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Energy and resources management for Multiple Access in Massive IoT network

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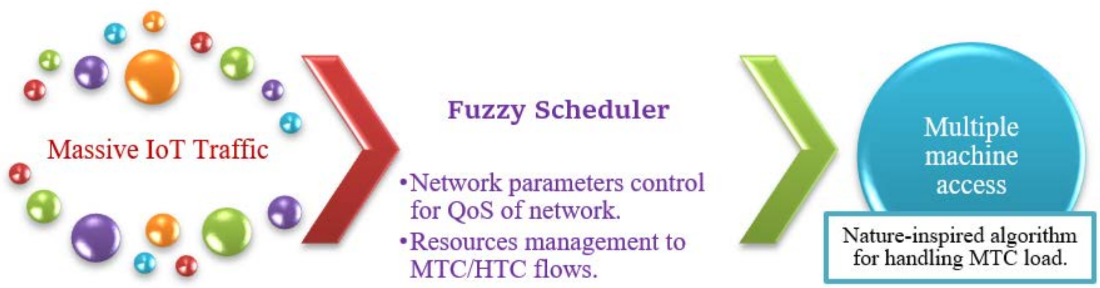
ABSTRACT



Recent advancements in wireless communications and smart device technology have driven the development of the Internet of Things (IoT), which enables millions of physical products to be connected to the Internet through ubiquitous sensing and computing capabilities. Currently, IoT is an essential component of the future Internet and has attracted the interest of both academics and industry because of its enormous potential to offer services to consumers in many sectors of modern life. The progress of technology has oriented researchers towards the creation of a massive Internet of Things (IoT). It aims to overcome the IoT challenges, such as providing connectivity to massive power-constrained devices distributed over a large geographical area. To accomplish this objective, the paper presented a fuzzy logic and optimization-based resource management algorithm for Massive IoT network. The result analysis was evaluated in terms of average path loss, average delay and average energy requirement. The methodology shows its efficiency and achieved desired goals with varying IoT environments.

Keywords: Resource Management, Scheduling, Load balancing, Massive, IoT.

INTRODUCTION

In today's digital world that are empowered by the Internet of Things (IoT) have advanced technologies. Due to limitations, it is becoming difficult for the ever-evolving Internet of Things system to be supported by 5G. By knowing the limitations of 5G, the necessity to develop 6G, and by understanding the evolution of IoT, this study will provide a vision that explains the development of the 6G, as presented in Figure 1. With the help of bringing 5G in IoT, the Internet of Things has changed the nature of human life such as autonomous driving, industry Internet, smart healthcare, smart homes, and cities, and smart education/training. The Internet of Things has not only created several more opportunities in many several domains but at the same time, several developers are working on this technology to create more forms of IoT. Some of the few forms are five-sense, even brain-computer approaches, and holographic. These emerging applications raised requirements for wireless communication networks which are enabled by the Internet of Things. Further, by providing a summary of new applications that are enabled by IoT, we here attempted to present the development of IoT. In the future, many individuals are discovering new forms of IoT-enabled interactions, such as five-sense communications, holographic communications, and so on, which can lead to a true immersion into a remote environment. With the introduction of IoT-enabled interactions, people can exchange images, videos, and voices with one another. IoT-enabled apps of the future will require a more sophisticated ecosystem than ever before to support their wide range of features, including sensing, communication, caching, computation, localization, and identification/authentication. A common architecture for these Internet of Things-enabled applications comprises three layers: an application layer, a network layer, and a perception layer. These layers are typically organized in this order. The term "perception layer" refers to the physical systems that Internet of Things devices

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interact with in order to gather data and exercise control over the surrounding environment. Computing systems in the network's periphery, known as the application layer, are in charge of handling the storage, decision-making, and data processing necessary to arrive at a final control setting.

Edge computing is quite crucial for computation task execution (e.g., rendering for VR videos) and prediction, decision-making, and data analysis with computation capability and limited energy in IoT devices. In order to save energy and decrease latency, devices that are connected to the internet of things (IoT) could offload certain types of operations to edge servers. Some data-reusable applications, such as VR/AR and high-definition live streaming, can make use of the caching capacity of edge computing to further boost the efficiency of Internet of Things (IoT) systems.

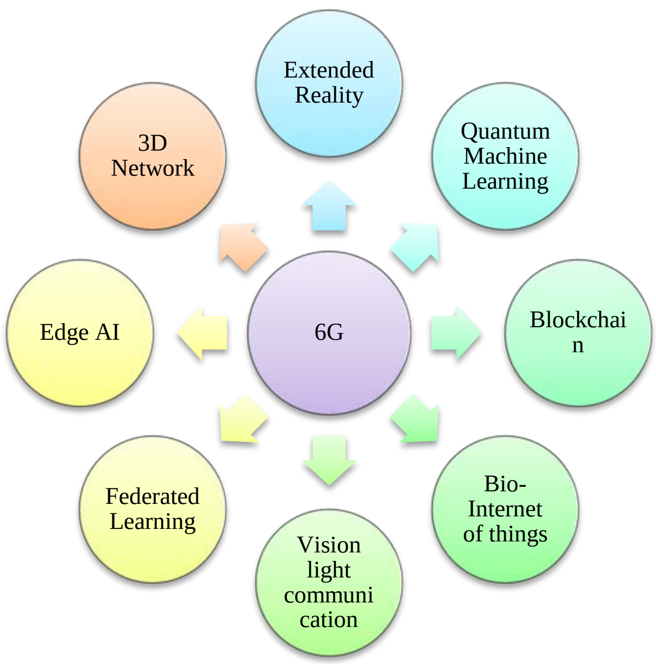

Figure 1. Vision of 6G Network

Literature Review

Due to the continued growth of wireless technology over the past time, future 6G networks are likely to focus on more sophisticated ways to enable services that go beyond typical mobile use scenarios. In order to enhance various access techniques for 6G, researchers have emphasized on multiple ways to meet this objective. This paper uses AI and Deep Learning techniques to intelligently reflects all these considerations and objectives. Using deep RL we can adjust resources within each tenant's admitted slice and regulate requests from numerous renters, Guan et al.[1] present a hierarchical architecture for managing resources. In particular, we begin by discussing the difficulties associated with individualized resource management in 6G. In the second part of this article, we will discuss the rationale behind using artificial intelligence (AI) in the process of resource customization for multi-tenant slicing, as well as provide some historical context. Third, E2E resource management is divided into two issues: real-time slice adaptation intended to prevent service quality degradation and multi-dimensional resource allocation decision based on slice-level feedback.

An AI-enabled intelligent architecture for 6G networks is proposed by Yang et al.[2] in order to automate network adjustment, intelligent service provisioning, knowledge discovery, and realize smart resource management. The architecture is divided into four layers, which are as follows: an intelligent control layer, an intelligent sensing layer, a smart application layer, and a data mining and analytics layer. The state-of-the-art in AI-powered resource management is assessed by et al.[3], who consider not only radio resource management but also other types of resources like caching and computing. In addition to this, we talk about the difficulties and potential benefits of AI-based resource management for the widespread implementation of AI in future wireless communication networks. Zhang et al.[4] conducted an exhaustive analysis of how AI-enabled networks are progressing toward 6G. We begin by outlining our vision for an AI-enabled 6G system, discussing the motivating factors behind incorporating AI into 6G. Shehzad et al.[5] investigated the most intriguing difficulties, specifically at the physical layer (PHY) and link layer in cellular networks. These are the layers in which ML has the potential to provide considerable advances. In addition, we examine standardization activities in relation to the use of machine learning in wireless networks and provide a prospective timetable on the readiness of standardization organizations to respond to these changes. In conclusion, we discuss the major challenges that machine learning faces when applied to wireless technology and offer some suggestions for how 6G wireless networks might address some of these challenges. Loven et al.[6] analysis offer a comprehensive perspective on the AI methodologies and capabilities that are relevant to edge computing. According to our perspective, a comprehensive view of AI methodologies for edge computing includes well-known paradigms such as machine learning, reasoning, autonomous agents, and predictive data analysis with the capacity to learn and think for themselves. In addition, the edge environment, with its intermittent connectivity, the interplay of numerous stakeholders, and its opportunistic nature presents a one-of-a-kind environment for the deployment of such applications that are based on computation units that have varying degrees of intelligence capabilities. According to Shafin et al.[7], adopting artificial intelligence in fifth generation (5G) networks and beyond will involve overcoming considerable technical challenges in terms of performance, complexity, and robustness. Researchers Han et al.[8] looked into the possibility that AI could have an effect on the design and standardization of air interfaces. The first topic of discussion is the design of the AI-enabled network. Further presentations cover the higher layer, the physical layer, and the cross-layer design, all of which are enabled by AI capability. On the basis of these concepts, it is anticipated that the future of 6G and beyond will usher in an era of AI. An end-to-end system architectural design scope for 6G is proposed by Wu et al.[9], who also discuss the requirement of incorporating a novel intelligent and independent data plane, with a focus on management, orchestration, and operation of AI workflows from beginning to finish.

The goals, metrics, technologies, and offerings of sixth-generation wireless networks are outlined by Rasti et al.[10]. The framework for Distributed AI as a Service (DAIaaS) provisioning for IoE and 6G contexts is proposed by Janbi et al.[11]. Network usage, energy consumption(different energy techniques are used)[12], financial savings, and End-to-end delay are presented as evaluation metrics for both the case studies and the DAIaaS architecture, along with suggestions for improving performance. DAIaaS will aid in the systematisation of the mass manufacturing of technologies for smarter settings, allow developers to concentrate on domain-specific aspects without worrying about distributed training and inference, and facilitate standardization of distributed AI provisioning. Possible foundational ideas for Network Slicing and AI are described by Debbabi et al.[13]. For integration into B5G Network slicing for Resource Management, this paper presents a literature evaluation based on research into the potential of artificial intelligence (AI) and its promising approaches, architectures, and training models. For the case of cybertwin-driven 6G on IoE, Jain et al.[14] introduce a novel metaheuristic using a blockchain-based resource allocation approach (MWBA-RAT). In order to meet the demands of 6G wireless networks, Nouruzi et al.[15] develop a novel intelligent software-defined radio access network (RAN) architecture with desirable features such as adaptability and traffic awareness. For the proposed smart soft-RAN model, in particular, we take into account a hierarchical resource allocation architecture in which the software-defined network (SDN) controller plays a central role. For intelligent decision-making, this section dynamically analyses the network to determine whether to use a decentralized or centralized approach to allocating network resources. In order to standardize service data sharing at the network's edge and to allocate network resources for AI services, Li et al.[16] offered a novel resource-pooling mechanism. Network resources can be effectively allocated to network slices in order to meet the needs of AI services using this strategy. With the use of a Recurrent Neural Network (RNN), and Convolution Neural Network (CNN), Ashwin et al.[17] created a model called Hybrid Quantum Deep Learning (HQDL). Recurrent neural networks (RNNs) are used for error proportion, load balancing, etc., whereas convolutional neural networks (CNNs) accomplish network reconfiguration, resource distribution, and slice collecting. Multiple infinite endpoints, slice characteristics, and congestion settings are used to assess the quality of service provided by the future model. Achieving a precision of 97.16 % confirms the usefulness of the presented model. Liu et al.[18] create a unique learning framework for signature-based GF-NOMA in mURLLC service. Our learning framework's overarching objective is to optimize the long-term average number of serviced users (UEs) subject to a latency limitation. Network Slicing (NS) is a paradigm for allocating network resources, and Lopes et al.[19] describe a method for doing this using the Double Deep Q-Network (DDQN) Reinforcement Learning (RL) algorithm for wireless networks. In particular, author suggested an approach for allocating power and Scheduling Blocks (SBs) in NS networks simultaneously. To solve the resource allocation problem, a reinforcement learning method is implemented, and this approach is formulated utilizing system state transitions.

To quickly change ITS to a dynamic traffic control algorithm Liu et al.[20] presented the signal light switching techniques. In an experiment combined with SUMO, DDaaS constructed an urban road simulation that has significant advantages compared to other schemes whose basic purpose is to reduce traffic congestion in an effective way. For the challenge of selecting a radio channel in the midst of a large crowd, Beraedinelli et al.[21] suggest a possible application of the presented framework. Additionally, descriptions of possible research directions that could leverage the suggested framework are also included. By specifically designing machine learning frameworks and recognizing the inherent feature of the underlying optimization problem from the perspective of optimization, Shi et al.[22] presented “learning to optimize” techniques in varied domains of 6G wireless networks. Based on power, latency, coverage, stability period, and scalability, the optimized LEATCH protocol outperforms other energy-efficient clustering protocols.[23]

SYSTEM MODEL

6G's smart network design is an important indicator of effectiveness in massive IoT apps that rely heavily on the technologies such as automation of commercial applications. This work uses a multiple intelligent agent system for 6G applications to address the problem of energy consumption in a huge IoT system model with dynamic network architecture. In addition, the work evaluates the relationship to optimally allocate resources to specific nodes. By reducing unnecessary data, this work aims to increase the channel's energy performance while also preserving valuable information. The work will be performed in following steps:

- Network Uncertainty Handling: Intelligent scheduling mechanism to satisfy QoS requirement using fuzzy logic that can handle unpredictable network uncertainties. This results in achieving QoS for delay sensitive applications and reduces the battery usage of machine type communication (MTC) devices such as IoT.
- Optimized Resource management: Formulation of server policies are to support efficient resource scheduling for multiple access to meet higher resource utilization and latency-less allocation. Access and allocation features are analyzed using optimization to meet the requirements.

Based on proximity and classes, initially, the nodes are ordered in distinct regions. K-Means++ clustering is the clustering technique that is used here. Before moving on to the traditional K-means clustering, K-Means++ clustering is first employing a mechanism to initialize the cluster centers. It has been seen that after some time period x, the nodes tend to group together, as our nodes are mobile in nature and depend largely on x. It has been noticed that from the total number of clusters present in the region, using that adequate energy and load can be updated. Moreover, it can be customized during the set-up time. After a time period, x, we recluster our nodes due to their mobile nature.

Network Uncertainty Handling

Using the fuzzy logic, the regions with a larger number of nodes, low mobility, and high residual energies load can be Low (L), medium (M), and high (H) as the linguistic variables we've chosen for the input parameters (L). Despite this, we have utilized the scales of High (H), Medium (M), Low (L), Very Low (VL), and Very High (VH) for the output parameters (VL). The triangular membership function is the membership function used for fuzzification, whereas, for defuzzification, the Mamdani Centroid Technique is used. By the selection of cluster, the ultimate goal of load balancing is to provide efficient energy consumption. This step involves processing these targeted areas.

It has been noted that there are three parts to the Fuzzy Logic Controller (FLC): processing, output, and input. We have used the linguistic variables "Medium" (M), "Low" (L), and "High" (H), as the input parameters (L). For our output parameters, we have utilized the scales of High (H), Medium (M), Low (L), Very Low (VL), and Very High (VH) for the output parameters (VL).

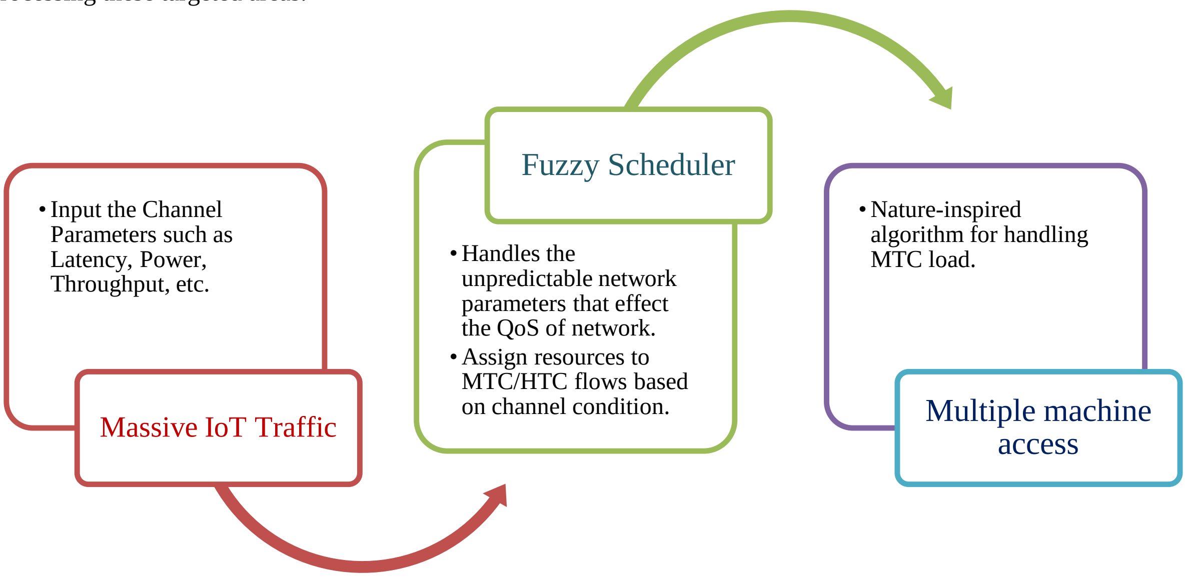

Figure 2. Methodology Used

For fuzzification, we employ a triangle membership function. For defuzzification, we employ the Mamdani Centroid function. As input parameters, the fuzzy logic controller takes into account the cluster's residual energy, the cluster's mobility, the cluster's load-handling capacity, and the current load. We have used the linguistic variables "Medium" (M), "Low" (L), and "High" (H), as the input parameters (L) for the language levels employed (H). The controller's layout is based on a triangular membership function. To pick a cluster based on the preference value and the input and output variables which are defined on a normalized domain of [0, 1]. The preference Value is the cluster's final output variable.

The design of the fitness function ensures that the combinations of nodes that are used for load balancing have the largest residual energy, updated information, and minimal mobility. This ensures that the load is distributed evenly across the network. With the aim to improve the likelihood of effective load balancing and extend the lifetime of the network amongst devices fitness functions are used that are functionally equivalent.

In the next step, in order to optimally allocate resources, evolutionary algorithms are utilized. The purpose of this step is intending to ensure an extension of the lifetime of the network.

Optimized Resource management

For optimal resource management, the paper implemented three optimization algorithms i.e., particle swarm optimization (PSO), grey wolf optimization (GWO) and cuckoo search (CS) algorithm. The term "optimization" refers to the procedure of determining the best values for a system's particular parameters to satisfy all design objectives while taking the lowest cost into account. There are optimization issues in every branch of research. A potent meta-

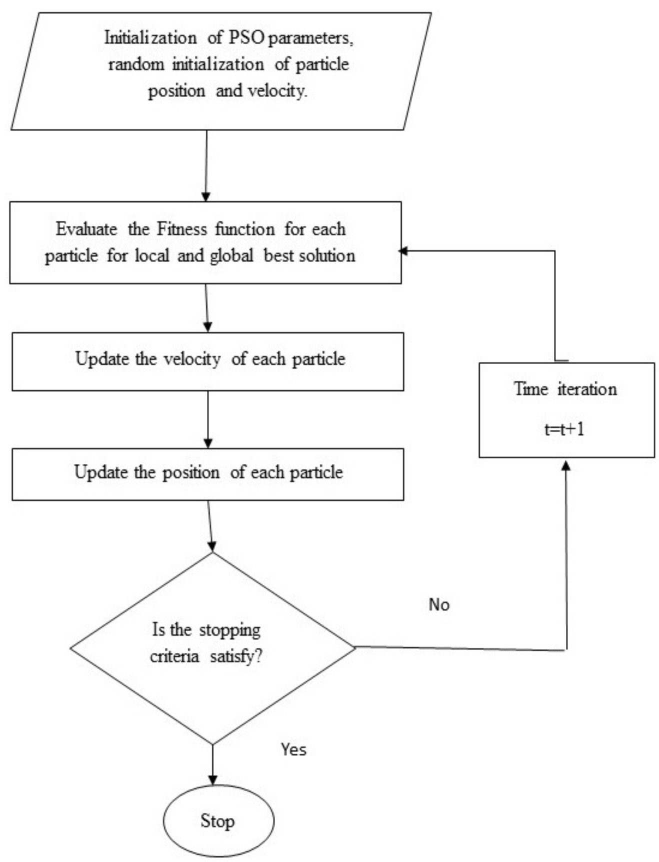

Figure 3. Flowchart of PSO

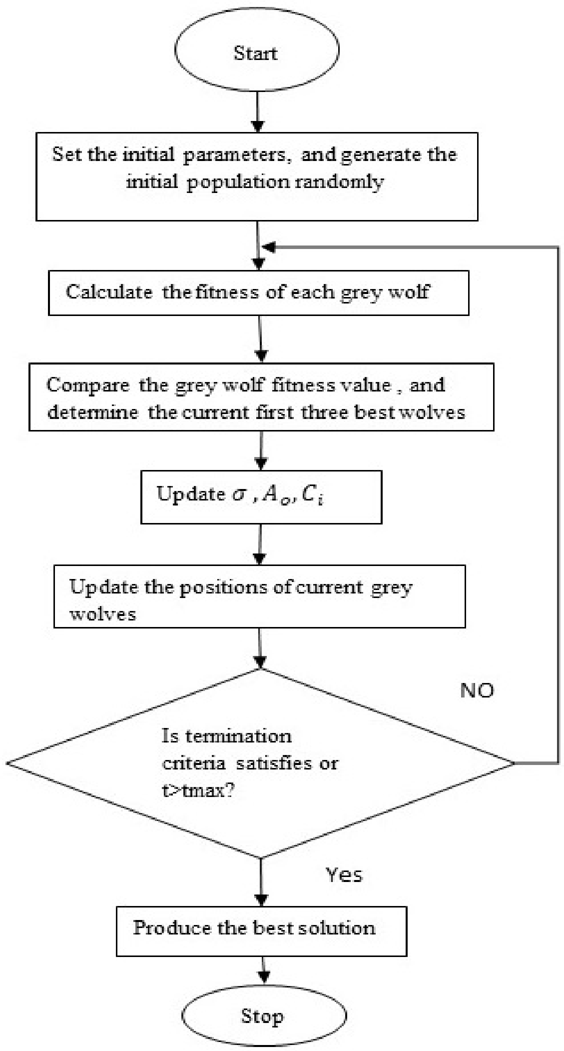

Figure 4. Flowchart of GWO

heuristic optimization approach, Particle Swarm Optimization (PSO) is motivated by swarm behaviours seen in environment, including fish as well as bird swarming. PSO simulates a streamlined social structure. The PSO algorithm's is described as below (Figure 3).

The GWO is a novel metaheuristic algorithm which is built on three steps: surrounding prey, trapping, and bombarding prey, and simulates the social structure and hunting procedure of grey wolves in nature. Suppose the best answer is alpha, and the second and third best solutions are beta and delta, respectively, to mathematically simulate the wolf leadership hierarchy. Omega is presumed for the remaining of the possible solutions.

Figure 4 depicts the rigid social dominating hierarchy of grey wolves. Throughout the chase, grey wolves surround their prey. The following equations are presented to mathematically mimic the surrounding behavior of grey wolves:

$$\vec{B} = |\vec{N} \cdot \overrightarrow{X_{prey}}(t) - \overrightarrow{X_{wolf}}(t)| \quad (1)$$
$$\overrightarrow{X_{wolf}}(t) = \overrightarrow{X_{prey}}(t) - \vec{M} \cdot \vec{B}$$

Where t denotes the current iteration, M and N denote coefficient vectors, X_{prey} denotes the prey's position vector, and X_{wolf} is a grey wolf's position vector. The following is how the vectors M and N are computed:

$$\vec{M} = 2\vec{m} \cdot \vec{r_1} - \vec{m}, \quad (2)$$
$$\vec{N} = 2 \cdot \vec{r_2}$$

Where $\vec{m}$ decreases linearly from 2 to 0 over the duration of repetitions, and r1 and r2 are random vectors in the range [0, 1]. Alpha is typically in charge of the search. Foraging may be done by both beta and delta occasionally. The first three best solutions (alpha, beta, and delta) acquired so far are stored, as well as the other searching agents (omega) are required to adjust their positions in order to mathematically simulate the foraging behavior of grey wolves.

$$\overrightarrow{B_{alpha}} = |\vec{N_1} \cdot \overrightarrow{X_{alpha}} - \vec{X}| \quad (3)$$
$$\overrightarrow{B_{beta}} = |\vec{N_2} \cdot \overrightarrow{X_{beta}} - \vec{X}|$$
$$\overrightarrow{B_{delta}} = |\vec{N_3} \cdot \overrightarrow{X_{delta}} - \vec{X}|$$
$$\vec{X_1} = \overrightarrow{X_{alpha}} - \vec{M_1} \cdot \overrightarrow{B_{alpha}}$$
$$\vec{X_2} = \overrightarrow{X_{beta}} - \vec{M_2} \cdot \overrightarrow{B_{beta}}$$
$$\vec{X_3} = \overrightarrow{X_{delta}} - \vec{M_3} \cdot \overrightarrow{B_{delta}}$$
$$\vec{X}(t+1) = \frac{\vec{X_1}}{3} + \frac{\vec{X_2}}{3} + \frac{\vec{X_3}}{3}$$

Cuckoo Search Algorithm: The Cuckoo Search method is a recently created meta-heuristic optimisation technique used for problem solving. This is a nature-inspired metaheuristic algorithm that is based on cuckoo egg parasitic infection and Levy flights random walks. The following representations are used by Cuckoo Search (CS): A cuckoo egg signifies a new solution, and each egg in a nest indicates a solution. The goal is to employ new and maybe superior solutions (cuckoos) to replace a less-than-ideal option in the nests. Each nest has one egg in its most basic form. An optimisation problem's globally optimum solution.

Results and Discussion

For performance evaluation, the proposed model is implemented on MATLAB platform and extensive results are evaluated according to Monte Carlo simulations. The propagation parameters of each environment are presented in Table 1. Here result is presented in three levels: one is according to number of search agent used with optimization algorithm, second is according to number of iterations and finally according to environemnt such as the IoT, Dense IoT, massive IoT environments.

Table 1. Simulation Scenario

Parameters	Values
Area	$1km^2$
No. of Devices	10-100
Search Agents	5-100
Iterations	0-500
Carrier Frequency	200Hz
Environment	IoT, Dense IoT, massive IoT

In Figure 6, result analysis of path loss is presented with respect to variable search agent for algorithms. The search agent is varied from 5-100 and simulation scenario is considered for IoT environment. The result shows that with increasing search agents, the path loss decreases. Among all least path loss was achieved by PSO whereas GWO and CS algorithm shows nearly similar outcomes. Similarly, in Figure 7, result analysis is presented with respect to variable iteratons for algorithms. The iteratons is varied from 10-500 and simulation scenario is considered for IoT environment. The result shows that least path loss is achieved at iteration 100. Among all least path loss was achieved by PSO whereas GWO and CS algorithm shows nearly similar outcomes. In Figure 8, result analysis is presented with respect to variable environment such as IoT, Dense-IoT and Massive-IoT. The result shows that least path loss is achieved in IoT environemnt and path loss increases with increasing number of IoT devices i.e., from Dense to Massive IoT. Among all least path loss was achieved by PSO whereas GWO and CS algorithm shows nearly similar outcomes.

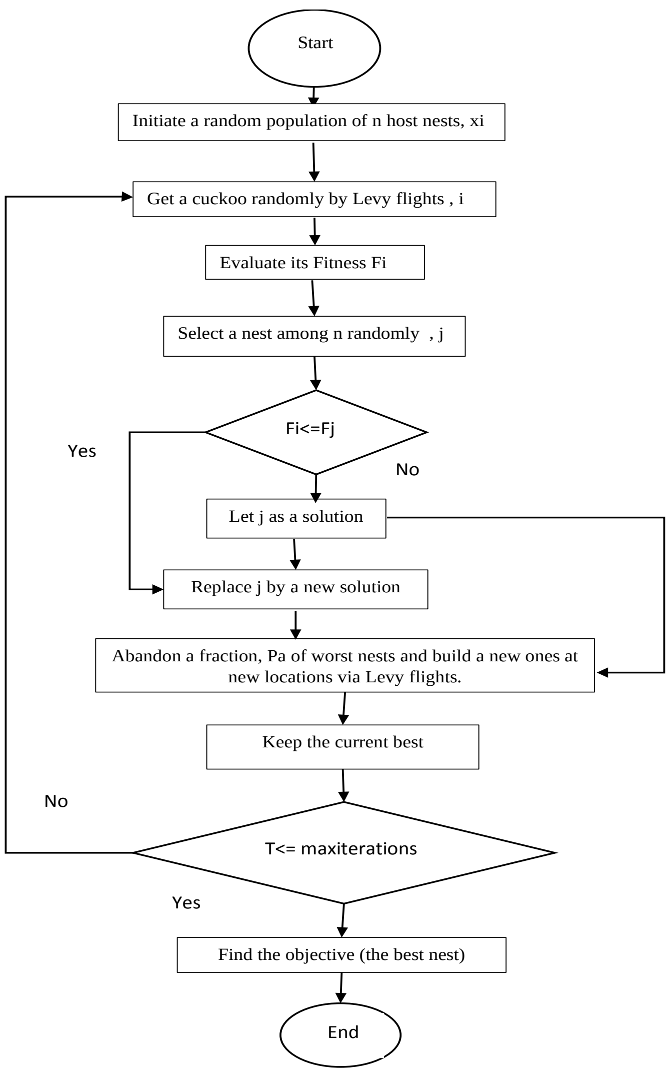

Figure 5. Flowchart of CS Algorithm

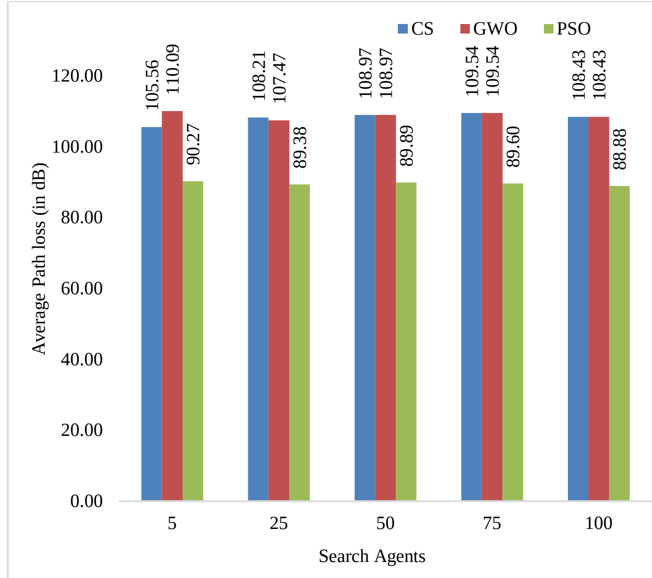

Figure 6. Average Pathloss with Increasing Search Agents of Optimization Algorithms

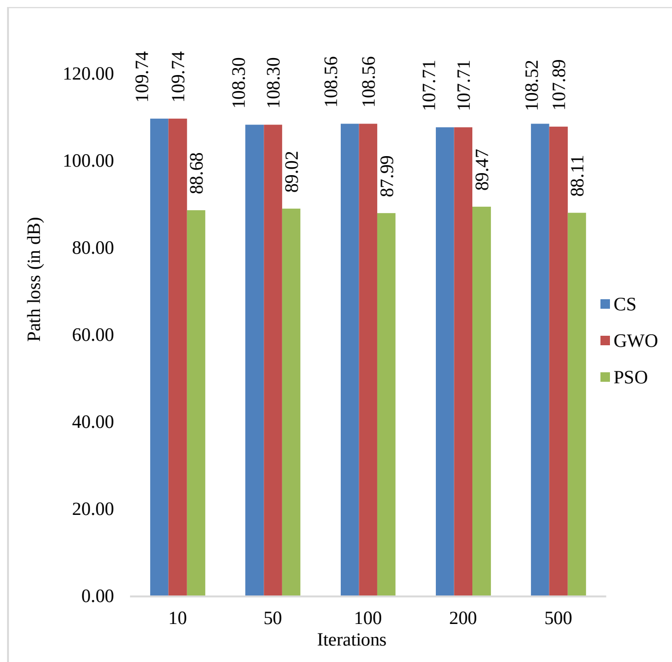

Figure 7. Average Pathloss with Increasing Iterations of Optimization Algorithms

Figure 9 shows the average delay of algorithms under different environments such as IoT, Dense-IoT and Massive-IoT. The result shows that least delay was observed by IoT environemnt and it is increased with increasing number of IoT devices i.e., from Dense to Massive IoT. Among all least delay was achieved by PSO whereas GWO and CS algorithm higher delay as compared to PSO. Figure. 10 shows the average energy requirement of algorithms under different IoT environments. The energy requirement in PSO was high as compared to GWO and CS.

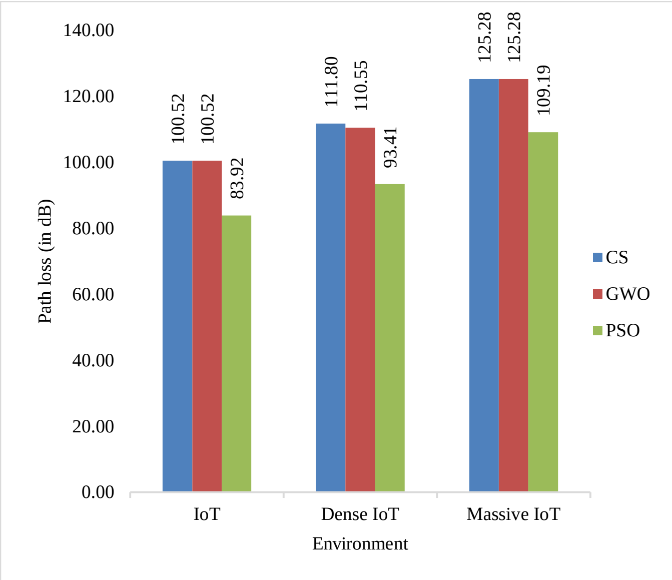

Figure 8. Average Pathloss Varying with Environment

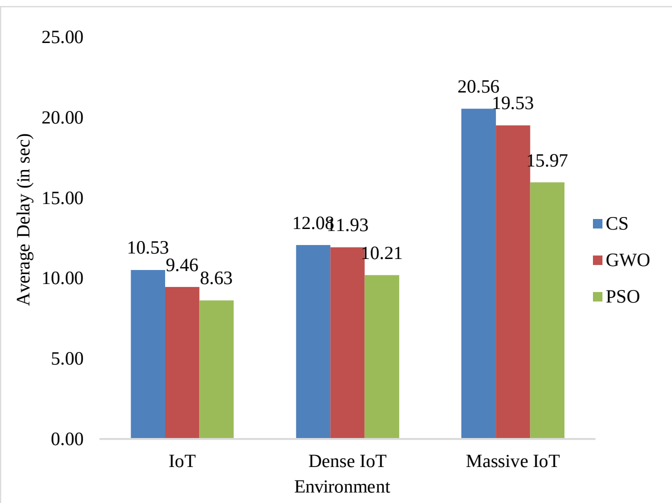

Figure 9. Average Delay Comparison

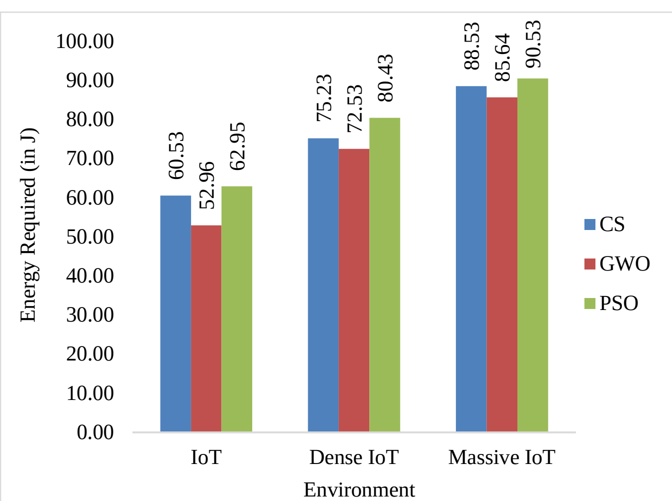

Figure 10. Average Energy Consumption

CONCLUSION

This work discusses design of massive IoT architecture for optimal resource utilization for 6G platform. In this method, multiple access service allocation processes are performed using fuzzy logic and optimal scheduling using nature inspired algorithms. Fuzzy logic schedules the MTC applications to access the channel. The available response slots are optimally allotted to the devices. Motivated by the emergence of massive-IoT and the associated challenges in terms of massive connectivity, the paper investigated the efficiency of PSO, GWO and CS algorithms on optimizing the resource management and resource deployment. The result analysis was investigated in terms of path loss, energy and average delay. The PSO algorithm have achieved better efficiency in terms of achieving minimum path loss and GWO have achieved least energy requirement to reach optimal solution. Therefore, in future, this investigation will be extended on improvising the path loss and delay of scheduling resources in massive IoT environment.

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