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Research Article

An Efficient Sustainable Energy Utilization and Scheduling for Fog Environment Using Glowworm Swarm Optimization

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Abstract. The primary benefits of fog computing are a considerable reduction in the volume of data sent across the cloud. This, in turn, results in preserving the network bandwidth from being overcrowded. Also, the use of fog computing has a vital role in minimizing Internet and network latencies. However, Fog computing being distributed in nature faces its own challenges. Two of the primary challenges in Fog computing are distributed scheduling and reduced power utilization in a distributed environment. This study addressing these two challenges optimally and efficiently. This paper proposed a novel hybrid approach for enhancing the load balancing and scheduling process, promoting considerable energy and power consumption. The hybrid approach integrates the Glowworm Swarm Optimization algorithm as the practical functionalities for load balancing and scheduling jobs in *Fog Computing Network* (FCN). Our proposed GSWOM approach can perform optimized resource allocation, de-allocation, and management. Also, this study proposed FCN which implemented and experimented with in python software to verify the results. The performance of the proposed approach is evaluated by comparing the obtained results with the earlier contemporary works. From the comparison, it has been found that the proposed GSWOM-FCN outperforms other methods. The results indicate stark improvement in energy consumption and significant improvement due to effective and optimal scheduling. The overall jobs assigned percentage was 96.49% in the case of GSWOM, while it was 86.78% for the existing approach. The classification accuracy is obtained by analyzing the Smart grid stability dataset is 97.73%. Thus, the sustainability prediction using FCN is better than others.

Keywords. Load balancing, Scheduling, Glowworm swarm optimization, Fog computing, Energy utilization, Power utilization, Energy consumption, Cloud computing

Mathematics Subject Classification (2020). 41-00, 90-00, 76-XX

1. Introduction

Fog computing is defined as an architecture that uses network edge to perform cloud computing. Fog computing is another distributed computing paradigm that extends cloud computing, providing the best possible data access for *Internet of Things* (IoT) based applications. Fog computing offers a differentiation between which data can be shared across the cloud and which data contents can be retained locally at the network edge. Fog computing has been considered an effective remedy to several problems posed by cloud computing, such as security threats to data across cloud platforms, Internet downtime and delays, data latency, network latency, bandwidth-related issues, etc. When it comes to fog computing, not all the data generated by smart IoT devices will be shared across the cloud platform. An intermediary layer termed a fog node resides in the individual cloudlets. Some of the data generated by the smart devices are retained in these fog nodes, and only essential data about cloud services is shared across the cloud platform. A typical fog computing architecture is shown in Figure 1. These intermediate *Fog Nodes* (FN) serve as a liaison between the cloud platform and the local network to share the essential data to the cloud space. In turn, this has significantly reduced the volume of data transmitted across the cloud platform.

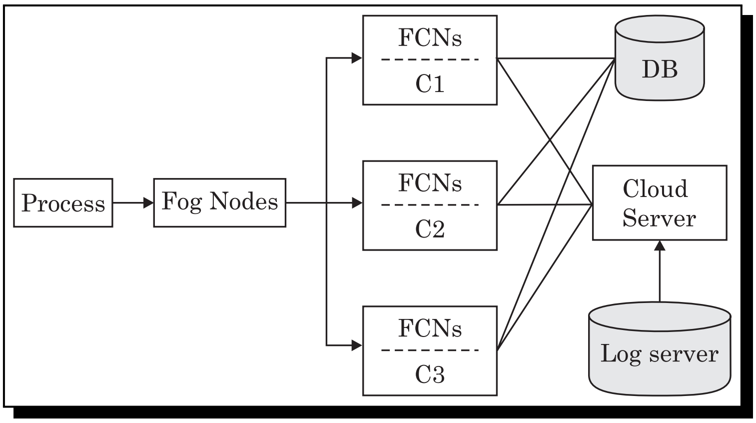

Figure 1. Fog computing architecture

Despite that fog computing promotes better functional allocation, minimal data latency, highly scalable capabilities in terms of data and network security and efficiency, fog computing has its own set of challenges. The fact that fog computing is distributed in the natural environment poses many security challenges in data and network security. Since fog computing is distributed in nature and highly scalable, resource allocation and de-allocation is a pretty tedious task and involves careful scheduling. Resource-intensive scheduling is highly critical in ensuring the efficient performance of the fog-based application. Equal to scheduling, balancing the load of available resources also plays a vital role in ensuring the best performance of the fog network. Well-planned load balancing strategies need to be adopted to ensure that resources are optimally utilized, and none of the resources get over utilized while at the same time none of the resources available are underutilized. Efficient load balancing and scheduling will result in effective resource utilization, resulting in less power consumption and subsequently less energy utilization to accomplish tasks. The contributions of this study are summarized as follows:

- Develop a novel hybrid optimization algorithm GSWOM-FCN that reduces power and subsequently energy consumption in the fog computing environment.

- Apply effective and efficient load balancing strategies, which help optimize energy consumption and smart scheduling approaches that promote effective energy utilization across the fog environment.
- Implements the Glowworm Swarm Optimization algorithm for creating a fog computing network.
- Conduct experiments to evaluate the time, energy efficiency, and resource allocation performance.

The rest of this article is structured as follows. Section 2 provides the background and related works. Section 3 presents the materials and the proposed methodology. Section 4 describes the experimental settings. Section 5 presents the results and discussions. Section 6 provides the conclusion and suggestions for further research.

2. Related Works

Fog architectures, as have a vital role in the efficient working of the fog environment. Effective centralized and distributed solutions have been proposed by Bozorgchenani *et al*. [3] to minimize energy consumption and delays across fog networks. It used the partial offloading method to periodically offset the nodes to reduce the energy used by unnecessary nodes. In [9], Lyu *et al*. used Gaussian mechanism-based privacy preservation technique to maintain data privacy and increase efficiency. The study tried to achieve maximum efficiency in energy consumption without compromising security. They used intermediate nodes to collect data from the nearby nodes and are aggregated through fog level aggregation. Fu *et al*. [4] is discussed a secure data storage mechanism in a fog environment and explored the possibilities of faster data retrieval from the stored spaces. A novel approach to determine less utilized edge data centers was proposed by Puthal *et al*. [12]. It was used to authenticate EDCs and find the EDCs with minimum load for allocating extra tasks. It improved the load balancing efficiency and improved security. A specific case of Vehicular Fog Computing has been considered by Han *et al*. [5], and Zhou *et al*. [16]. A distributed approach for computing and allocating resources has been provided bu Liu *et al*. [8], and a novel offloading strategy named *Non-Orthogonal Multiple Access* (NOMA) has been suggested. A distributed offload forwarding strategy has been proposed by Xiao and Krunz [15] that enables effective fog node collaboration to enhance energy consumption. User participatory fog architecture has been proposed by Kim and Chung *et al*. [6]. In the proposed architecture, the fog computing devices are optimized through instance placement by using the users' service usage. Also, several theoretical modeling-based architectures for fog computing, such as one described by Mukherjee *et al*. [11], have been developed to focus on energy consumption and green computing. In [2] a sequential probing approach is proposed for load balancing. A comprehensive review of the smart grid systems based on IoT and EC is provided by Mehmood *et al*. [10]. The development in the rising technologies, the framework for EC-IoT-based SG, and requirements to implement the EC-IoT-based SG system are highlighted in the paper. Framework for EC-IoT-based SG is examined, and important requirements to implement the EC-IoT-based SG system are outlined. A hybrid computing architecture based on Fog and cloud with 5G-based V2G networks applications in [13]. This architecture allows the bi-directional flow of power and information between schedulable EVs and Smart Grids (SGs) to improve energy service providers' quality and cost-effectiveness. In [14] a hybrid blockchain mechanism based on the 5G MEC smart grid is proposed. where public and private blockchain is deployed on the MEC gateway/server. A novel conjoint architecture integrating all the network roadmap modernization is also presented by Kumar and Pindoriya [7]. Moreover, technical resource allocation approaches for dynamic network slices in the proposed architecture are analyzed. A comprehensive review of potential applications of 5G IoT technologies is provided by Ahmadzadeh *et al*. [1].

Based on the literature survey, it is observed that most of the works were focused on devising either an effective load balancing approach or smart resource allocation and scheduling strategies that promote effective energy utilization and sustainable energy management. But, when fog computing has to be extended across high-performance real-time applications, it is essential to have effective resource allocation and scheduling plans. In addition to that, advanced load balancing strategies need to ensure the energy is effectively measured, monitored, and optimally distributed. A highly sustainable fog computing network can be developed without compromising the *Quality of Service* (QoS) parameters. Hence, our proposed approach comprises a hybrid solution that addresses the need for smart resource scheduling using Job Shop Scheduling and effective load balancing using Glowworm Swarm Optimization. The proposed work aims to optimally associate the sustainable energy consumption efficiently and optimally by the FCNs to minimize optimal energy utilization.

3. Proposed Methodology

This paper use *Glowworm Swarm Optimization* (GSO) as load balancing strategy. In this optimization algorithm using the local decision range, the server's *Fog Node* (FN) is allocate resources to *Fog Computing Node Servers* (FCN-S). Here data processing is done at the server level, whereas allocating resources is done at the client level. The prioritized process is allocated to the corresponding FCN server and recorded in the database. Cloud server communicates with FCN servers and stores the result in the log server. Relevant resources are allocated by comparing the nearest neighbors in the fog network. Since a greater number of neighbors, the probability-based neighbor selection is obtained. The prime consideration strategic technique here is the public cloud. In the public cloud, the nodes are distributed in different geographical locations and controlled by the cloud manager. The proposed methodology is flown with the nearest cloud called *Fog Computing Node* (FCN), which controls and coordinates the different IoT devices and cloud. IoT devices are linked and send sensor information to the cloud. The load balancing technique does allocate resources to one or more servers. The architecture diagram is shown in Figure 1. Relevant resources are allocated by comparing the nearest neighbors in the fog network. Since a greater number of neighbors, the probability-based neighbor selection is obtained. Here, a single process entering into Fog-nodes is forwarded to the appropriate FCN-S (FCN server) based on the behavior or the job requests. Following the job requests, the associated data is obtained from the DB, processed into the cloud, where the cloud keeps the meta-information about the job requests in log-server interlinked with the cloud server. It is illustrated in Figure 2. The FCN is the intermediate layer that coordinates the IoT, mobile, or WSN nodes and cloud. It is represented in (M/M/C):(∞/FIFO). The value C indicates multiple servers receive a prioritized job from the FCN client allocator. The arrival of a job is dynamic and distributed in sequential order. The client of FCN acts as a distributor based on the priority. Figure 2. also represented the work is assigned to the servers in FCN and communicated with the cloud.

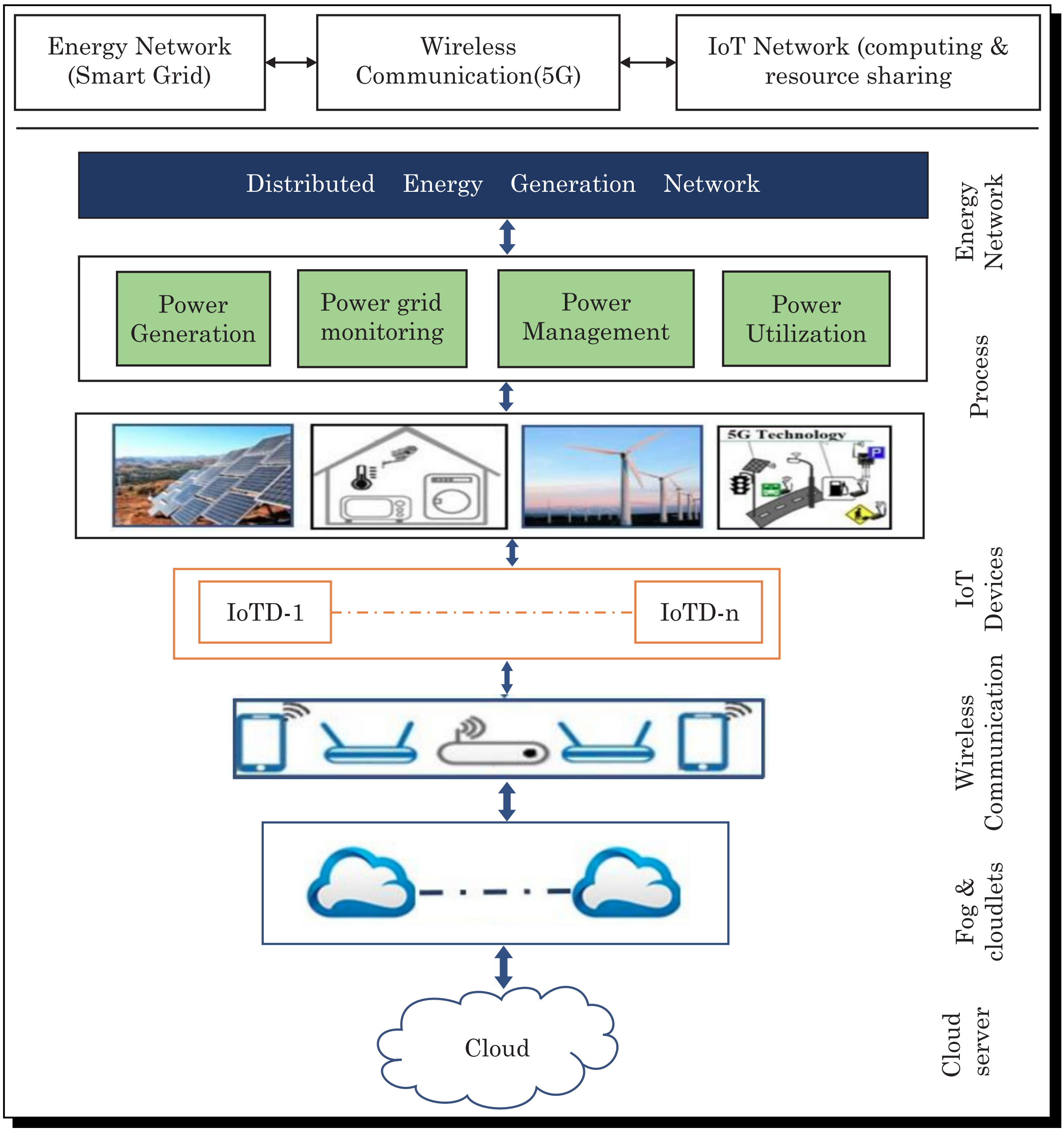

Figure 2. Multiple processors processing single process

The service time taken by the client node to distribute the process is considered based on the sensor output. The server is multiple processors which receive a task from the client. Queue discipline is an ordered number assigned uniquely by the processor to different server nodes. Execution of the process will be taken once servers receive the job. The tendency to receive the job is based on the scheduler. It is represented by the flow diagram shown in Figure 3.

3.1 Glowworm Swarm Optimization (GSO) Based Load Balancing

The contribution of the work is concentrated towards implementing a hybrid optimization algorithm for load balancing and scheduling optimally. The hybrid optimization algorithm incorporates the essential features of the Glowworm Swarm Optimization algorithm and the Job Scheduling algorithm for load compensation and scheduling the jobs towards resources, respectively. GSO algorithm is one of the swarm intelligence algorithms, where the entire network is decentralized and self-organized.

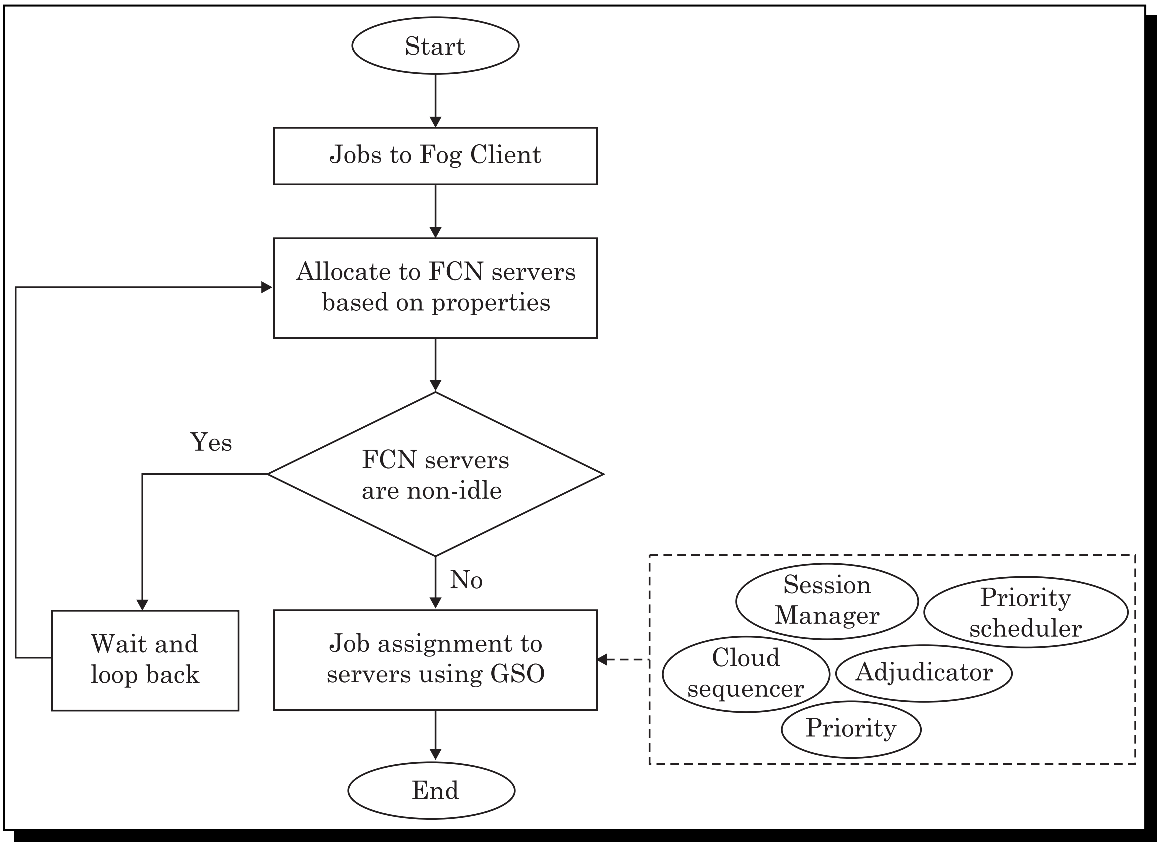

Figure 3. Flowchart of proposed approach

Let N number of job requests (JREQ) from different IoT environment that is queued to FCNs is $Q = \{\mathrm{JREQ}_1, \mathrm{JREQ}_2, \dots, \mathrm{JREQ}_\mathrm{n}\}$, for all $n = 10$. This is assigned to the appropriate resources $R = \{\mathrm{R1}, \mathrm{R2}, \mathrm{R3}\}$. It is considered that the number of JReq is 10, and the number of resources is 3 at the time (t). For allocating the resources, the GSO algorithm is used here. For example, each JReq(i) Resource Ri is encoded with priority Ψi and will be given to FCN's. FCN takes the incoming Req(i).data, and based on the GSO algorithm, and the appropriate cloud server will be selected under a distribution rate λ. The replica of the distributed Req(i) is stored in the cloud server for further recovery options. The distribution rate is used to keep track of the time and energy consumption between job-release from job entering to FCN into job execution. In GSO, each swarm is attracted by the nearest neighbor in brighter while moving. Due to a greater number of neighbors, the probability function is used to choose the neighbors. Swarms are referred to JREQ, where their load, available resources, resource ability, execution time, priority, and job queue length are verified for allocating the jobs into the appropriate resources. Comparison between the JREQ and the Ri is carried out using the GSO algorithm. If multiple JREQ have the same priority, then it follows the FCFS fashion. In case of more execution time and same priority, the context-switching methodology is used in cloud resources to preempt the current execution job, continue with the next JREQ, and complete all the JREQ based on the remaining execution time. In the case of any contingency, the replica stored in the cloud server is reverted to the execution server for execution starts.

4. The Experimental Settings

There are four different processes carried out in the GSO algorithm: initialization, updating the luciferin, movement, and neighborhood range update. The number JREQ, available resources, approximate computation time, available resources, and other meta-information about the resources are initialized. Then the job request information is compared with the resource information for allocation. The best suitable resources are allocated and the jobs completed within the determined time (t). The knowledge predictor predicts the guidance based on data received in the past and current updated sensor data. It is like an independent sequencer in which any abnormalities will be taken. If knowledge predictor lacks in the past data, then based on certain rules, it will act and work on the data using sensor information. The session manager keeps track of the information, and the adjudicator is the scheduler linked with the priority scheduler assigned to different servers. Cloud sequencer is a resource allocator and database manager to deliver the work in a scheduled manner. The new job arrivals to the network for load balancing and FCN usage is given in Table 1.

Table 1. FCN-s

Job	TTE (Time to Execute)	Completed	Priority	Queue Order	CS (Cloud Allotted)	Load in Percentage
IoT_i1	600	240	1	2	C1	70
IoT_i2	1200	640	1	3	C2	45
IoT_i3	300	660	2	1	C1	70
IoT_i4	60	30	2	5	C3	28
IoT_i5	240	180	3	4	C3	28

4.1 Dataset

The dataset chosen for this machine learning exercise has a synthetic nature and contains results from simulations of grid stability for a reference 4-node star network. The original dataset contains 10,000 observations. As the reference grid is symmetric, the dataset can be augmented in 3! (3 factorial) times, or 6 times, representing a permutation of the three consumers occupying three consumer nodes. The augmented version has then 60,000 observations. It also contains 12 primary predictive features and two dependent variables.

5. Results and Discussion

The proposed approach is considered for 10 IoT sensor Jobs with a redundant approach. Sensor data is processed and sent to FCN through connectivity, and based on the load balancing optimization technique, the work is allotted to one of its central clients. The main technique here is that one of the efficient FCN nodes acts as a client node and main node for work distribution. Here 10 different sensor nodes are considered. If the intermediate monitor node receives a request in the fog layer, allotment of request will be done if it is not idle. Most of the requests are highly prioritized; hence, most job requests are assigned to client1. The load balancing optimization using GSWOM optimization compared with Beraldi and Alnuweiri [2] is carried out and shown in Figure 4. GSWOM has also ensured that the faulty nodes that demanded more energy than required were ignored. In contrast, allocating tasks to nodes happened so that optimal usage of sustainable energy is managed effectively.

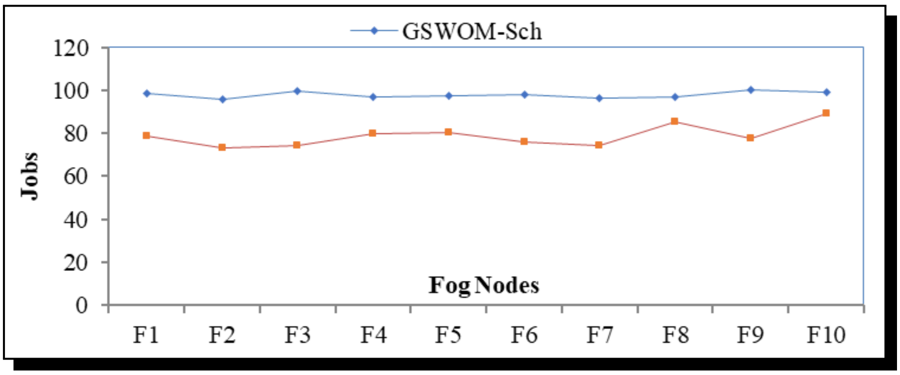

Figure 4. Job-machine allocation comparison

The energy generated from various sustainable sources such as wind, solar and thermal is monitored and measured using various smart IoT devices. Figure 4 shows the energy demand vs. energy generation graph. It can be observed that the proposed hybrid load balancing approach has ensured that the energy demand has never exceeded the energy generated from various sustainable sources, thereby ensuring that the energy demad of various devices is always catered to. Most optimization is allotted in the request time itself if the FCN node is a non-idle state using the proposed approach. Individual jobs and their time are specified. The possible extent time for all the jobs is related to dynamic time, and the service offered is considered. It is to be noted that the GSWOM ensured that as part of the load balancing strategy, none of the available resources was left idle, thereby ensuring that the resource underutilization scenario was avoided. At the same time, SWOM has also ensured that the resources were not overloaded and burnt out. The FN allocations were done based on priority, time taken for completion with peak TTE being 1200, current utilization percentage, and load percentage with cloud node 1 taking 70% while the others share lesser nodes. Also, it is to be observed that the SWOM has considered priority while ensuring the load balancing was carried out effectively. The overall jobs assigned percentage was 96.49% in the case of GSWOM, while it was 86.78% for the existing approach.

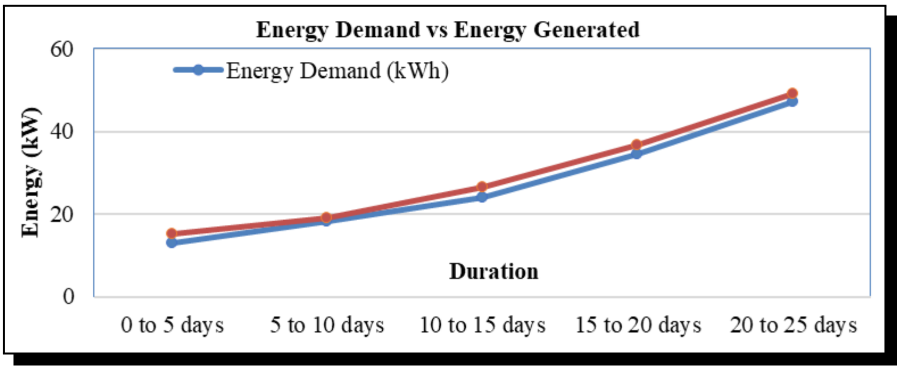

Figure 5. Job-energy demand vs. Energy generated

The SWOM also ensured that none of the cloud servers which contain multiple FNs were overloaded. Another striking aspect observed was that the overall execution time of the tasks did not increase a great deal for any specific task. Again, this is a significant aspect to be considered for effective load balancing and efficient energy sharing among available resources. This analysis is provided in the Figure 5. The classification accuracy is obtained by analyzing the Smart grid stability dataset, and the confusion matrix is given in Table 2. The estimated accuracy for the confusion matrix is 97.73% from the table values. Thus, the sustainability prediction using FCN is better than others. Experimental results show positive insights and indicate that the new approach performs better compared to other contemporary approaches in energy saving and energy utilization. For providing a better solution for the above-said performance.

Table 2. Prediction accuracy

	Predicted Unstable	Predicted Stable
Actual Unstable	3699	54
Actual Stable	82	2165

6. Conclusion and Future Work

In this work, we presented a Glowworm Swarm Optimization (GSO) based hybrid optimization algorithm that focuses on effective load balancing. In addition, the work uses the same IoT devices that utilize the energy to monitor the load and manage load-sharing among them effectively. The experiment was conducted with 10 FCNs, and the allocation of tasks to available machines was recorded. It is found that the proposed GSWOM approach is pivotal in effectively allocating the resources to the required tasks without overloading any specific resource and ensuring that there were also no idle resources. It, in turn, helps in effectively mapping the energy available to the desired resources. The results of load balancing were compared with contemporary approaches and shared. Further, it can be noted that the load balancing algorithm has ensured that the energy demand was completely under control by allocating tasks in such a way that the energy demand value was always maintained to be less than the sustained energy generated. Future work will enhance the GSWOM approach to include additional parameters like idle time, wait time, execution time, etc., as a feedback input and fine-tune itself just like a feedback loop and enhance the overall load balancing of the system.

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Competing Interests

The author declares that she has no competing interests.

Authors' Contributions

The author wrote, read and approved the final manuscript.

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