

Resource Allocation in Massive Internet of Things-Edge Network with Optimal Path Planning and Scheduling

Ajay K. Barapatre¹ Ritesh Sadiwala²

Department of Electronics and Communication, Ram Krishna Foundation University, Bhopal, Madhya Pradesh, India

ABSTRACT

Although an Ultra Dense deployment is required for 5G services, it will be nearly impossible to achieve 60 service coverage with the dense deployments due to the even shorter transmission range. In light of 5G's impressive technological advance, 5G and data centers are now capable of handling an increasing number of real-time and complicated computational tasks from Internet of Things (IoT) systems. This paper proposes an optimal mobile resource-sharing approach to confront this underlying limitation of 5G. In contrast to conventional algorithms, the designed optimal path planning and scheduling for mobile edge server (OPPSMES) is proposed that have the advantage of a synchronization among request being received and achieved lower delay and resource demand for as computing this allowed for the parallel processing of task and server in mobile condition. The OPPSMES includes two steps, i.e., path planning and optimal task scheduling, to improve efficiency. According to simulation outcomes, there is a significant increase in resource utilization and a decrease in average response time.

Keywords: 5G, ACO, IoT, mMTC, OPPSMES, PSO.

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INTRODUCTION

The spread of the Internet of Things (IoT), which enables the connection of millions of physical things to the Internet, has been facilitated by recent advancements in wireless communications and smart device technology. Due to its enormous potential to provide consumer services in numerous facets of contemporary life, IoT now forms an essential component of the future Internet and has drawn noteworthy consideration from business and academia.^[1] The IoT provides seamless connections and automatic administration amongst heterogeneous gadgets without any need for user involvement; it has the potential to change industry drastically and offer significant benefits to society. Technology tools from the first to fifth generation have been suggested and commercially implemented to support IoT systems and applications.

Notably, the most current fifth-generation (5G) technology has demonstrated that it can provide IoT ecosystems with a variety of low latency, energy-efficient services, and high throughput services.^[2,3] This is made possible by inherent usage features like massive machine-type communication (mMTC), ultra-reliable low-latency communication (URLLC), and enhanced mobile broadband (eMBB) services. However, 5G cannot fully meet the evolving technical requirements. Due to the previously unheard-of popularity of digital devices and the explosive growth of IoT networks, services like autonomously, ultra-large-scale, extremely dynamic,

Corresponding Author: Ajay K. Barapatre, Department of Electronics and Communication, Ram Krishna Dharmarth Foundation University, Bhopal, Madhya Pradesh, India, e-mail: barapatre.ajay@yahoo.co.in

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and completely intelligent ones are now possible. The rapid development of automatized Networks is expected to outperform the capability of 5G wireless technologies. Further improvements to the current 5G systems are also necessary to improve the quality of IoT service delivery and business due to the introduction of new IoT services and applications like flying vehicles and remote robotic surgery.^[4] Sixth-generation (6G) wireless network research^[5] and the associated technology advancements have recently attracted a lot of attention from both academia and industry, paving the way for advancements in the IoT and beyond. As compared to prior networks generations, it has more superior qualities, including exceptionally high throughput, satellite-based consumer services, large, autonomous networking, and ultra-low-latency communications, and more, 6G is

likely to offer to improve users' experiences in current IoT systems and entirely new service quality.^[6-8] These previously unheard-of capacity levels will hasten the applications and deployments of 6G-based IoT networks in device connectivity, IoT data sensing, 6G network management, and wireless communication. Many attempts have been made to conduct research in this promising field, made possible by the enormous potential of 6G-IoT.

Massive IoT

Massive IoT, also known as massive Machine-Type Communications (mMTC) in the context of 5G, refers to software programs with many terminals that continually deliver little data bits, typically rarely and even remotely. It involves low-energy, low-cost, apps that submit vast amounts of modest data volumes to the cloud on a frequent basis. Scalability and adaptability are necessary for IoT machines, objects, and devices to connect. Although they give good coverage, these devices are often inexpensive and consume relatively little energy. In order to connect potentially millions of devices, sufficient capacity is essential, along with network effectiveness. Massive IoT also needs a large coverage area and lengthy battery life. The needs of numerous IoT devices and apps can best be met by LPWANs (Cellular Low Power Wide Area Networks), where 5G can help. A temperature readout from a device in your house or place of business, or a straightforward on/off application for a group of smart devices or single smart devices, are examples of huge IoT. Smart agriculture, fleet management, smart meters, and smart buildings could serve as more examples.

Numerous IoT solutions that are backed by 4G networks are already operational. But with 5G, we will be able to link billions of IoT devices consistently and seamlessly. By 2025, there will be more than 64 billion IoT devices, up from just 10 billion in 2018, according to Business Insider. According to Cisco, IoT connections between machines are predicted to reach 14.6 billion by 2022.

Challenges of Massive IoT

Along the path to full 5G, enormous IoT must overcome a number of obstacles. These include, as previously indicated, enhancing the capability of advanced LTE networks to manage growing volumes of data traffic as millions more mobile and IoT devices go online in the upcoming years. The following list of difficulties is provided:

IoT security concerns: The number of potential ports of entry for cybercriminals into a private system is dramatically increased by IoT devices in terms of cybersecurity. To get access to private information, cybercriminals don't even need to break the plastic casing of an IoT device. They can quickly obtain access by utilizing one of the various IoT security holes that exist. Numerous IoT devices have unpatched software, default passwords that have not been updated and other significant security flaws.

Lack of regulation about IoT: Government regulation frequently takes a while to catch up with the state of technology, another hallmark of technical advancements. Businesses are frequently left without the vital data needed to make decisions due to the government's slow pace of catching up with the daily rapid expansion of the Internet of Things.

Challenges with compatibility: IoT is undoubtedly no exception to the rule that emerging waves of technology are frequently accompanied by a sizable stable of rivals vying for market dominance. More alternatives for customers may be good, but this might also result in unpleasant compatibility issues. One area where compatibility issues are present is home mesh networks. For many years, the IoT device compatibility standard has been Bluetooth. In actuality, it bears the name of a legendary monarch named Harald Bluetooth, who was renowned for uniting feuding tribes. But when it comes to mesh networking for home automation, a number of rivals have emerged to take on Bluetooth's mesh network options, including protocols like Z-Wave and Zigbee. Years may pass before the industry has had sufficient time to settle and a single worldwide norm for household IoT has been named.

IoT device compatibility also depends on consumers updating and patching their devices, which, as we just saw, may be quite challenging. Performance problems and security flaws might arise when IoT devices that need to communicate with one another are using different software versions. This is a key reason why IoT users must maintain their gadgets patched and up to date.

Limited bandwidth: There are more connection issues with the IoT than we imagine. Some industry analysts worry that the present server-client IoT architecture may soon run out of room for bandwidth-demanding IoT applications like video streaming as the IoT market expands dramatically.

This is so that traffic on IoT networks can be authenticated and directed using a central server under the server-client model. However, these networks frequently struggle to handle the demand as more and more devices connect to them.

Literature Review

Mukherjee *et al.*^[1] used a huge IoT system model with dynamic network architecture or clustering employing a multi-agent system (MAS) for industrial 6G applications to address the issue of energy consumption. To locate the primary node and forecast its location, the study clusters the sensor nodes in the system using distributed artificial intelligence (DAI). Back-propagation neural networks (BPNN) and convolutional neural networks (CNN), introduced for optimization, are initially used in work. To optimally distribute resources to each cluster's individual nodes, the study also analyzes the correlation between related clusters. According to the simulation results, the suggested solution preserves information while reducing resource waste brought on



by redundant data and enhancing the network's energy efficiency.

Massive IoT made possible by 6G was reviewed by Guo et al. [2]. The upcoming applications and 5G's potential constraints were outlined in our analysis of the motivations and needs. smart healthcare, smart education/training, industry Internet, completely autonomous driving, ultra-smart city/home, five-sense communications, Holographic communications, and WBCI, are a few of these applications. The visions of 6G are then discussed in terms of fundamental technical specifications, application cases, and trends. 6G offers a four-tier network architecture augmented by edge computing to fulfill the demands of IoT apps, especially the complete coverage need. In addition to being an omnipotent network, 6G offers some ground-breaking technologies, such as blockchain and machine learning, to enable distribution and intelligence in future IoT systems. These technologies are crucial to the entire IoT architecture, from the network layer and perception layer to the application layer.

In order to provide terminals with high-efficiency, low-energy, and widespread technical services, Lv et al.^[3] improved the analysis of large-scale Internet of Things (IoT) devices. Also discussed is large-scale gadget accessibility in the mobile narrowband Internet of Things (NB-IoT), which is based on big data analysis technologies. The energy loss and channel models examine the data transmission path delay, energy consumption, and devices' access performance in the IoT. According to the findings, a preamble resource number (K) of 25 and access time (T) of 5 s have had the highest access success rates in the access success rate analysis. The access success rate has an inverse relationship with the restriction factor. Varied transmission node priorities lead to different node utilization, and priority 2's node usage is better than priority, according to the node utilization analysis.

Mumtaz et al.'s^[4] focus was on 6Gen-enabled huge IoT networks' requirements, critical technologies, interoperability difficulties, system designs, intelligence, spectrum efficiency, secrecy and privacy, affordability, and customization. A thorough review of cutting-edge technology, sophisticated architectures, and potential difficulties for 6G-enabled large IoT is what this special issue seeks to give the scientific community.

Massive IoT applications, 6G technology, and energy concerns in fog computing were all described by Malik et al..^[5] An overview of recent studies on energy-efficient fog computing for IoT networks is presented to researchers. They categorize recently put out energy-efficient technologies into several groups and list their benefits and drawbacks. Finally, they outline upcoming research prospects and explore unresolved issues for enhancing fog computing's energy efficiency in 6 G-enabled IoT.

To achieve widespread VR/AR services in women 6G, Liao et al. [6] concentrated on creating an IC-mIoT network. To offer consumers ubiquitous VR/AR services, researchers developed an information-centric network architecture for the mIoT

and fully exploited the features of 6G. They have created a brand-new consensus mechanism called PoCO to safeguard various kinds of content and resource interactions in IC-mIoT by improving the fundamental concept and application architecture of the blockchain. The ideal cache scheduling approach between nodes was also created as part of this effort, along with the appropriate algorithm for the PoCO consensus mechanism. The simulation results clearly show how great and workable the plan put out in this paper is.

To fulfill the demands of new services and applications, such as multi-gigabit rate of transmission, increased dependability, lower latency, and ubiquity connectivity for the enormous Internet of Things, the sixth-generation (6G) networks must perform much better than earlier generations (IoT). The lack of spectrum resources, however, makes effective resource management and dissemination essential to meeting all of these demanding specifications.. The sixth-generation (6G) aims to provide global coverage, enhanced energy and cost efficiency, better intelligence level, and security. While deploying 6G network, the major issue arise is the energy consumption problem. This work uses a multi-layer system for 6G applications to address the energy consumption problem in a huge IoT system model with dynamic network architecture for efficient resource utilization.

Problem Formulation

As presented in the above literature, deployment of 6G network (such as 6G IoT or Edge network) results in higher cost than 5G in terms of computational resources, energy requirement and efficient resource utilization. There is a requirement of optimal techniques to handle massive IoT requirements. Two main issues is needed to be focused on, path planning and resource utilization. By jointly optimizing the server mobility path and task scheduling while fulfilling the storage space limitation in mobile servers, we aim to reduce the total delay across every IoT system throughout the region. Maximizing aim because a small overall delay will allow the MSE to provide service to additional large-scale IoT systems in the further area as quickly as feasible. The system's total latency can be reduced by scheduling highly computationally demanding activities to the server. The amount of tasks sent to the edge server is restricted by the server's low storage capability. Since this path planning sub-task may be the reason of knapsack problem, this optimization issue is NP-hard. To effectively tackle our scheduling challenge, machine learning with the optimization algorithm.

System Model

Under this part, outlining the system architecture implementing optimized path planning and task scheduling issues for 6G model. Assume a 6G edge computing network having several Internet of Things equipment with a mobile edge server, as depicted in Fig 1. The group of n IoT

Algorithm 1: Optimal Path Planning and Scheduling for Mobile Edge Server (OPPSMES)

1. Begin
2. Initialize No. of IoT devices (U), No. of tasks (T), Path Queue (Q)
3. For i=1:U
4. For j=1:T
5. Selection of Transmitting Path
6. Maintain Q
7. Offload using GWO
8. End for
9. End for
10. End



Figure 1: Optimal Path Planning and Scheduling for Mobile Edge Server (OPPSMES)

appliances is represented by the notation $D = \{d_1, d_2, \dots, d_n\}$. Such devices can produce a large number of compute-intensive as well as delay-tolerant task offers. A 3-term description of the job request from the device d_i is given by $q_i = \{c_i, u_i, s_i\}$. So, c_i stands for the number of CPU cycles required for the completion, u_i for the amount of calculation input data, while s_i for the amount of storage space required (for example, coding libraries along with datasets specific for particular computational works). We disregard the time it takes by edge server to communicate the calculation findings directly to IoT systems. Since this amount of computing output data is frequently significantly lower than the amount of calculation input data. Additionally, a 2-D coordinate is used to explain where the device d_i is located (x_i, y_i) . The mobile edge server S can travel at speed of v . Additionally, the server includes a limited amount of storage C which is used to data storage using for computing jobs as well as CPU that operates at its optimum frequency F (cycles/Sec) to handle computing duties that are offloaded of IoT devices.

Therefore, in this research work, we have presented optimal task scheduling of tasks from IoT devices to mobile server nodes. The model is designed in two basic steps: Path Planning and optimal task scheduling, as depicted in figure 1. The algorithm of designed model is presented as below in Algorithm 1.

Path Planning

Path planning as well as task scheduling, these two must be done by a server S prior it started beginning to move while gathering task requests from IoT systems.^[12] Not like that usual mobile cloudlet having path planning issue where cloudlets simply transit every IoT device one time. This mobile

edge server could transit an IoT device once (the server done a computational job in place) or two times (the server done a computation job in moving) under the proposed system. To properly illustrate the two given possibilities to mobile edge server (MES) only with a single IoT system, utilizing a $1 \times 2n$ dimensional vector $P = (p_1, p_2, \dots, p_{2n})$ for representing the edge server mobile path. We can find server moving time by:

$$t_{i,j}^{move} = \frac{dis(i,j)}{v} \quad (1)$$

Here, Euclidean distance from I_i to I_j depicts by $dis(i,j)$, calculation can be done as :

$$dis(I_i, I_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (2)$$

Task Scheduling

The proposed scheduling application's mobile edge server would use the parallel among server movement as well as task computing; therefore it implies the mobile edge server may include numerous jobs. It is essential to create an effective task scheduling framework to make the most of the server's computing and storage capabilities and shorten the duration it takes to finish serving every nearby IoT system.

Throughout this study, the task scheduling outcome is represented by $R = (r_1, r_2, \dots, r_n)$, where r_i represents the task q_i 's priority through device d_i . The importance increases as the value decreases. The mobile edge server would execute the job with the greatest priority whether there are numerous tasks running at once. Meanwhile, the tasks sets having greater priority over q_i , depicts by $higher(i)$, the equation can be written as:

$$higher(i) = \{q_j | r_j < r_i, \forall j \in N\} \quad (3)$$

The MES's arrival time at the location p_i will be indicated by the time stamp t_i^{arrive} . Additionally, let t_i^{leave} represent the moment the MES departs from the point p_i . The position of every device would show up two times in server moving path, this is important to note. The first one for jobs involving uploading and the other for those involving computation. The time at which the edge server arrives to p_i may be calculated using the server mobility model as:

$$t_i^{arrive} = t_{i-1}^{leave} + t_{i-1,i}^{leave} \quad (4)$$

To be specific, $t_i^{arrive} = 0$ the total delay after the MES serving every of the IoT systems in this region is indicated by the term t_i^{leave} .

T_i can be used to express length of time spent at the location p_i . The total duration of the arrival of edge server on point p_i and leaving from a particular point are related.

$$t_i^{leave} = t_{i-1}^{arrive} + T_i \quad (5)$$



Algorithm 3: Optimal Scheduling (GWO Algorithm)

1: Begin, Randomly initialize the population of grey wolves X_i ($i=1,2,\dots,n$)
 2: Initialize variables
 3: Calculate the fitness of each member of the population
 4: X_α =member with the best fitness value
 5: X_β =second best member (in terms of fitness value)
 6: X_δ =third best member (in terms of fitness value)
 7: For $t = 1$ to Max_number_of_iterations:
 8: Update the position of all the omega wolves
 9: Update variables
 10: Calculate Fitness of all search agents
 11: Update X_α , X_β , X_δ .
 12: End For
 13: return X_α
 14: End

If the MES stops at position l_k along the path between points p_i and p_j , then $p_i = p_j = l_k$. The stop time on p_i calculated by:

$$T = \begin{cases} uk/yk \\ \frac{ck}{F} + t_{higher(k)}^{finish} - t_i^{arrive} \text{ if } i < j \\ t_i^{arrive} \text{ if } i > j \end{cases} \quad (6)$$

According to Eq. (6), the edge server can halt in 2 different circumstances.

- The server pauses at l_k during the first moment for the route point p_i . For such instance, this particular server expends time obtaining job q_i 's input data. Therefore, u_k/k may be used to describe the length of stay T_i .
- The server pauses at l_k for the route point p_i in 2^{nd} time. This particular edge server expends time tasks efficiently and computes findings to devices in such scenario. The time it takes the server to communicate computed outcomes for Internet of Things device is disregarded in the system architecture previously stated. The likelihood that when servers get to p_i , the greater priority jobs $higher(k)$, offloaded to them, have not been finished. There are 2 related circumstances.
- $t_{higher(k)}^{finish} > t_i^{arrive}$, whenever arrival of server at p_i , processing of the remaining much greater works, prior to computing q_k just to $t_{higher(k)}^{finish} - t_i^{arrive}$. Then the server halt time on p_i , calculation is done by $c_k/F + (t_{higher(k)}^{finish} - t_i^{arrive})$.
- $t_{higher(k)}^{finish} < t_i^{arrive}$, whenever arrival at p_i , this q_k were still calculated for $t_{higher(k)}^{finish}$ time. Therefore, the server halt time on p_i is $c_k/F - (t_i^{arrive} - t_{higher(k)}^{finish})$.

So, in short the server halt time is expressed as $c_k/F + \dots$. Hence, depicts the time duration whenever much greater jobs over q_k were finished.

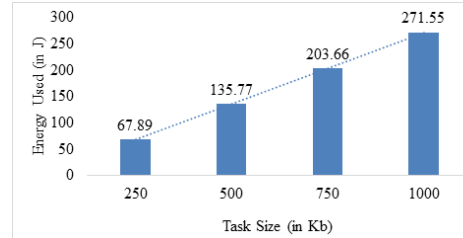
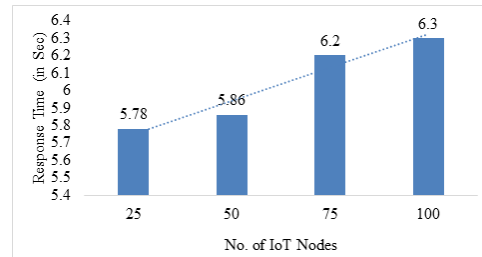
This is written as:

$$t_{higher(k)}^{finish} = \max_{p_i=l_m; d_m \in higher(k)} \{t_i^{leave}\} \quad i=1 \dots 2n \quad (7)$$

For this optimization algorithm (algorithm 2) is designed.

Table 1: System Parameters Used

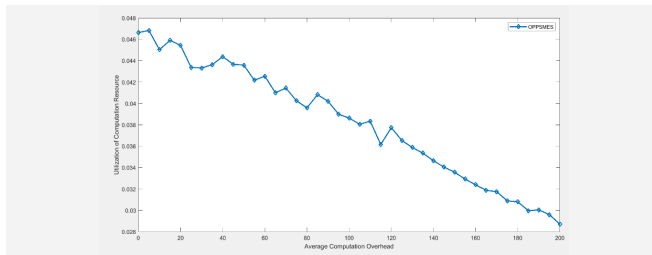
Parameters	Value
Number of mobile users	100
Number of servers	10
Bandwidth of edgeserver	12MB/s
Bandwidth of IoT nodes	300MB/s
Data Size	250kb-1Mb
Ideal delay of request	0.4-0.6s

**Figure 2: Energy Usage with Variable Task Size****Figure 3: Response Time with Variable User****Result Analysis**

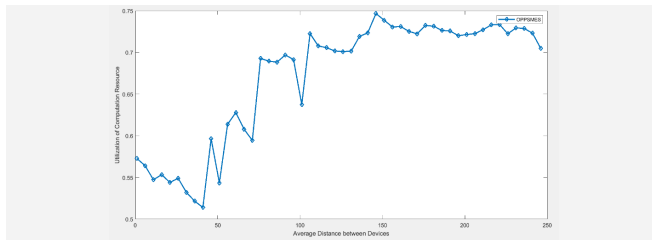
To evaluate the effectiveness of the OPPSMES, the proposed algorithm is implemented using Matlab R-2020a. The simulations were conducted on an Intel i5, 3.7Ghz PC with 8 GB RAM. In this work, mobile node-server computing system consisting of mobile users and multiple edge servers is designed. Each MES equipped with edge servers. The parameters of the simulation are shown in Table 1.

The result was evaluated in terms of response time as well as energy used. Figure 2 shows the energy usage of the proposed algorithm with variable task size. In this case number of IoT nodes are fixed and task size is varied. The task size was taken from 250Kb to 1000Kb. The result analysis presented in Figure 2 shows that with increases size of task energy utilization also increases. Figure 3 shows the response time of proposed algorithm with variable number of mobile IoT nodes. In this case number of nodes is varied and task size is fixed. The number of nodes was taken from 25-100. The result analysis presented in Figure 3 shows that with increases size of users, response time also increases.

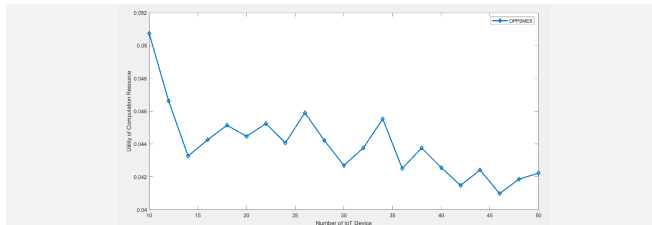
The performance analysis between OPPSMES for resource optimization is shown in Figure 4. The amount of time needed for calculation out of the total lag is utilized to determine the computation resource utilization. The performance in



(a) Resource Utilization with respect to Computational Overhead



(b) Resource Utilization with respect to Average Distance Among Mobile Devices



(c) Resource Utilization with respect to Mobile Devices

Figure 4: Resource Utilization of OPPSMES

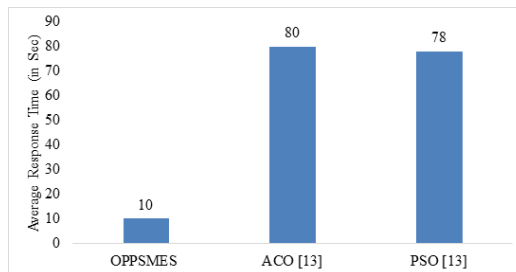


Figure 5: Average Response Time Comparison

respect of resource usage under variable conditions are shown in Figures 4(a) to 4(c). From the findings, we learn the following things. Figure 4(a) demonstrates the resource utilization of OPPSMES under variable computational overhead. With increases computational overhead, resource utilization decreases. Figure 4(b) demonstrates the resource utilization with increasing distance among mobile nodes. With increases and distance resource utilization increases. Figure 4(c) demonstrates the resource utilization with increasing of mobile nodes. With increases nodes resource utilization decreases. The usage of resources is enhanced by reduction in parallelism. The optimization space for task scheduling time is less than the space for path planning in dense networks (with short distances), so OPPSMES's fraction is less.

Figure 5 compares the OPPSMES with PSO and ACO scheduling techniques with the variable total number of nodes and shows the average response times of the offloaded tasks. In this case, when the number of tasks is expanded by adding additional sensors, the overall response time increases. OPPSMES average response time ranged from 6-10 seconds, as seen in the graph, but ACO and PSO's reaction times increased from 79 to 100 seconds as the number of nodes increased.

CONCLUSION

In this paper we suggest OPPSMES a cutting-edge computing Framework for 6G networks such as mobile IoT-Edge systems. OPPSMES integrates both stationary and mobile servers to effectively and compass edge computing number of servers required to provide 6G can be significantly reduced by using server mobility. Additionally, OPPSMES takes advantage of 6G's ultra-high bandwidth capabilities and decouples request from the outcome of edge task of loading greatly enhancing the versatility and optimization outcomes of task scheduling. The evaluation findings indicate a significant decrease in response time, energy and advancement in resource usage.

REFERENCES

- [1] Mukherjee, Amrit & Goswami, Pratik & Khan, Mohammad & Yang, Lixia & Pillai, Prashant. (2020). Energy-Efficient Resource Allocation Strategy in Massive IoT for Industrial 6G Applications. *IEEE Internet of Things Journal*. PP. 1-1. 10.1109/JIOT.2020.3035608.
- [2] Guo, F., Yu, F. R., Zhang, H., Li, X., Ji, H., & Leung, V. C. M. (2021). Enabling Massive IoT Toward 6G: A Comprehensive Survey. *IEEE Internet of Things Journal*, 8(15), 11891–11915. <https://doi.org/10.1109/JIOT.2021.3063686>
- [3] Lv, Z., Lou, R., Li, J., Singh, A. K., & Song, H. (2021). Big data analytics for 6g-enabled massive internet of things. *IEEE Internet of Things Journal*, 8(7), 5350–5359. <https://doi.org/10.1109/JIOT.2021.3056128>
- [4] Mumtaz, S., Menon, V. G., Al-Dulaimi, A., Ashraf, M. I., & Guizani, M. (2021). Guest editorial: Special issue on enabling massive iot with 6g: Applications, architectures, challenges, and research directions. *IEEE Internet of Things Journal*, 8(7), 5111–5113. <https://doi.org/10.1109/JIOT.2021.3061231>
- [5] Malik, U. M., Javed, M. A., Zeadally, S., & Islam, S. ul. (2021). Energy efficient fog computing for 6G enabled massive IoT: Recent trends and future opportunities. *IEEE Internet of Things Journal*, 4662(c), 1–22. <https://doi.org/10.1109/JIOT.2021.3068056>
- [6] Liao, S., Wu, J., Li, J., & Konstantin, K. (2021). Information-centric massive iot-based ubiquitous connected vr/ar in 6g: A proposed caching consensus approach. *IEEE Internet of Things Journal*, 8(7), 5172–5184. <https://doi.org/10.1109/JIOT.2020.3030718>
- [7] Liao, Z., Peng, J., Huang, J., Wang, J., Wang, J., Sharma, P. K., & Ghosh, U. (2021). Distributed probabilistic offloading in edge computing for 6g-enabled massive internet of things. *IEEE Internet of Things Journal*, 8(7), 5298–5308. <https://doi.org/10.1109/JIOT.2020.3033298>
- [8] Verma, S., Kaur, S., Khan, M. A., & Sehdev, P. S. (2021). Toward green communication in 6g-enabled massive internet of things. *IEEE Internet of Things Journal*, 8(7), 5408–5415. <https://doi.org/10.1109/JIOT.2020.3038804>



- [9] Hong, H., Zhao, J., Hong, T., & Tang, T. (2021). Radar-Communication Integration for 6G Massive IoT Services. *IEEE Internet of Things Journal*, 4662(c), 1–11. <https://doi.org/10.1109/JIOT.2021.3064072>
- [10] Jang, H. S., Jung, B. C., Quek, T. Q. S., & Sung, D. K. (2021). Resource-Hopping-Based Grant-Free Multiple Access for 6G-Enabled Massive IoT Networks. *IEEE Internet of Things Journal*, 8(20), 15349–15360. <https://doi.org/10.1109/JIOT.2021.3064872>
- [11] Sodhro, A. H., Zahid, N., Wang, L., Pirbhulal, S., Ouzrout, Y., Sekhari Seklouli, A., Lira Neto, A. V., MacEdo, A. R. L. D., & Albuquerque, V. H. C. D. (2021). Toward ML-Based Energy-Efficient Mechanism for 6G Enabled Industrial Network in Box Systems. *IEEE Transactions on Industrial Informatics*, 17(10), 7185–7192. <https://doi.org/10.1109/TII.2020.3026663>
- [12] Y. Liu, Y. Li, Y. Niu, and D. Jin, "Joint optimization of path planning and resource allocation in mobile edge computing," *IEEE Transactions on Mobile Computing*, 2019.
- [13] Hussein, M. K., & Mousa, M. H. (2020). Efficient task offloading for IoT-Based applications in fog computing using ant colony optimization. *IEEE Access*, 8, 37191–37201. <https://doi.org/10.1109/ACCESS.2020.2975741>