0)**
41. **Print the Best solution details**

In AOAPSO, the best-obtained solution, or roughly the current optimum, is considered the best candidate solution in each iteration, where the optimization process starts with a collection of randomly generated candidate solutions (X). Prior to beginning its job, the AOAPSO should choose the search phase. As a result, a determined coefficient is the Math Optimizer Accelerated (MOA) function as shown in formula 2.1.

$$MOA(C\_I\ ter) = Min + C\_I\ ter\ \times (Max - Min\ M(C_{Iter}) \ldots \ldots (2.1)$$

Where MOA (C_Iter) stands for the function's value; between 1 and the maximum number of iterations, (C _Iter) stands for the current iteration (M _Iter). Values of the accelerated function at the minimum and maximum are indicated by the letters Min and Max, respectively.

A random set of potential solutions are first created as part of the AOAPSO optimization process (population). The positions of the nearly ideal during the repeat trajectory, a solution is estimated by D, M, S, and A. In relation to the top solution, each solution modifies its positions. With a linear increase from 0.2 to 0.9, the MOA parameter emphasizes exploration and exploitation. Candidate solutions attempt to deviate from the almost ideal solution when r1 > MOA and converge to it when r1 MOA, respectively. The AOAPSO algorithm is ultimately terminated when the end criterion is satisfied. In Algorithm 3.3, the pseudo-code of the proposed algorithm AOAPSO is described. The clear and thorough proposed algorithm procedure is displayed in Figure 3.

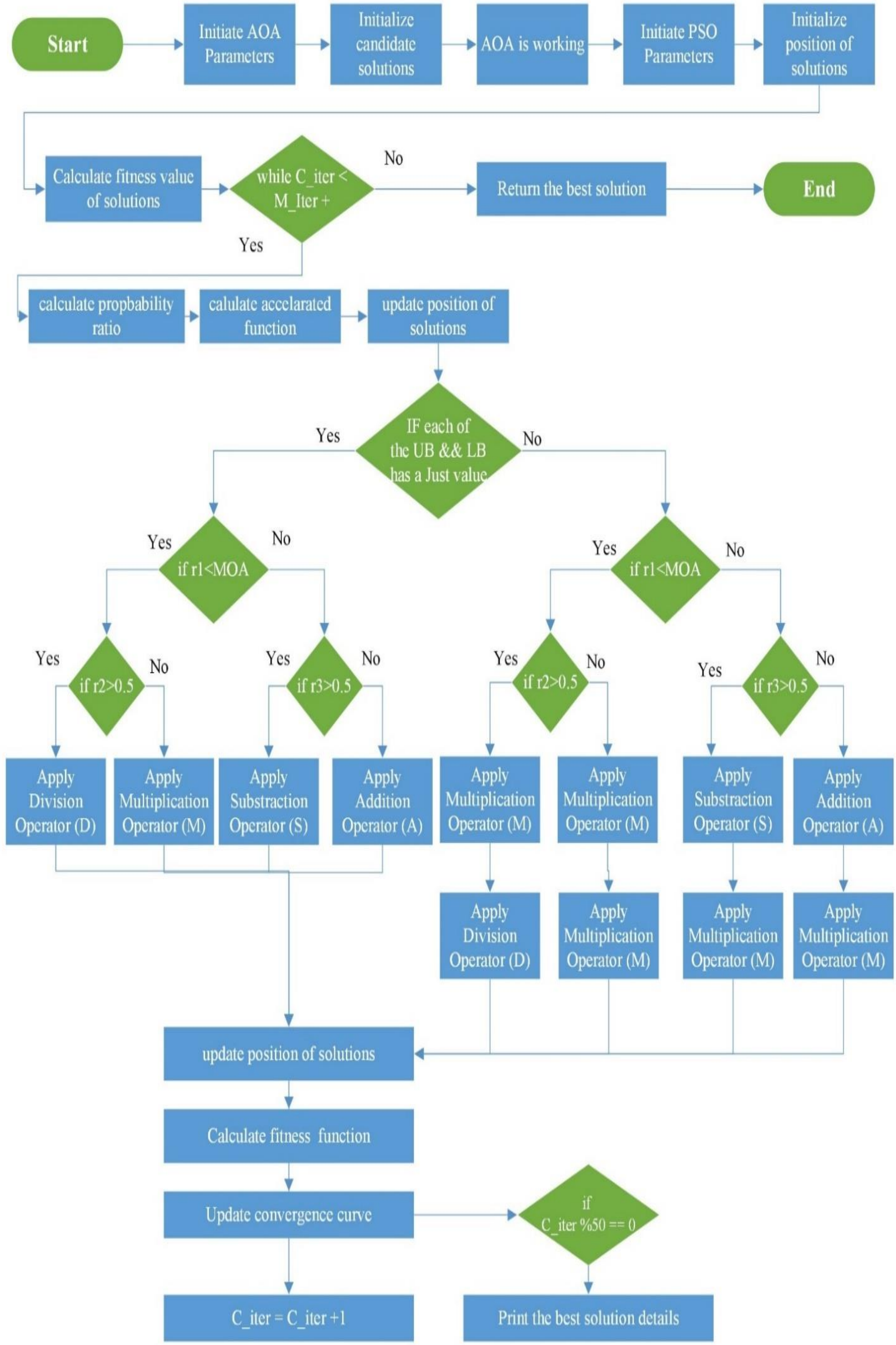

Figure 3 Proposed Algorithm.

4.2 Exploration phase

This section provides an overview of AOAPSO's exploratory behavior. Calculations with the division (D) operator or even the multiplication (M) operator produce numbers or conclusions that are widely disparate (see various reigns), which commit to the exploratory search mechanism. However, due to their high dispersion compared to other operators, these operators (D and M) find it difficult to approach the target (S and A).

The consequences of the various operators' distribution values are illustrated using a function based on four mathematical operations. As a result, after several tries, the exploration search discovers the almost perfect solution. Additionally, at this stage of optimization, the exploration operators (D and M) were operated to support the exploitation stage of the search process by improving communication between them. The exploration operators of AOAPSO use the two main search strategies (Division (D) search strategy and Multiplication search strategy) to randomly explore the search area on different regions and try to discover a better solution.

The parameters for this phase of the search are set by the Math Optimizer accelerated (MOA) function. For the condition of r1 MOA, the other operator (M) followed by (M) will not be used until the first operator (D) followed by (M) completes its current task, which is conditioned by r2 > 0.5 in this phase. If not, the D will be replaced by the second operator (M) to complete the current task (r2 is a random number). If r3 is greater than 0.5, the first operator is (S), then (M). If not, the current task will be carried out by the (M) operator and the second operator (A). Be aware that a stochastic scaling coefficient is considered for the element in building more diversification courses and look into different areas of the search space. To simulate the actions of arithmetic operators, we utilized the simplest rule possible.

4.3 Exploitation phase

This section introduces AOAPSO's exploitation strategy. Calculations involving subtraction (S) or addition (A) produced incredibly dense results, according to the arithmetic operators, and were associated with the exploitation search method if r3 > 0.5. These operators (S and A) can more easily approach the target due to their reduced dispersion than other operators (M or D), which are utilized if r2 > 0.5. As a result, after several tries, the exploitation search discovers the almost perfect solution. Additionally, the exploitation operators (S and A) or (M and D) were operated to help the exploitation stage through increased communication between them at this stage of the optimization. The condition of this phase of searching (exploitation search by executing (S or A) and (M or D)) is determined by the MOA function value for the condition that r1 is not bigger than the current MOA (C Iter) value. The exploration operators in AOAPSO use one of two major search strategies Subtraction (S) and Addition (A) search strategy or Multiplication (M) and Division (D) search strategy to find a better solution.

5. Fair power distribution for B5G networks in NOMA-VLC

The formulation of the "fair power allocation problem" is described in this section. For B5G networks using NOMA-VLC and how AOAPSO is used to find the best power allocation for the greatest number of users. This part also includes a performance study, where the results are compared to other current meta-heuristic optimization methods in terms of data rates and convergence rates.

Numerous strategies, including non-orthogonal multiple access (NOMA) and visible light communications (VLC) have been suggested in fifth generation as essential enabling technologies (5G) and beyond networks. Due to their unique qualities and advantages, there are two candidates who show promise (Fang et al., 2020; Obeed et al., 2021) predict that the combination of NOMA and VLC will have the following benefits:

- NOMA aims to provide a single resource for a large number of consumers. The VLC systems, they typically only have a modest user base, are consistent with this.
- When the receiver and transmitter have access to channel state data, NOMA frequently beats its orthogonal multiple access (OMA) rival. In VLC systems, user mobility is the only factor that alters the channel state. When compared to comparable OMA-based systems, this characteristic makes VLC a promising method for enhancing the performance of NOMA-based systems.
- For better NOMA system performance, line-of-sight transmission in VLC systems can provide outstanding signal-to-noise ratios, which is occasionally not the case with other communication systems. This can enhance the effectiveness of systems based on NOMA when compared to comparable OMA-based systems.

- Last but not least, VLC systems can be modified to change the transmission angles and field-of-views, which increases the functionality of NOMA systems and expands the range of user channel circumstances.

In this study, it is made clear how the suggested AOAPSO algorithm may be used to handle a fair power distribution problem in NOMA-based VLC systems, which is a crucial metric in B5G wireless networks. The goal of this task is to maximize the sum rate of all users while maintaining adequate levels of user fairness. Consequently, the logarithmic utility function is a practical choice that has been taken into account in a number of renowned studies in the field of wireless networks and communications. The peak optical intensity, the maximum transmit power, and assuring the non-negativity of the transmitted optical signal are among the optimization constraints (Zhu et al., 2017).

The light emitting diode (LED) transmitter assigns users values for transmit power, such as pm of the m^{th} user, which are the optimization variables. The optimization issue can be mathematically stated as follows when p = pnN and n=1 (Lin et al., 2017):

$$\max \sum_{m=1}^{M} log2\left(\log\left(1+\frac{hmpm}{n0+hm\sum_{t=m+1}^{M} Pl}\right)\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.1)$$

Subject to

$$\sum_{m=1}^{M}\sqrt{p} \leq C, p \geq 0, \;\; for\; all\; m \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (4.2)$$

where M is the overall user base, n0 is the Powerful noise, $Pmax$ stands for the LED's maximum transmit power, and C is equal to 1 minute's worth of A, B, and A. Here, A and B stand for the peak optimum density and DC-offset, respectively, and is a modulation scheme-specified coefficient constant. It is also important to note that the channel gain is arranged in ascending order. The following criteria are established for this work:

- Maximum transmit power $Pmax = 25\; dBm;$
- Coefficient $value = 3\,5\,/5;\; A = 30\; and\; B = 20;$
- Bandwidth $B = 10\; MHz;\; Noise\; power\; n0 = B\; 10\; 13;$

It is impossible to initially solve this non-convex issue optimally. The authors of (Zhu et al., 2017) can accomplish the globally optimal solution (Boyd et al., 2004) by using commercially convex solvers such as the interior point method are available to manipulate and transform the data to modify the VLC system and change the transmission angles and field-of-views. In this work, we demonstrate that the proposed AOAPSO algorithm outperforms different other well-known meta-heuristics and can achieve very competitive performance

6. DISCUSSION AND RESULTS

The trend in telecommunications is towards heterogeneous network structures, with an increased number of Small, Macro, Micro, and Pico cells. This has led to an increased interest in energy efficiency (EE) and its probable role in future mobile communication systems, particularly as part of the 5G standard. Initiatives to improve EE in 5G include reducing operational expenditures (OPEX) from the operator's perspective and introducing "Green radio" initiatives to reduce power consumption in RAN components. In 5G networks, digital processing in base stations can increase over 300 times compared to early LTE products. This increase is expected to become even larger in 6G. To handle this increase responsibly, the future 6G standard should be lean and minimize mandatory and always-on signaling. The evaluation of AOAPSO's capability to identify, seize, and avoid stagnation in local optimal solutions is described, using benchmark functions and unimodal and multimodal test functions for dimensions of 50, 100, 500, and 1000. The investigated algorithms' parameters values are clarified in Table 1.

Table 1: Algorithms Parameters Values

Algorithm	Parameter	Value
MVO	Wormhole maximum value The probability Existence	1

Algorithm	Parameter	Value
MFO	constant a	0.2
SSA	phases of (exploration and exploitation) Parameters	10
GWO	Constant a	20
WOA	Constant a Convergence	20
PSO	C1, C2	2,2
DE	Factor of scaling	0.5
	The probability crossover	0.2
NMPA	FAD	0.2
	P	0.5
AOAPSO	C1, C2, Convergence constant a	2,2,20

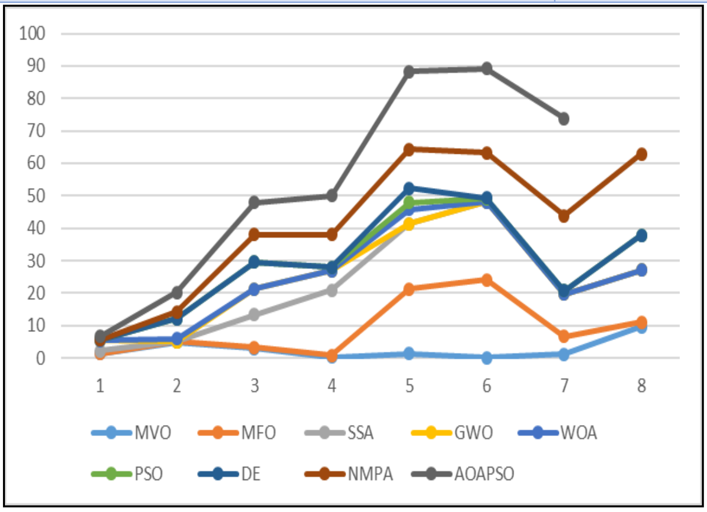

Figure 4 Results of benchmark functions, with 50 dimensions

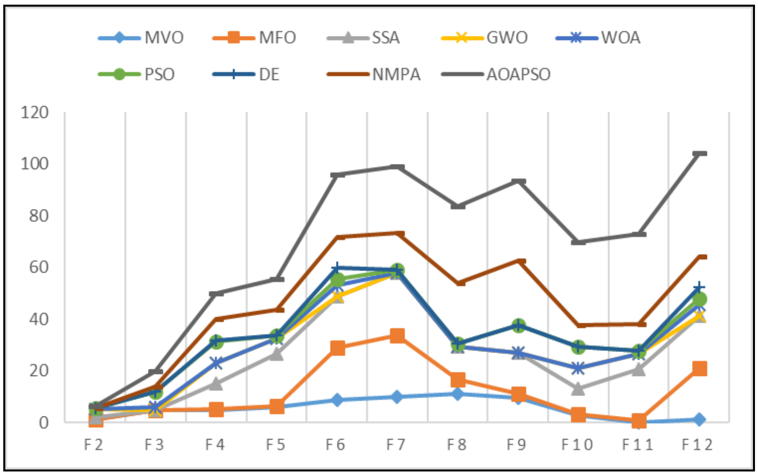

Figure 5: Results of benchmark functions, with 1000 dimensions

In Figures 4 and 5, with 50 and 1000 dimensions, respectively, the results of AOAPSO and other approaches on unimodal test functions are displayed. The numerical results demonstrate that AOAPSO has been able to outperform other optimization techniques in nearly all test functions using average and standard deviation values.

AOAPSO Results and Other Approaches Unimodal test functions are shown in figures 4 and 5 using mean and standard deviation values. Numerical results show that in almost all test functions, AOAPSO was able to outperform other methods.

These tests demonstrate AOAPSO's ability to perform better utilization rates, which will help AOAPSO find an accurate estimate of global optimization problems.

This amplitude is derived from a new adaptive CF parameter and micro-stepping motions along with a nonlinear parameter that modulates the AOAPSO exploitation and exploration phases. In all experiments with different dimensions, the proposed algorithm in the exploitation phase in most cases obtained better results than other methods.

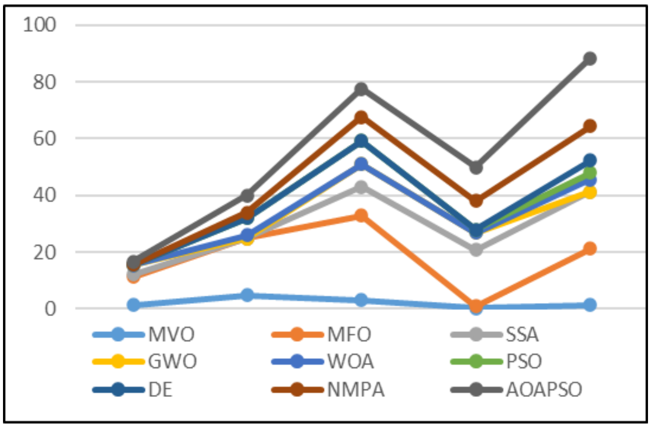

Figure 6: Composition Functions Results

Figure 6 shows the performance of AOAPSO and other ways to solve this type of functionality. The results are consistent compared to those presented in the previous figures. In most jobs, AOAPSO scores are very competitive and tend to be better than others. This reflects that our proposed AOAPSO algorithm can find the optimal solution that takes advantages gained from nonlinear behavior with multiple factors that can avoid trapping in local optimal solutions.

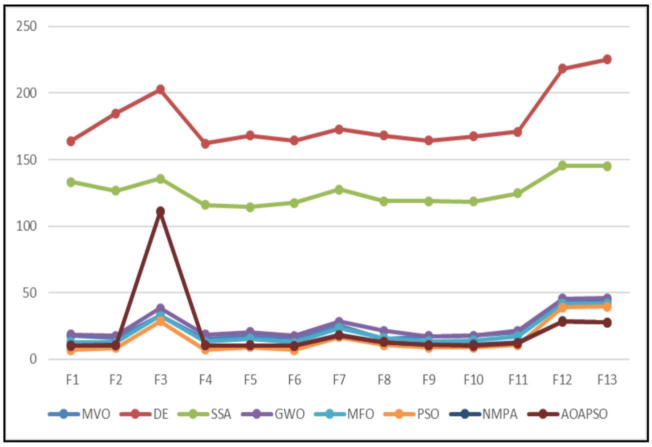

Figure 7: Over 30 runs, the average running time

Figure 7 shows the average time taken by each implemented algorithm to achieve the optimal global value of each optimization function (F1-F13) for 30 runs with 1000 dimensions. We can observe that our proposed AOAPSO slightly showed reduced time compared to other algorithms, which indicates that the introduced changes in the proposed method have not only improved the performance of the algorithm but also has reduced some of the additional costs, such as high execution time (CPU/ GPU computing, memory usage and other loading/buffering times. As a result, AOAPSO is an inexpensive optimization technique that may be used in applications with a tight deadline.

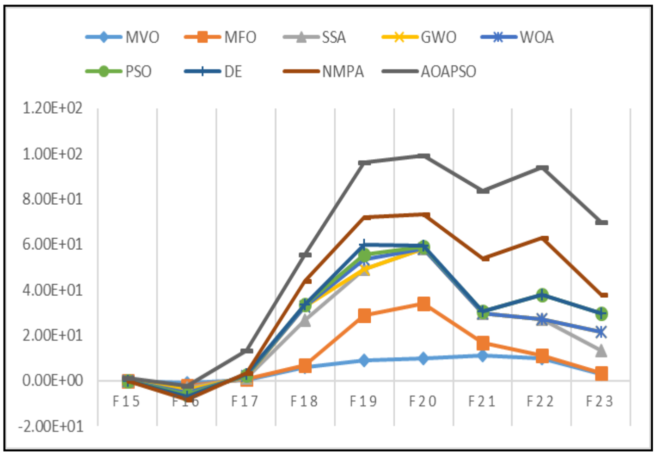

Figure 8: Benchmark functions Results (F14–F23).

Figure 8 displays the results for fixed dimensional functions (F14–F23). The global optimum has been reached by AOAPSO for the majority of accuracy problems (STD), which is on par with high-performance optimization methods. The impact of C1 and C2, as well as the numerous optimization phases, drive the exploration of AOAPSO. Avoidance of Local Optima, some unimodal and multimodal functions were combined, rotated, and moved to produce the test composition functions (CF21-CF26). These operations are designed to evaluate an algorithm's ability to provide robust exploration and exploitation skills while avoiding local optima stagnation.

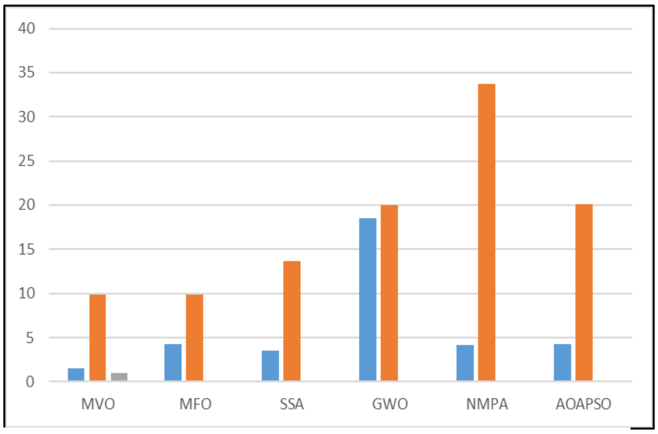

Figure 9: Dimension 30 Results

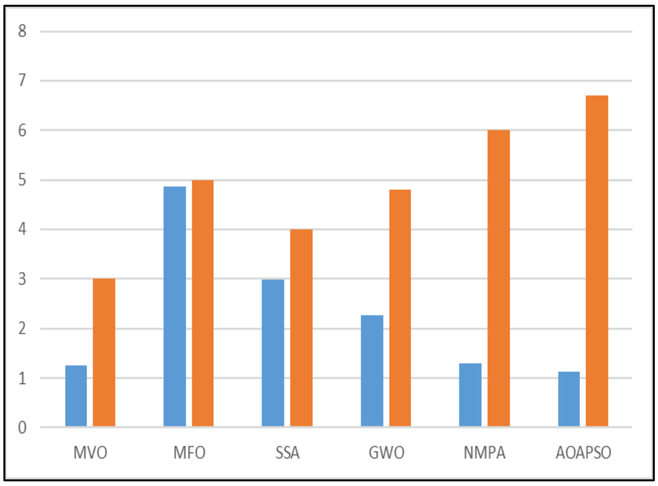

Figure 10: Dimension 50 Results

Figures 9 and 10 show that performance for various ways is nearly same when the user count is small enough (M = 2, for example). It makes sense since the greater the user base, the more constrained the set of viable solutions is. While the suggested AOAPSO method's average Min Rate across all users was superior to other algorithms it was. This illustrates how our suggested strategy could sustain efficiently distributed, optimally utilized electricity systems. However, as the number of users grows, our proposed AOAPSO technique starts to outperform the opposition in terms of Log Sum Rate and Min Rate. For instance, when the dimension/number of users is 20, the AOAPSO approach might outperform all benchmark methods.

The same thing happened when there were 40 users. Despite having a rather large standard deviation, the average Log Sum Rate for the 30 users of the MFO, SSA, and GWO algorithms was 6.53E + 02. This demonstrates that, even though MFO, SSA (Bairathi & Gopalani, 2019) (Abualigah et al., 2020) and GWO were able to produce the optimum solution for Log Sum Rate—which was the same as AOAPSO—its statistical the measurement was untrustworthy. In terms of Min-Rate, AOAPSO performed better than these two methods.

Another conclusion is that algorithms need more rounds and iterations to converge the more users they have. For example, AOAPSO needed 10 rounds and 100 iterations for user counts of 2, 10, 30 and 350 rounds and iterations for user counts of 40 and 50, respectively. It's interesting to note that Fig. 4 shows that the proposed AOAPSO is convergent in every case, whereas certain other techniques, such as the MVO for 10, 20, 30, 40, and 50 users, and the MFO for 30 users, are unable to converge within the specified iteration range.

Another observation from the convergence curves was that the AOAPSO method may exhibit almost the same pattern of convergence throughout the duration of iterations with any implemented set of users. At roughly equal iteration points, the algorithm has experienced incredibly strategic turning points. Following a brief cycle with average best scores, the algorithm begins to progress toward more advantageous optimal solutions. The two main characteristics that the AOAPSO algorithm may acquire are the behavior of strategic marine predators in nature and the non-linear ability that might advance the algorithm towards more viable locations to get evaluated.

It can be inferred that the performance of AOA can be greatly enhanced by balancing the exploration and exploitation stages of the algorithm as well as by defining new C parameters to have more exploitation capacity. The outcomes of the suggested strategy are consistent with this conclusion in both real-world applications like Fair Power Allocation in NOMA-VLC for B5G Networks and mathematical optimization test functions. With the help of the information gathered, examined, and analyzed in this section, it is clear that C parameters could maintain reasonable control over the step size of the suggested AOAPSO algorithm while convergent with stable behavior to achieve the best power allocation for the largest number of users. Due to this, the algorithm could continue to act in a fairly consistent and similar manner as it converged toward the optimal maximum number of users that the 5G network could supply using VLC resources without hurting the network provider's utilized transmission power.

7. CONCLUSION AND FUTURE WORK

The proposed optimization algorithm (AOAPSO) maximizes the benefits while preserving the users' experience of service availability and quality, and it achieves greater energy efficiency in 5G network technology. In terms of performance and energy efficiency, AOAPSO outperforms the NPMA, MFO, MOV, PSO, SSA, and GWO. We can plainly see that the AOAPAO algorithm's C parameters may provide the best power distribution for the greatest number M of users while still having adequate control over the proposed AOAPSO algorithm's step size. The algorithm was able to maintain a predictable and comparable behavior as it converged to the ideal maximum number of users that the 5G network could sustain using without cutting down on the network provider's utilization of transmission power. In addition to being put into practice, the performance of our AOAPSO algorithm was assessed and compared to that of other algorithms. On the other hand, there may be some limitations and potential drawbacks when applying AOAPSO such as choosing the appropriate various parameters for both AOA and PSO which may affect time and computational cost.

A real-world issue that AOAPSO has excelled at resolving is the largest Fair power distribution in Beyond 5G (B5G) networks using visible light communications (VLC) and non-orthogonal multiple access (NOMA). The suggested AOAPSO approach might help to solve the B5G networks power distribution issue. The log sum rate of NOMA-VLC, which was developed as the objective value of the B5G networks resource allocation issue is optimized in this work. The proposed AOAPSO approach could, on average, maintain a swift and efficient convergence rate 30 simulation runs were performed. In the future, we plan to optimize the Multi-User Outdoor VLC (MUO-VLC) for B5G Networks using the AOAPSO method we've presented. You can create a VLC access point using the lighting systems for parking lots and streets to transmit data to numerous B5G network users. In order to mitigate the adverse effects of the sun's and other external illumination sources' tainted light, our algorithm will choose the best configuration for the VLC system.

REFERENCES

- Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., & Gandomi, A. H. (2021). The Arithmetic Optimization Algorithm. Computer Methods in Applied Mechanics and Engineering, 376, 113609. https://doi.org/10.1016/j.cma.2020.113609
- Abualigah, L., Shehab, M., Alshinwan, M., & Alabool, H. (2020). Salp swarm algorithm: a comprehensive survey. Neural Computing and Applications, 32(15), 11195–11215. https://doi.org/10.1007/s00521-019-04629-4
- Agushaka, J. O., & Ezugwu, A. E. (2021). Advanced arithmetic optimization algorithm for solving mechanical engineering design problems. PLOS ONE, 16(8), e0255703. https://doi.org/10.1371/journal.pone.0255703
- AlQerm, I., & Shihada, B. (2017). Energy-Efficient Power Allocation in Multitier 5G Networks Using Enhanced Online Learning. IEEE Transactions on Vehicular Technology, 66(12), 11086–11097. https://doi.org/10.1109/TVT.2017.2731798
- Al-Samarrie, A. K., Alyasiri, H., & Al-Nakkash, A. H. (2016). Proposed multi-stage PSO scheme for LTE network planning and operation. Int. J. Appl. Eng. Res, 11, 10199-10210.
- Alyasiri, H., AL-Samarrie, A. K., & AL-Nakkash, A. H. (2016). Interference Mitigation of Heterogeneous Networks by Proposed Combined Optimal Frequency and Power Allocations Scheme. International Journal of Applied Engineering Research, 11(24), 11925-34.
- Bahmanyar, D., Razmjooy, N., & Mirjalili, S. (2022). Multi-objective scheduling of IoT-enabled smart homes for energy management based on Arithmetic Optimization Algorithm: A Node-RED and NodeMCU module-based technique. Knowledge-Based Systems, 247, 108762. https://doi.org/10.1016/j.knosys.2022.108762
- Bairathi, D., & Gopalani, D. (2019). Salp Swarm Algorithm (SSA) for Training Feed-Forward Neural Networks (pp. 521–534). https://doi.org/10.1007/978-981-13-1592-3_41
- Boccardi, F., Heath, R. W., Lozano, A., Marzetta, T. L., & Popovski, P. (2014). Five disruptive technology directions for 5G. IEEE communications magazine, 52(2), 74-80. https://doi.org/10.1109/MCOM.2014.6736746
- Choubey, P. K., Chung, K.-S., Kim, M., Lee, J., & Srivastava, R. R. (2017). Advance review on the exploitation of the prominent energy-storage element Lithium. Part II: From sea water and spent lithium ion batteries (LIBs). Minerals Engineering, 110, 104–121. https://doi.org/10.1016/j.mineng.2017.04.008
- Fang, F., Xu, Y., Pham, Q.-V., & Ding, Z. (2020). Energy-Efficient Design of IRS-NOMA Networks. IEEE Transactions on Vehicular Technology, 69(11), 14088–14092. https://doi.org/10.1109/TVT.2020.3024005
- Lin, B., Zhang, K., Tang, X., Li, Y., Zhang, M., & Ghassemlooy, Z. (2017). Optical MIMO NOMA-PON based on single carrier transmission and polarization interleaving. Optical Fiber Technology, 36, 412–416. https://doi.org/10.1016/j.yofte.2017.05.019
- Lin, Z., An, K., Niu, H., Hu, Y., Chatzinotas, S., Zheng, G., & Wang, J. (2022). SLNR-based secure energy efficient beamforming in multibeam satellite systems. IEEE Transactions on Aerospace and Electronic Systems.https://doi.org/10.1109/TAES.2022.3190238
- Liu, Z., Han, Q., Guo, Y., Lang, J., Shi, D., Zhang, Y., Huang, Q., Deng, H., Gao, F., Sun, B., & Du, S. (2019). Development of interatomic potentials for Fe-Cr-Al alloy with the particle swarm optimization method. Journal of Alloys and Compounds, 780, 881–887. https://doi.org/10.1016/j.jallcom.2018.11.079.
- Manssour, J., Frenger, P., Falconetti, L., Moon, S., & Na, M. (2015, May). Smart small cell wake-up field trial: Enhancing end-user throughput and network energy performance. In 2015 IEEE 81st Vehicular Technology Conference (VTC Spring) (pp. 1-5). IEEE.https://doi.org/10.1109/VTCSpring.2015.7146092
- Mendis, H. K., Balapuwaduge, I. A., & Li, F. Y. (2019). Dependability-based reliability analysis in URC networks: Availability in the space domain. IEEE/ACM Transactions on networking, 27(5), 1915-1930.https://doi.org/10.1109/TNET.2019.2934826
- Mobile Data Growth Forecast. (2017, February 8). TAdviser.ru. Retrieved June 6, 2023, from https://tadviser.com/index.php/Article:Cellular_(mobile)_communication_(global_market)
- Ning, Z., Wang, X., Rodrigues, J. J. P. C., & Xia, F. (2019). Joint Computation Offloading, Power Allocation, and Channel Assignment for 5G-Enabled Traffic Management Systems. IEEE Transactions on Industrial Informatics, 15(5), 3058–3067. https://doi.org/10.1109/TII.2019.2892767
- Obeed, M., Dahrouj, H., Salhab, A. M., Chaaban, A., Zummo, S. A., & Alouini, M.-S. (2021). Power Allocation and Link Selection for Multicell Cooperative NOMA Hybrid VLC/RF Systems. IEEE Communications Letters, 25(2), 560–564. https://doi.org/10.1109/LCOMM.2020.3029178
- Purushothaman, K. E., & Nagarajan, V. (2021). Multiobjective optimization based on self-organizing Particle Swarm Optimization algorithm for massive MIMO 5G wireless network. International Journal of Communication Systems, 34(4). https://doi.org/10.1002/dac.4725
- Rathore, A., & Sharma, H. (2017). Review on inertia weight strategies for particle swarm optimization. In Proceedings of Sixth International Conference on Soft Computing for Problem Solving: SocProS 2016, Volume 2 (pp. 76-86). Springer Singapore.DOI: 10.1007/978-981-10-3325-4_9

- Sadiq, A. S., Dehkordi, A. A., Mirjalili, S., & Pham, Q.-V. (2022). Nonlinear marine predator algorithm: A cost-effective optimizer for fair power allocation in NOMA-VLC-B5G networks. Expert Systems with Applications, 203, 117395. https://doi.org/10.1016/j.eswa.2022.117395
- Tang, L., He, Y., Zhou, Z., Ren, Y., Mumtaz, S., & Rodriguez, J. (2019). A distance-sensitive distributed repulsive sleeping approach for dependable coverage in heterogeneous cellular networks. Transactions on Emerging Telecommunications Technologies, 30(11), e3784.https://doi.org/10.1002/ett.3784
- Tao, R., Liu, W., Chu, X., & Zhang, J. (2019). An energy saving small cell sleeping mechanism with cell range expansion in heterogeneous networks. IEEE Transactions on Wireless Communications, 18(5), 2451-2463.https://doi.org/10.1109/TWC.2019.2895028
- Venkateswararao, K., & Swain, P. (2022). Binary-PSO-based energy-efficient small cell deployment in 5G ultra-dense network. The Journal of Supercomputing, 78(1), 1071-1092.https://doi.org/10.1007/s11227-021-03910-5
- Xiao, Z., Li, H., Li, Z., & Wang, D. (2015, August). Load-awareness energy saving strategy via success probability constraint for heterogeneous small cell networks. In 2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC) (pp. 743-747). IEEE.https://doi.org/10.1109/PIMRC.2015.7343396
- Xiao, Z., Zhu, L., Choi, J., Xia, P., & Xia, X.-G. (2018). Joint Power Allocation and Beamforming for Non-Orthogonal Multiple Access (NOMA) in 5G Millimeter Wave Communications. IEEE Transactions on Wireless Communications, 17(5), 2961–2974. https://doi.org/10.1109/TWC.2018.2804953
- IEEE.https://doi.org/10.1109/CSO.2009.420
- Zhao, Y., Zhao, X., Ren, T., Liu, X., & Wang, W. (2020). Application Analysis of 5G Communication in Power System. Journal of Physics: Conference Series, 1584(1), 012042. https://doi.org/10.1088/1742-6596/1584/1/012042
- Zhu, J., Wang, J., Huang, Y., He, S., You, X., & Yang, L. (2017). On Optimal Power Allocation for Downlink Non-Orthogonal Multiple Access Systems. IEEE Journal on Selected Areas in Communications, 1–1. https://doi.org/10.1109/JSAC.2017.2725618