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Hybrid Energy Saving and Scheduling Scheme for Quality of Service Enhancements in the Internet of Things

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ABSTRACT

Wireless networks such as the Internet of Things (IoT) integrate heterogeneous paradigms—including fog, cloud, and edge computing to provide pervasive services to users. The Quality of Service (QoS) depends on energy efficiency, resource scheduling, and optimal traffic management across the various employed paradigms. However, existing approaches often fail to dynamically adapt to varying resource demands while maintaining a balance between energy efficiency and service latency. This article introduces a Hybrid Energy Saving and Scheduling Scheme (HES3) to enhance QoS in wireless paradigms associated with IoT for service handling. HES3 incorporates multi-level federated learning to achieve optimal resource sharing through demand analysis. The demands related to energy, delay, and applications are identified using federated learning, and local decisions over allocations are performed. The decisions on energy saving are constructed using resource allocation and revocation for resource sharing, whereas the maximum wait time of the service demands is used for decisions on delay-less resource sharing. These decisions are adaptable to the pervasive paradigms integrated with IoT. This hybrid scheme effectively balances resource allocation and energy conservation with better Quality of Service.

1. INTRODUCTION

The Internet of Things (IoT) is a network that connects physical objects using wireless sensors, software, and technologies. IoT provides effective interaction and communication services to users [1]. IoT exchange data from one user to another using an internet connection. Energy-saving techniques and methods are used in IoT to ensure the energy-efficiency range of the network. The smart lighting system is used in IoT which reduces the overall energy consumption range of the network [2, 3]. The smart lighting system uses LED lights which save energy while performing tasks. The smart lighting system controls the energy consumption ratio by scheduling tasks based on priorities [4]. The smart lighting system is used in signals that maximize the efficiency level of the network. An optimization technique is also used for energy-saving processes in IoT-enabled applications [5]. Cloud computing (CC) system is used in optimization which analyzes the information to perform tasks in IoT. CC provides sustainable services to the users in the IoT network. The optimization technique improves the overall Quality of Service (QoS) and energy-efficiency range of the systems [6].

Energy-efficient resources are used in the IoT which enhances the performance level of the systems. Energy-efficient resources provide relevant resources to IoT that reduces the latency in performing tasks [7]. Energy-efficient resource sharing is a process that shares the necessary resources to the IoT network. Various energy-efficient resource-sharing techniques are used in IoT that share the resources to perform tasks [8]. Fog-enabled joint computation technique is commonly used for resource sharing process. The fog-enabled technique identifies the exact capabilities and functionalities of IoT-assisted devices [9]. The fog-enabled technique also provides optimal energy-efficient resources to the networks. The computation technique reduces both time and energy consumption levels in computation which enhances the feasibility level of IoT systems [10]. An efficient incentive mechanism is used for the resource-sharing process in IoT. The incentive mechanism uses the contract theory to analyze the servers which required resources to perform tasks in IoT. The actual computational resources are necessary to share among the individual which enhances the energy-efficiency range of IoT networks [11, 12].

Machine learning (ML) algorithms and techniques are widely used for the detection and production process. ML techniques are also used for energy-efficient resource-sharing processes in the IoT [13]. Deep reinforcement learning (DRL) based energy-efficient resource-sharing approach is used for IoT systems. DRL uses a feature extraction method that extracts the important features and patterns for the resource-sharing process [14]. DRL also explores the sharing characteristics level of the system which produces necessary data for further processes [15]. The DRL-based energy-efficient sharing approach improves the QoS and Quality of Experience (QoE) range of the systems. The deep Q-learning network (DQN) technique is also used for the resource-sharing process in IoT systems [16]. The DQN identifies the agents and provides optimal resources for sharing and communication services. The DQN algorithm minimizes the latency in the computation process. The DQN stimulates the effectiveness level of the network which improves the performance ratio of the IoT systems [17, 18]. The existing network IoT connectivity facing challenges in QoS and service provider availability in heterogeneous users with difficult to identify the user requests, service availability, and density of the users, flexibility in resource utilization and service responses while allocating resources systems require to cover the constraint handling features for improving the resource allocation process. This study introduces a Hybrid Energy Saving and Scheduling Scheme (HES3) employs multi-level federated learning for classifying the energy and delay-based constraints and decentralized scheduling. Federated learning [19] is one of the effective machine learning approaches which helps to collaborate the different devices to perform the task effectively. The federated learning approach trains the network to distribute the data in the network, which minimizes the need for the data to be broadcast to the central server. McMahan et al. [20] proposed the phrase "federated learning" in 2016. In Federated learning, building machine learning models for data-driven applications is a collaborative effort across distributed clients without centralizing client data. So, the federated learning process manages the energy while performing the data broadcast. The federated learning process creates the training architecture by considering the number of nodes that forms the clusters to update every transaction, which reduces the unwanted transaction and energy factors. In addition, the federated learning factors maintain the Quality of Services due to the effective generation of the training model. The contributions/ objectives are listed below:

(a) Analyze the energy and delay constraint-causing factors in QoS-centric integrations in IoT regardless of user density and service availability.
(b) Identify and leverage the flexibility in resource sharing and allocation that balances resources, energy conservation, and delay suppression persistently.
(c) Evaluate the proposed scheme's performance using standard metrics such as resource allocation, delay, energy conservation, and scheduling rate under varying users, resources, etc.

2. RELATED WORK

Castillo-Atoche et al. [21] developed a power management strategy (PMS) based weighted order statistics (WOS) classification technique for wireless sensor nodes. The developed technique is used for energy harvesting (EH) which enhances the efficiency of wireless sensor networks (WSN). The developed technique classifies the wireless nodes based on priorities and characteristics. The WOS classification technique gathers the necessary information from the WSN database that minimizes the latency in the computation process.

Tong et al. [22] proposed a dynamic energy-saving offloading strategy for the IoT enabled devices. A Lyapunov optimization algorithm is used in the strategy which balances the tasks and reduces the energy consumption level in IoT devices. The actual bandwidth and frequency level of the devices is identified using mobile edge computing (MEC) systems. The proposed strategy maximizes the performance and efficiency level of IoT systems.

Qi et al. [23] designed a two-stage queueing communication scheme for energy-saving in IoT networks. The designed scheme is a traffic-aware scheme that analyzes the access point (AP) level of the nodes. A queue analysis technique is used in the scheme which analyzes the power consumption level of the nodes and produces feasible data for the optimization process. The designed scheme provides optimal services to the IoT network that enhances the feasibility ratio of the systems.

You et al. [24] introduced a multi-QoS disk scheduling strategy (MQDS) for cloud storage systems. The benefit function-based disk algorithm (BFDS) is used in the scheme which schedules the disks based on priorities and functions. BFDS minimizes the energy consumption ratio in the computation process. Experimental results show that the introduced MQDS improves the energy efficiency level of storage systems.

Li et al. [25] designed an energy-saving service management model using edge computing for the IoT. The proposed model is used a prediction model which uses long short-term memory (LSTM) algorithm. LSTM algorithm is mainly used to predict the nodes and servers to perform tasks in IoT systems. The designed model improves the energy-saving range while performing tasks that increase the reliability range of IoT devices.

Feng et al. [26] introduced an extreme value theory (EVT) embedded in intelligent learning for energy-efficient offloading in IoT systems. The main aim of the introduced method is to minimize the energy optimization range of the systems. The offloading technique minimizes the problems which are presented in the database. When compared with other methods, the introduced method maximizes the QoS range of IoT systems.

Liu et al. [27] presented a novel approach to enhance the energy efficiency of federated learning (FL) systems through dynamic hyper parameter tuning. The paper introduces a mechanism that allows hyper parameters to be adjusted in real-time based on training performance and energy consumption. The experimental results show that FedEco significantly reduces energy consumption compared to baseline FL methods, demonstrating that energy efficiency can be achieved without sacrificing model accuracy.

Liaq and Ejaz [28] addressed the challenges of computational resources and latency in federated learning scenarios enhanced by unmanned aerial vehicles (UAVs). The study proposes strategies to optimize the offloading of computations from edge devices to UAVs, aiming to improve the overall efficiency and performance of federated learning systems. Through simulations and experiments, the study demonstrates that the proposed methods significantly reduce delays and enhance the overall efficiency of federated learning, leading to improved model training times and resource utilization.

Samikwa et al. [29] presented a novel approach to improve machine learning in IoT environments using a technique called Dynamic Federated Split Learning (DFL). DFL evaluates the capabilities of each IoT device and assigns tasks accordingly, optimizing both computation and communication. The learning model is adjusted based on the specific data distributions and computational power of participating devices. Table 1 summarizes the rest of the references with their results.

Table 1. Summary of the rest of the references

Authors	Titles	Key Areas	Advantages	Results
Wang et al. [30]	Radiofrequency (RF) EH based data and energy integrated management (DEIN) strategy for IoT devices.	DEIN manages the database which reduces the complexity of the identification process.	Decreases the energy consumption level in the computation process.	Improves the energy-efficiency range of IoT devices.
Chen et al. [31]	Bandwidth-aware multi-interface (BMS) scheduling for IoT.	The main aim is to improve the energy efficiency (EE) range in communication services.	BMS is mainly used for the gateway-to-device (G2D) communication process.	Minimizes the latency in the interaction process.
Kaur et al. [32]	ML based load scheduling method for IoT systems.	ML classifies the tasks based on load and resources.	ML train the datasets for the scheduling process.	Enhances the performance and feasibility range of the systems.
Kim et al. [33]	Run-time scheduling method for service-oriented IoT systems.	It is used as adaptive scheduling that enhances the efficiency level of the systems.	An incremental heuristic method is used here for the task scheduling process.	Increases the performance level of IoT systems.
Abdul-Qawy et al. [34]	Threshold-oriented and energy-harvesting enabled multi-level stable election protocol (TEMSEP) for WSN.	Identifies the parameters and variables for the scheduling process.	Maximizes the feasibility and efficiency range of the systems.	Increases the accuracy of the energy-harvesting process.
Li et al. [35]	DRL based throughput maximization for renewable ultra-dense IoT.	Qualitative services are provided to IoT device users.	DRL is mainly used here to solve the issues in the computation process.	Enhances the feasibility range of the systems.
Mahmoudi et al. [36]	Quantum-inspired clustering method for IoT networks.	The Firefly algorithm is used here to identify the problems which are presented in the optimization process.	Increases the performance range of IoT networks.	Reduces the energy consumption level of IoT systems.

3. FEDERATED LEARNING IN WIRELESS PARADIGMS WITH IOT

Federated Learning is called the collaborative learning process, one of the machine learning techniques [37]. The federated learning algorithm trains the network using the dataset to improve overall efficiency. The federated learning process is a robustness model that trains the system without sharing the data and addresses several factors, such as data security, data privacy, and access rights on heterogeneous data. During the learning process, network parameters such as weight and bias values are continuously observed and fine-tuned to reduce the deviations between the outputs. In addition, the learning process exchanges the network parameters between the local nodes and gets the global solutions to improve the network performance [38]. The main objective of federated learning is to minimize the loss of function or deviation between the outputs. Then the federated learning objective function is defined as follows:

$$f(x_1, x_2, \dots \dots x_k) = \frac{1}{k}\sum_{i=1}^{k} f_i(x_i) \tag{1}$$

In Eq. (1), k is denoted as the number of nodes involved in the data transactions. x_i is the weight value of node i, and the local objective function is defined as f_i. The main intention of federated learning is to train the entire node in the network to optimize the network performance and reduce the difficulties in data transmission like energy factor and network quality. During the training process, the number of learning rounds (T), the total number of nodes involved in the process (K), fractions of nodes in the iterations (C), batch size (B), learning rate (η), and the number of iterations in the pooling layer (N) is utilized as the parameters. These parameters are continuously observed according to the machine learning algorithm to improve the network performance. The frequent learning process maximizes the QoS without requiring centralized data [39]. The federated learning process ensures the QoS regarding personalization, low latency, resource efficiency, and robustness. Therefore, the federated learning procedure addresses the latency and robustness issues successfully.

4. METHODOLOGY

The design goal of HES3 is to maximize the energy conservation and response rate of the wireless networks-assisted IoT users by reducing lag, delay, failures, and energy drain in IoT-based industrial platforms. In the IoT environment, the heterogeneous users and technological paradigms assimilated IoT QoS are identified through performance-hindering constraints. The wireless paradigms associated with IoT is controlled using privacy measure that is to be incorporated pervasive paradigm with IoT for secure and optimal operations pursued using HES3. The proposed scheme is capable of providing pervasive services for the users and QoS performance of wireless paradigms in all the IoT layers based on energy conservation, resource scheduling, and traffic management across different paradigms processed. In particular, resource sharing through IoT is employed from lag, delay, and failures to improve the wireless network performance in IoT for maximizing resource allocation for various paradigms. The proposed scheme is diagrammatically illustrated in Figure 1.

The function of HES3 is to balance optimal resource allocation and optimal energy conservation for making-decision on delay-less resource sharing. Gathered data from heterogeneous users and technological paradigms is pursued and reliable resources can be shared for a lot of service handling in IoT. The heterogeneous users and technological paradigms are connected through IoT for optimal resource sharing. User demands rely on energy and delay is administered to prevent the forging of devices and energy drains in IoT. The heterogeneous paradigms ensure unchangeable resource sharing between the IoT layers and the processing center. The functions of energy-saving users' demand and delay-less used demands are segregated in the IoT layer and are performed for resource allocation, scheduling, sharing, and verification of energy conservation and user responses. The process of identifying lag, delay, failures, and energy drains in IoT-based service handling is analyzed using federated learning. The aforementioned energy-saving and scheduling processes and QoS are discussed in the following sections.

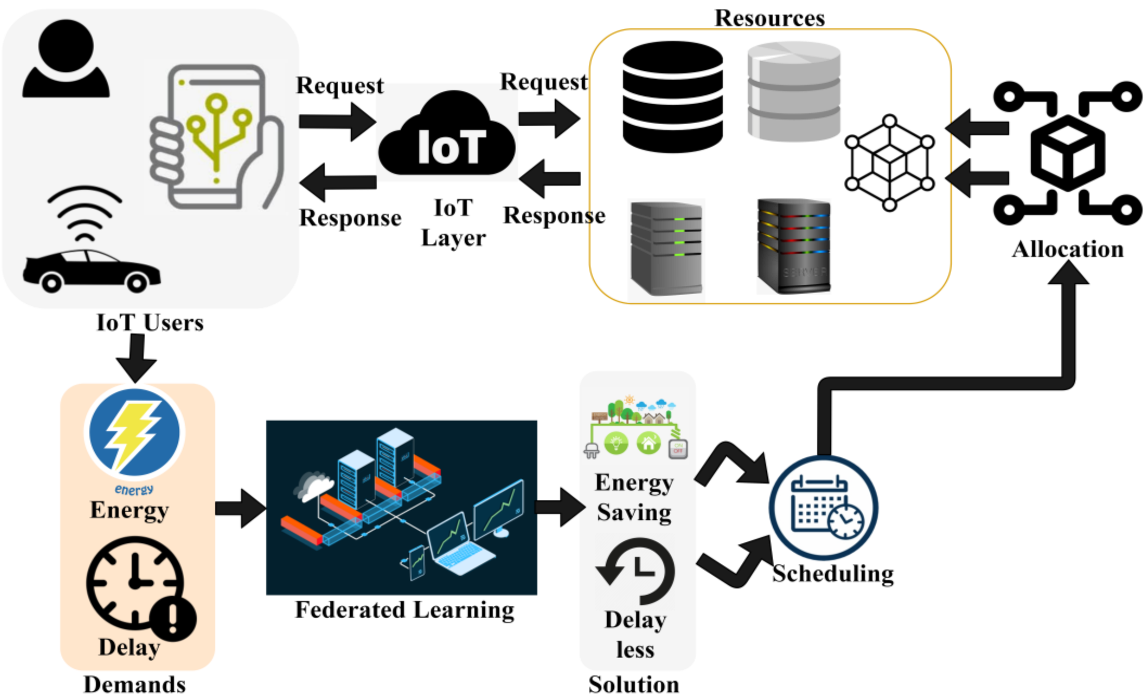


Figure 1. Illustration of the proposed HES3

4.1 QoS performance assessment

The wireless network-assisted heterogeneous paradigms are performing two types of processes on both the sender and receiver sides. The two processes are user requests and user responses based on their demands and needs for improving optimal resource sharing. Request processing is responsible for collecting data from the IoT users and processing reliable services whereas response processing administers service providers monitoring user's activities in IoT and then identifying forging devices and failures. The requests are processed for the set of IoT users that is denoted as $IoT^U = \{1,2, \ldots IoT^u\}$; these wireless field sensors are capable of processing data from all the operational layers of IoT. The FS processes different user requests and quantity of data in any instance with $TM = \{1,2, \ldots tm\}$. Let L illustrate the number of lag, failures, delay, and forging devices are occurs in the IoT layers. Based on the instance, the number of user requests processed per unit of time is $\emptyset_p$ such that the routine QoS performance of various wireless paradigms associated with IoT (QoS_{Pf}) for service handling S^H is given as:

$$QoS_{Pf} = \begin{cases} \dfrac{IoT^U \times S^H \times tm}{\emptyset_p} \ \forall\ IoT^U :: TM, if\ f = 0 \\ r_Q \times \dfrac{IoT^u - L}{RAL} \times \emptyset_p \ \forall\ (IoT^U, L) :: TM, if\ f \neq 0 \end{cases} \quad (2)$$

The total processed requests and requests under failure constraints are defined as:

$$IoT^U :: TM = \sum_{i=1}^{IoT^U} \emptyset_{p_i} \quad (3)$$

$$(IoT^U, f) :: TM = \sum_{i=1}^{IoT^u} \emptyset_{p_i} - r_Q \sum_{i=1}^{f} \emptyset_{p_i} \quad (4)$$

where, resource availability under failures is given by:

$$r_Q = \frac{\emptyset_p + f}{r_S + Usr_{Dm}} \quad (5)$$

where, the variables r_Q and f used to represent user requests and failures in IoT layers in different time intervals TM. If r_S and Usr_{Dm} means the service response and user demands observed from the IoT environment. In the above performance hindering constraints $IoT^U :: TM$ and $(IoT^U, f) :: TM$ used to identify the causing factor in QoS in IoT layers regardless of user density and service availability at any time interval TM. The flexibility of resource sharing is identified for balancing resources, energy conservations, and resource allocations in the IoT environment.

4.2 Classification of failure and QoS_{Pf}

The failure and QoS_{Pf} classification from the continuous intervals are illustrated in Figure 2.

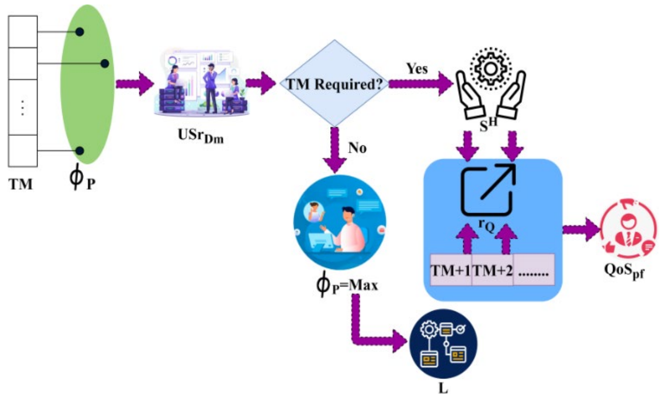


Figure 2. Classification of failure and QoS_{Pf}

The ϕ_P per $TM \,\forall\, IoT^U$ determines the Usr_{Dm} at that interval. The distributed TM for r_Q improves S^H provided if $Usr_{Dm} = \frac{\phi_P}{r_Q} = 1$ or $f = 0$. However, due to the different time requirements if TM is prolonged, then TM is increment for the pending r_Q. This part is classified for QoS_{pf} until L is at most 0. Contrarily for $Q_p = max$, the L is computed for preventing further failures. These two classifications are performed if TM extends for $\left(r_Q - \frac{\phi_P}{TM}\right)$ for which mapping is required (Figure 2). The classification process is tabulated in Table 2.

Table 2. f classification process

Input: IoT^U, r_Q
Step 1: $\forall IoT^U$\{
Step 2: Compute $(r_Q * TM)$ and Usr_{Dm}
Step 3: Set the condition $\forall\, f = 0$ and $f \neq 0$ using Eq. (1)
Step 4: Compute $\phi_P = \frac{r_Q * TM}{Usr_{Dm}} \,\forall\, IoT^U$
Step 5: If $[\frac{\phi_P}{TM} = r_Q \| \phi_P = max_i \,\forall\, i \in (1,2,..,TM)$ then
Step 6: Estimate $(IoT^U, f) :: TM$ using Eq. (3)
Step 7: If $[r_Q \notin (IoT^U, f)]$ then
Step 8: $\phi_P = max, f = 0$
Step 9: Else: $f \neq 0, f = (r_Q - \phi_P/T)$
Step 10: Allocate $TM \,\forall\, (r_Q - \phi_P/T)$\} end if
Step 11: Update $IoT^U :: TM$ using Eq. (2)
Step 12: \} end if
Step 13: \} end for

4.3 Analysis with federated learning representation

The collected data from the IoT users are employed in two ways namely requests and responses based on user demands are analyzed for optimal resource sharing and scheduling is performed. In the request processing, the observed data sequence and QoS_{Pf} are the buildup demands for ensuring the resource sharing for the optimal QoS performance of wireless paradigms in T is achieved by the multi-level federated learning. From the gathered IoT user data, the service responses identify the accurate and appropriate user demands maximizing resource allocation. The classification of user demands based on energy saving and delay-less $IoT^u \in IoT^U$ and f is processed using the observation of user density, service availability, and timed response in IoT. Based on the above equations, the constraint $f > IoT^u$ generates energy drain, lag, delay, and failures from the IoT layer. The resource allocation for the available users and the routine QoS_{Pf} is analyzed based on the $(IoT^u \times \emptyset_p)$ are the checking constraints for the classification of user demands computed as:

$$tm_f = \sum_{i=1}^{IoT^u} \frac{\alpha_A + \beta_d}{t_{r_S}} \tag{6}$$

and

$$\urcorner QoS_{Pf} = \frac{QoS_{Pf}}{(IoT^u - f)} - (\alpha_A - Usr_{Dm}) \tag{7}$$

In the above equation, tm_L and $\urcorner QoS_{Pf}$ variables represent the timed mapping and continuous IoT service processing instance. From Eqs. (2)-(7), the optimal resource sharing is performed through demand analysis of the IoT users R_{Shr} is validated for each instance of T. The variable α_A and β_d represents the service availability and user density for energy saving and scheduling. Therefore, this computation is pursuedto identify the condition either $f \neq 0$ or $f = 0$ for all T instances using federated learning. The FL representation for its processes is given in Figure 3.

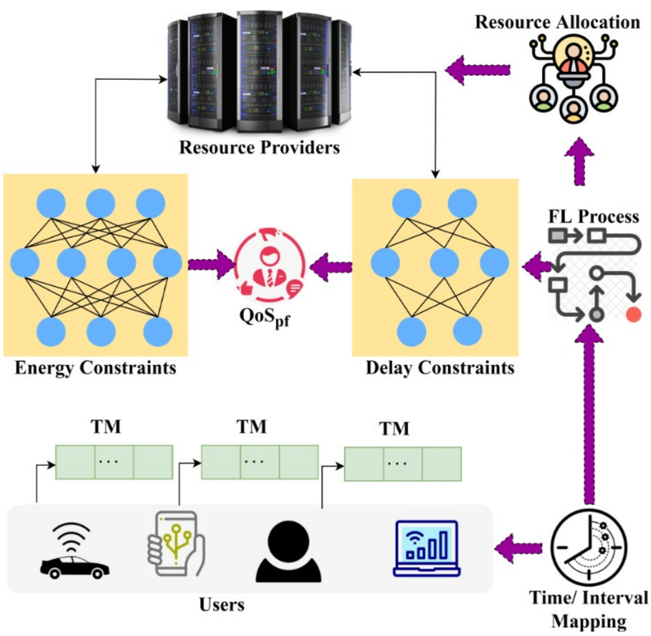


Figure 3. FL representation for its processes

The FL processes are illustrated in the above Figure 3 for handling energy and time constraints. The resource allocation for QoS_{Pf} is provided by suppressing different constraints such that t_{m_f} and $\urcorner QoS_{Pf}$ are consistent. Depending on the α_A and β_d from the user layer, the performance is retained. Therefore $IoT^U \times \phi_P$ is retained regardless of resource unavailability. In this case, the processes are classified from the previous TM such that USr_{Dm} is satisfied at the maximum rate. The FL classifies energy-saving-based demands and delay-less-based demands from the observed data such that R_{Shr} is determined for all the IoT mediate layer output (MLO) for the time interval. The linear solution of $\urcorner QoS_{Pf}$ in tm_f is the classification of user demands maximizing $(IoT^u \times \emptyset_p)$.

4.4 Mediate layer output (MLO) and federated learning

The MLO and final output $(\in^X)$ are crucial in determining R_{Shr}. The serving inputs for user demand analysis based on

QoS_{Pf} for satisfying both $IoT^U :: TM$ and $(IoT^U, f) :: TM$ instances. The federated learning process analyses and schedule the resources for both instances differently based on the constraints $f \neq 0$, $\neg QoS_{Pf} = (IoT^u - f)$, α_A and β_d. If the requestsfor handling services in IoT are available for delay-less resource sharing. In the result of MLO, the first user demand satisfies $IoT^U :: TM$ and outputs inoptimal traffic management, resource scheduling, and energy conservation whereas $(IoT^U, f) :: TM$ extracts the output of IoT^u from IoT^U with $f \neq 0$ cases. In Eqs. (8) and (9), the mediate output and final result for $IoT^U :: TM$ is estimated. The demands based on energy, delay, and applications are identified by the federated learning process for satisfying both the constraints and the conditional assessment of either $\alpha_A = 1$ or $\alpha_A = 0$ in different intervals TM. Therefore, the decisions on energy saving are required for all the resource allocated time TM. In the above demand analysis, f serves as an input, and after the detection of energy drain $IoT^U :: TM$ for reliable resource allocation:

$$\left.\begin{array}{r}
MLO_1 = \neg QoS_{Pf_1} * tm_1 + \emptyset_{p_1}\beta_d \\
MLO_2 = \neg QoS_{Pf_2} * tm_2 - \alpha_{A_1} + \emptyset_{p_2}\beta_d \\
MLO_3 = \neg QoS_{Pf_3} * tm_3 - \alpha_{A_2} + \emptyset_{p_3}\beta_d \\
\vdots \\
MLO_{TM} = \neg QoS_{Pf_{TM}} * tm_{TM} - \alpha_{A_{TM}} + \emptyset_{p_{TM}}\beta_d
\end{array}\right\} \quad (8)$$

$$\left.\begin{array}{rr}
\in^{X^1} = \boldsymbol{MLO_1} & \in^{X^1} = \boldsymbol{\neg QoS_{Pf_1} r_{Q_1} - \emptyset_{p_1} f_1} \\
\in^{X^2} = \boldsymbol{MLO_2 - \alpha_{A_1}\emptyset_{p_1}} & \in^{X^2} = \boldsymbol{\neg QoS_{Pf_2} r_{Q_2} - \beta_{d_1} - \emptyset_{p_2} f_2} \\
\in^{X^3} = \boldsymbol{MLO_3 - \alpha_{A_2}\emptyset_{p_3}} & \in^{X^3} = \boldsymbol{\neg QoS_{Pf_3} r_{Q_3} - \beta_{d_2} - \emptyset_{p_3} f_3} \\
\vdots & \vdots \\
\in^{X^{TM}} = \boldsymbol{MLO_{TM} - \alpha_{A_{TM-1}}\emptyset_{p_{TM-1}}} & \in^{X^{TM-1}} = \boldsymbol{\neg QoS_{Pf_{TM}} r_{Q_{TM}} - \beta_{d_{TM-1}} - \emptyset_{p_{TM-1}} f_{TM-1}}
\end{array}\right\} \quad (9)$$

From the above equation, the optimal resource sharing is given as $QoS_{Pf_{TM}} * tm_{TM} - \alpha_{A_{TM}} + \emptyset_{p_{TM}}\beta_d$. Therefore, in this constraint $f = 0$, then $\alpha_A = 1$ and $\neg QoS_{Pf_{TM}} = IoT^U QoS_{Pf}$. Hence, $MLO_{TM} = IoT^U QoS_{Pf}.tm + IoT^U QoS_{Pf} = IoT^U QoS_{Pf}(tm + 1)$ is the optimal result for resource sharing and $R_{Shr} = 1$. In this analysis, the reputation of such IoT devices/users is retained as 1 and the learning is trained using available resources and the constraint observed over the different distribution processes. The available resources store (R_{Shr}, r_Q, IoT^U) at each T and these local decisions over resource allocations are performed using resource allocation and revocation for resource sharing and scheduling whereas the maximum wait time is estimated for the delay-less resource sharing. Instead, $(IoT^U, f) :: TM$ is used for identifying the energy-saving-based or delay-less-based user demand over the various distribution process. The accurate decision to the incorporated a pervasive paradigm with IoT is computed as:

$$\left.\begin{array}{r}
MLO_1 = QoS_{Pf_1} \\
MLO_2 = QoS_{Pf_2} - \alpha_A\beta_{d_1} + r_{S_1}\emptyset_{p_1} \\
MLO_3 = QoS_{Pf_3} - \alpha_A\beta_{d_2} + r_{S_2}\emptyset_{p_2} \\
\vdots \\
MLO_{TM-1} = QoS_{Pf_{TM-1}} - \alpha_A\beta_{d_{TM-1}} + r_{S_{TM-1}}\emptyset_{p_{TM-1}}
\end{array}\right\} \quad (10)$$

$$\left.\begin{array}{r}
\in^{X^1} = \boldsymbol{MLO_1 = QoS_{Pf_1}} \\
\in^{X^2} = \boldsymbol{MLO_2 + tm_{f_1} - \neg QoS_{Pf_1} = QoS_{Pf_2} - \alpha_A\beta_{d_1} - \emptyset_{p_1} + tm_{f_1}F} \\
\in^{X^3} = \boldsymbol{MLO_3 + tm_{f_2} - \neg QoS_{Pf_2} = QoS_{Pf_3} - \alpha_A\beta_{d_2} - \emptyset_{p_2} + tm_{f_2}F} \\
\vdots \\
\in^{X^{TM-1}} = \boldsymbol{MLO_{TM-1} + tm_{f_{TM-1}} - \neg QoS_{Pf_{TM-1}} = QoS_{Pf_{TM-1}} - \alpha_A\beta_{d_{TM-1}} - \emptyset_{p_{TM-1}} + tm_{f_{TM-1}}F}
\end{array}\right\} \quad (11)$$

The Eqs. (10) and (11) are required by verifying the constraints $\neg QoS_{Pf} = (IoT^u - f)QoS_{Pf}$ and the service flexibility $F = 1$ or $F = 0$ are analyzed in a step-by-step manner for balancing energy conservation and resource allocation with better QoS. If $f = 0$ and then $\in^{X^{TM-1}} = QoS_{Pf} - \alpha_A\emptyset_p - \neg QoS_{Pf}$ is the last decision. Instead, $f = 1$, then $F = 0$, and hence the decision on energy saving is constructed using resource allocation and revocation for optimal resource sharing.

For this decision, $R_{Shr} = \left(\frac{F - \alpha_A \times \emptyset_p}{IoT^U}\right)$ is the energy-saving resource sharing whereas the maximum wait time of the service demands is used for decisions on delay-less resource sharing. In this case, is not applicable for the first user request processing as in above Eqs. (7) and (8) because it relies on all heterogeneous paradigms in different TM intervals. Therefore, the optimal resource sharing across various paradigms with local decisions over the allocation is observed by the federated learning and hence it remains unchanged. The MLO process is diagrammatically illustrated in Figure 4.

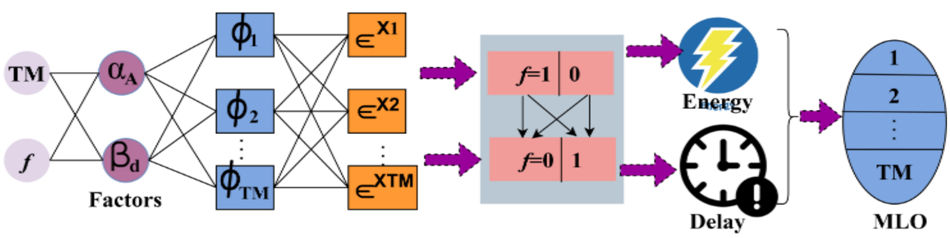


Figure 4. MLO process illustration

Table 3. MLO process for delay and energy constraints

Delay Constraint	Energy Constraint
Input: tm_f, β_d	Input: α_A, L
Step 1: $\forall\ USr_{Dm}\ do$ {	Step 2: $\forall\ \alpha_A\ d\{$
Step 2: Compute $7Qos_{pf}\ \forall TM$	Step 2: Compute $tm_f \forall\ TM$
Step 3: If $\{(IoT^U - f) = 7QoS_{Pf}\}$ then	Step 3: If $\{F = 1\}$ then
Step 4: Compute MLO_{TM} using Eq. (7) until $\phi_{PTM}\beta_d = \max\{R_{Q_{TM}}\}$	Step 4: Compute $\in^{x^{TM}}$ using Eq. (8)
Step 5: Compute MLO_{TM-1} using Eq. (9)	Step 5: Compute MLO_{TM} using Eq. (9)
Step 6: If $\{(tm_f.F) = (7QoS_{pf} - Qos_{pf}) = 0$ then	Step 6: If $\{MLO_{TM} = IoT^U.Qos_{pf} \forall\ (tm+1)$ then
Step 7: Update $r_{S_{TM-1}} = \left(r_{Q_{TM-2}} - \phi_d.\beta_d\right)$	Step 7: Compute $\in^{x^{TM-1}}$
Step 8: $t_{mf} = tM - r_{S_{TM-1}}$	Step 8: If $\{\in^{x^{TM-1}} \sim \in^{x^{TM}}) = 0$ then
Step 9: } end if	Step 9: Update $7QoS_{TM} = QoS_{TM-1}$
Step 10: } end if	Step 10: Update $\in^{x^{TM}}$ using Eq. (10)
Step 11: Update $F = 1$	Step 11: } end if
Step 12: } end for	Step 12: Update $TM = TM + 1$
	Step 13: } end if
	Step 14: } end if
	Step 15: } end for

The inputs TM and f from the initial allocation are influenced by α_A and β_d. This is validated for $\phi 1$ to ϕ_{TM} until $\in^{x^1}$ to $\in^{x^{TM}}$ be computed. The major difference between the two considerations is utilized for local decisions on $f = 1$ or $f = 0$. Contrarily the completion results of $F = 0$ or $F = 1$ are a global variation for energy and delay constraint existence. Based on the available t_m allocated for suppressing f and F the MLO outputs are tuned. The tuning relies on TM or the previous $(r_Q - \phi_P/T)$ for avoiding f. These processes form the MLO of the federated learning process (Figure 4). In Table 3, the MLO process is explained for delay and energy constraints.

4.5 Resource sharing and allocation mechanism

In this proposed hybrid energy saving and scheduling scheme, the demand analysis is pursued based on R_{Shr} on its previous processand identify the energy drain in IoT layers. If energy drain has occurred in any instances $f > IoT^u$, then the processing is discarded to prevent lag, failures, and forging devices in the IoT environment. The IoT assimilates heterogeneous paradigmsand generates an alert to the service providers and users to ensure appropriate actions to identify the failures. The demandof the IoT users relies on the energy, delay, and applications are detected using the learning process and then local decisions over allocations are performed in T intervals. This continuous demand analysis prevents failures and lag by processing incorrect data/unnecessary requests whereas, the response rate and waiting time are high. The decisions are adaptable and it ensures delay-less resource sharing within the IoT platform. However, the chance for sensitive data modification in the IoT environment is high and hence the end-to-end authentication is performed for secured resource sharing and allocation.

Demand analysis in IoT-assisting heterogeneous paradigms is becoming unmanageable based on increasing user requirements, energy, and applications. Amid the challenges in this proposed scheme, QoS and service availability and user density are the available demands satisfied by the IoT users in all the layers. The layers of users from diverse services are monitored and their energy can be saved through multi-level federated learning. Therefore, regardless of the user requests, service availability, and density of the users, flexibility in resource utilization and service responses is an important consideration here. The proposed scheme is focusing on this consideration by providing pervasive services for the users through optimal resource allocation and sharing. In this proposal, flexibility is administrable for IoT users and their service handling with the available service providers is analyzed for identifying energy drain occurrence. The IoT users used their resources through requests and responses by the applications. HES3 operates between IoT users and technological paradigms. In this scheme, resource allocation and energy conservation for the available resources are computed for achieving optimal resource sharing for the varying users and resources. Further, this proposed scheme aims to provide delay-less resource sharing and maximize resource utilization. The proposed scheme functions in two forms service handling and resource allocation. The optimal resource allocation is different for centralized and de-centralized scheduling, to handle different services for IoT users.

$$\left.\begin{matrix} \max\limits_{i\in TM} \emptyset_p\ \forall\ r_Q = r_S \\ \text{and} \\ \min\limits_{j\in r_S} F\ \ \forall\ r_Q \end{matrix}\right\} \tag{12}$$

The overall requests and user services are admittable for processing in IoT. Resource allocation and energy conservation are reliable based on user density and service availability of future requests. From these instances, the classification of energy saving and delay-less resource sharing is essential to identify decentralized scheduling in an IoT environment. Figure 5 presents the resource allocation based on energy and delay constraints.

The resource sharing and allocation are determined using tm_f and TM computed at the end of Usr_{Dm}. The proposed Scheme segregates the energy and delay demands based on $IoT^U, f)$ such that $f = 0$ or 1 is balanced with $F = 0$ or 1. Therefore, the learning process relies on MLO until $max_{i\in TM} \forall\ r_Q$ is achieved. Thus, if a r_Q is pending then it relies on tm_f and TM for sharing else TM is alone utilized (Figure 5). The demanding requirement is identified based on the energy, delay, and applications using federated learning for improving resource utilization and allocation. The final decision is adapted for service assigning for the available resources that are performable using the learning process.

Later, depending upon the user demands classification, resource scheduling, and allocation is the augmenting factor and reducing failures. From the above discussion, a few metrics are self-analyzed in this section. First, L classification before and after constraints for r_Q is analyzed in Figure 6.

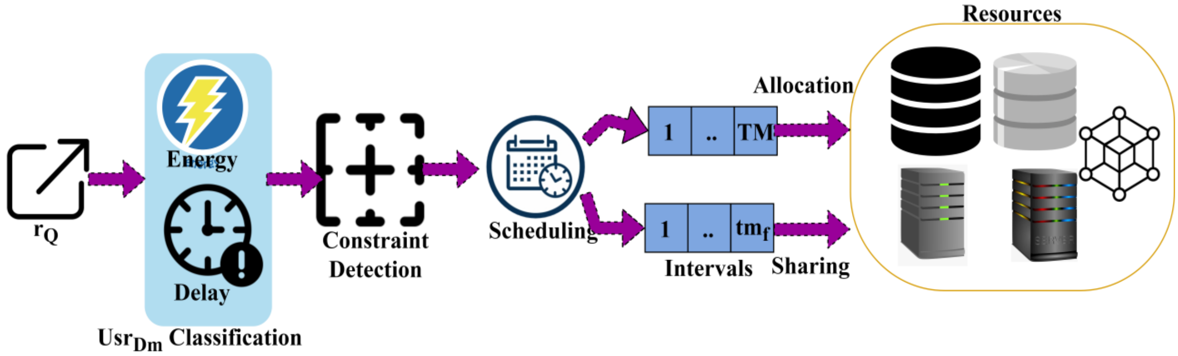


Figure 5. Resource allocation based on energy and delay constraints

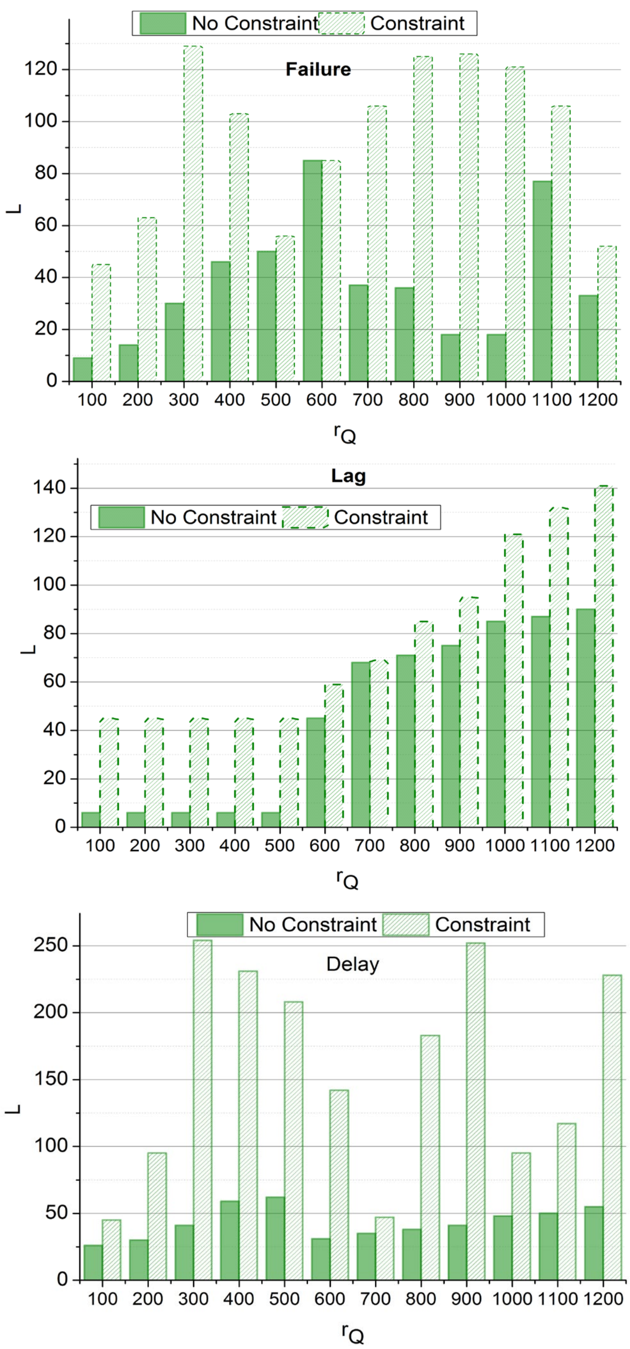


Figure 6. L analyses

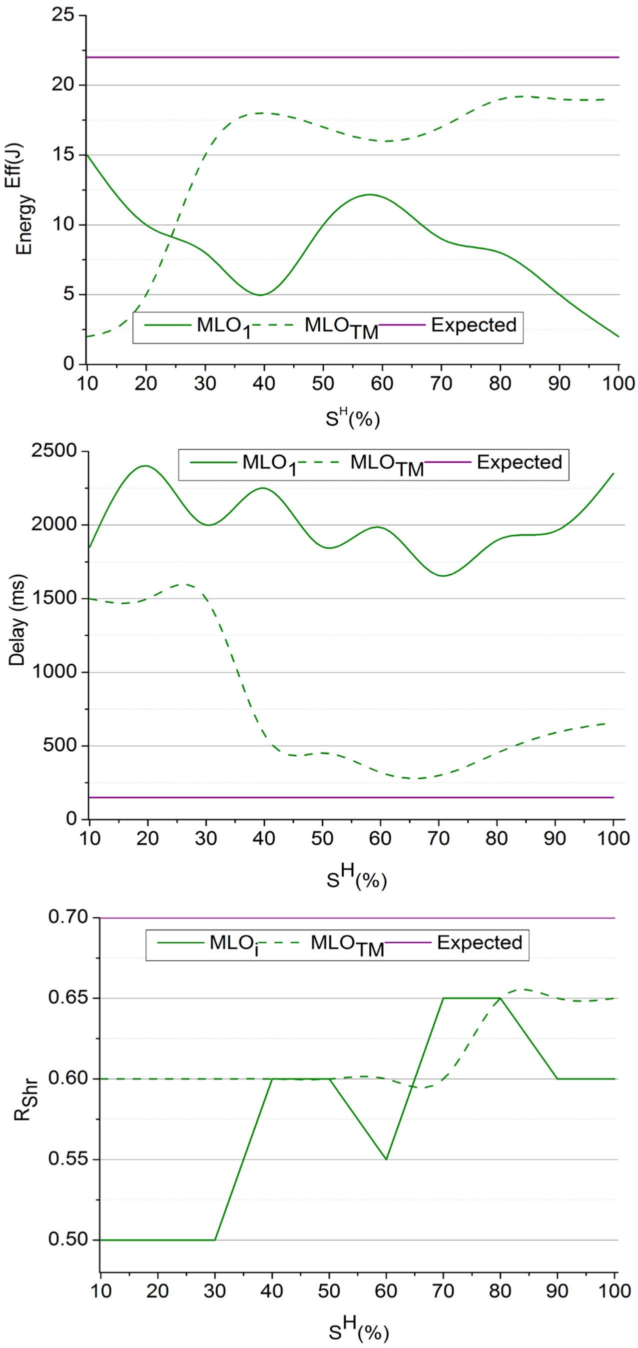


Figure 7. Energy and delay continuous analyses

The L analyses for failure, lag, and delay are presented in Figure 7. The L due to energy are classified under failure and lag; L due to time are lag and delay. The MLO, to MLO_{TM} are used for suppressing the constraints using FL. The previous local knowledge of $(IOT^U, f) :: TM$ and new tm_f allocation determining the constraint suppression. This is pursued based on the available r_Q that is applicable for TM and tm_f for allocation and sharing respectively. Pursued by this analysis, the energy efficiency and delay reduction for the S^H is analyzed using Figure 7 representation.

5. RESULTS AND DISCUSSION

This section presents a comparative analysis using resource allocation, energy conservation, energy utilization, delay, and scheduling rate metrics. The # users and # resources are varied from 10 and 120, and 1 and 16 respectively. The experiments are performed using the ONE simulator with the above setting and 100Mbps bandwidth for different user applications. In the experiment, a small city environment considering heterogeneous applications such as navigation, direction, search engines, etc. is considered. The service providers are distributed for file, data, multimedia, map, and storage-based applications. The methods considered with the proposed scheme for the comparative study are MQDS [24], LPM-LSTM [25], and QM-FF+PSO [33].

5.1 Resource allocation

In Figure 8, the energy saving and scheduling, and service handling in IoT assimilate wireless paradigms increasing resource access based on user demands, and does not provide pervasive services between the users and service providers in different time intervals. The wireless networks require service availability and user density is compared with the previous data for balancing resource allocation and energy conservation. The lag, delay, and failures are identified from the QoS performance of wireless paradigms satisfying both the constraints of $IoT^U :: TM$ and $(IoT^U, f) :: TM$ for demand analysis from the observed data in IoT layers. The user demands are identified using resource allocation and revocation based on the $(IoT^u \times \emptyset_p)$ and $\urcorner QoS_{Pf} = (IoT^u - f)$ achieves successive responses and maximizes resource allocation for the available services, preventing failures. Therefore, further service handling in IoT for optimal resource sharing is achieved. Both cases satisfy high resource allocation using federated learning based on energy saving and delay less resource sharing is identified from the wireless network the energy utilization is reduced and improving resource allocation due to adaptable decisions.

5.2 Energy conservation

This proposed scheme achieves high energy conservation for wireless networks-based resource access and QoS relies on energy, resource scheduling, and optimal traffic management in different time intervals is aided for identifying the energy drains (Figure 9). The lag, delay, and failure are mitigated using the condition $f > IoT^u$ for maintaining QoS with continuous service handling in IoT for improving energy conservation based on increasing user density and service availability through multi-level federated learning. The user demands are identified using federated learning and local decisions over the multiple distribution process due to the maximum wait time of the service demands in IoT. This waiting time is computed for making decisions on delay-less resource sharing and thereby reducing energy utilization and delay is accounted for based on both the constraints $IoT^u \in IoT^U$ and f for processing timed response and high energy conservation for optimal resource allocation is achieved. Therefore, if the energy drain occurs in any sequence, then that network is discarded for reducing delay and verifying the user response and energy scheduling depends on other computing factors in the proposed scheme, and hence, the energy conservation is high.

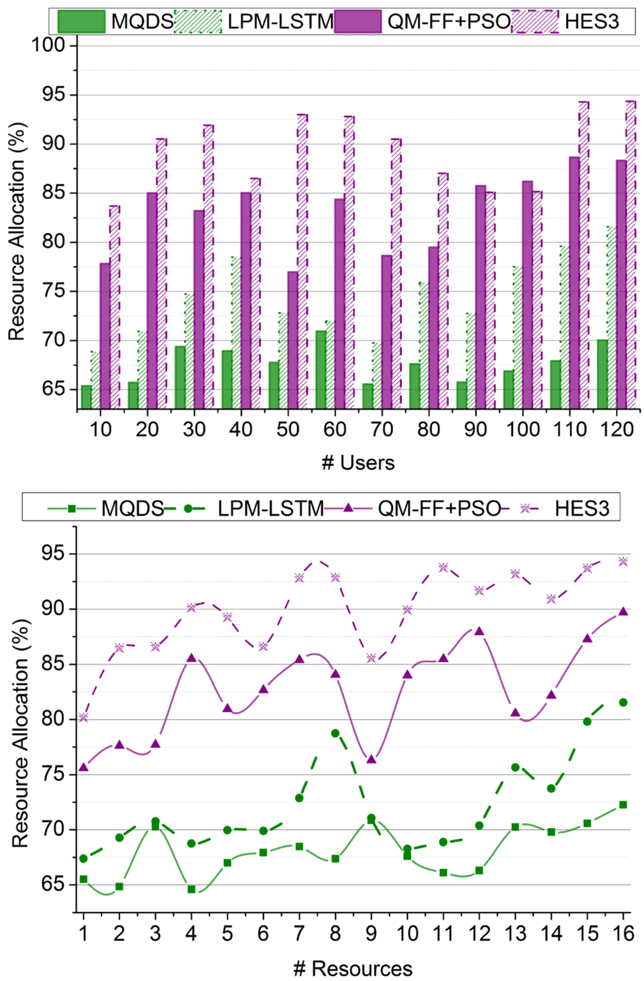
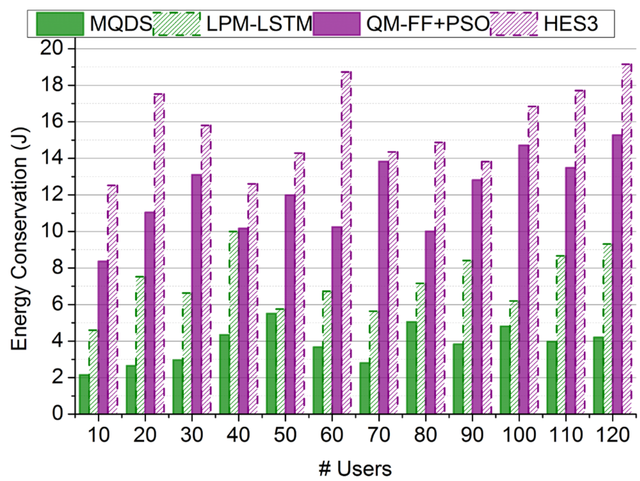


Figure 8. Resource allocation



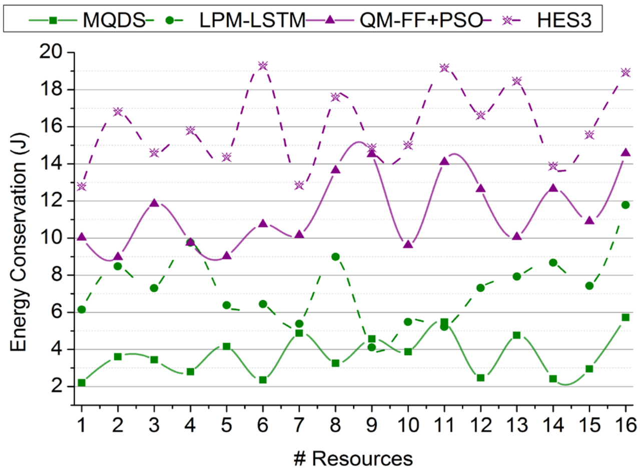


Figure 9. Energy conservation

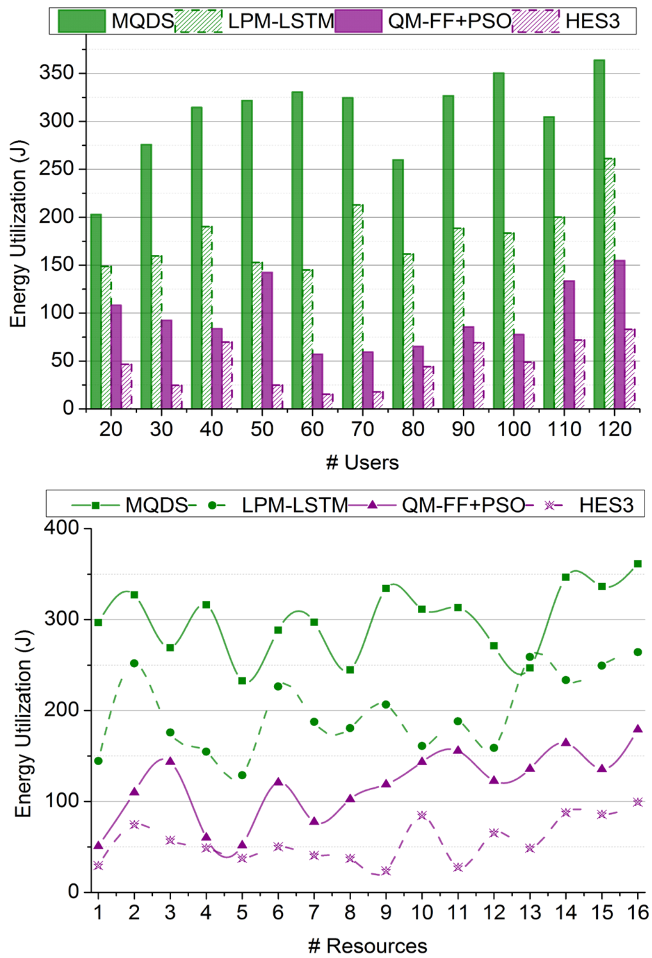


Figure 10. Energy utilization

5.3 Energy utilization

In Figure 10, the hybrid energy saving and scheduling scheme is aided for reliable QoS performance of heterogeneous paradigms associated with IoT and is identified for optimal resource allocation and sharing in any instance. The current user density and service availability are analyzed using federated learning for differentiating energy-based resource sharing and delay-based resource sharing for QoS performance. The energy drain is considered for improving resource allocation and distribution for IoT user services. The observed data from the IoT environment is analyzed and QoS_{Pf} are used to buildup the demands for ensuring optimal resource sharing and scheduling based onthe QoS performance of wireless paradigms in T. Both the constraints of $IoT^U :: TM$ and $(IoT^U, f) :: TM$ balances resource allocation and energy conservation with better QoS. This delay-less resource sharing is addressed using service handling and the service response timing is computed for identifying the accurate and appropriate user demands and then maximizing resource allocation. The wireless networks are analyzed and the learning is trained using the available resources and the constraints observed from the different processes in IoT. Based on the flexibility, energy saving, and scheduling are achieved in which the proposed scheme satisfies less energy utilization.

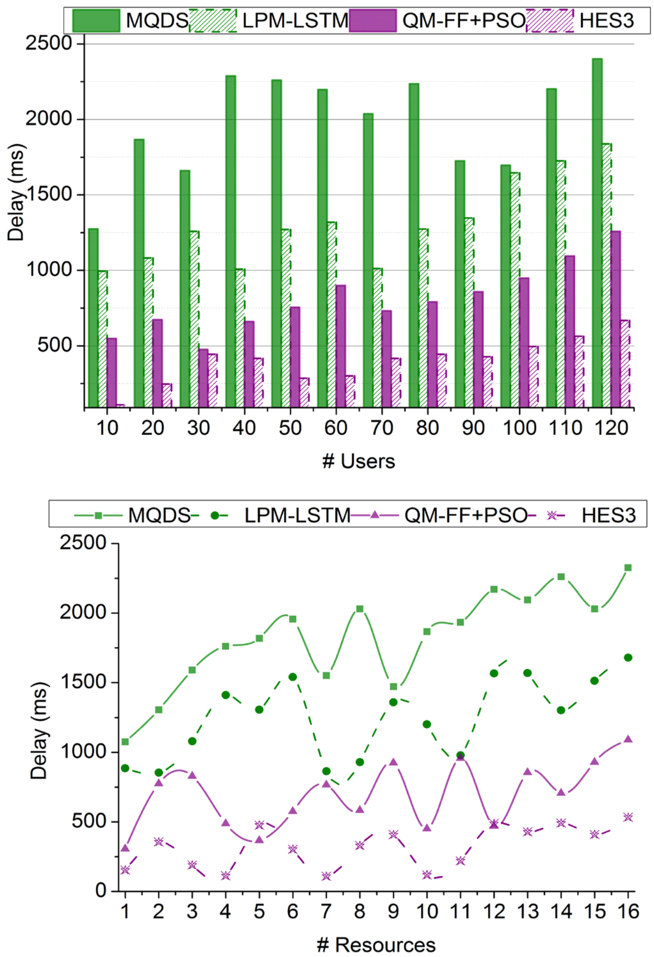


Figure 11. Delay

5.4 Delay

The lag, delay, and failure identification and demand analysis in IoT assimilate heterogeneous paradigms is illustrated in Figure 11. In this proposed scheme satisfies less energy drain and delay by computing the user density and service availability relies on delay-less resource sharing in different time intervals and the decisions are adaptable based on energy saving. In this energy drain and delay-less resource sharing detection from the available services. In the above performance hindering constraints of $IoT^U :: TM$ and $(IoT^U, f) :: TM$ used to identify the energy drain in QoS with IoT layers used regardless of user density and service availability at any time interval TM. The user density is controlled using multi-level service handling depending upon the demands and requirements of the user in IoT whereas the maximum wait time of the service demands used for making decisions is preceded using Eqs. (8)-(11) estimations. This sequential demand analysis in wireless networks reduces lag, delay, and failures as in Eq. (12). Therefore, the energy drain is high compared to the other factors in service handling. Based on this consecutive analysis, the delay is less with better QoS.

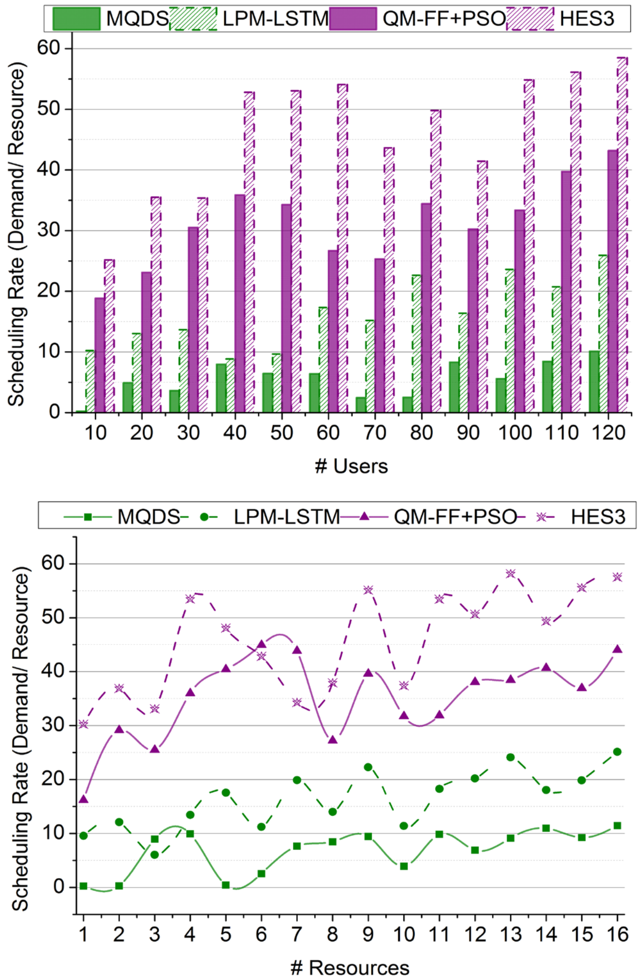


Figure 12. Scheduling rate

5.5 Scheduling rate

The wireless networks assimilated paradigms administered based on energy, delay, and application for improving optimal resource sharing and management with two decisions for preventing lag, delay, failures, and energy drain occurrence is represented in Figure 12. In this proposed energy saving and scheduling scheme, the decisions can be changed for service demands and resource allocation require QoS performance of all services in IoT platform. The high energy conservation satisfies fewer failures and waiting times over the different distribution processes using multi-level federated learning. The user density and flexibility of the resources are analyzed by the heterogeneous paradigms for differentiating the centralized and de-centralized scheduling for time. Hence, this differentiation is pursued by identifying the condition either satisfied this case $f \neq 0$ or $f = 0$ in all sequences using federated learning. The FL classifies energy-saving-based demands and delay-less-based demands such that R_{Shr} are defined for all IoT users concerning time intervals. Based on the hybrid energy saving and scheduling process, resource scheduling is less in this scheme. Tables 4 and 5 present the comparative analysis results for the varying users and resources.

The proposed scheme improves resource allocation, energy conservation, and scheduling rate by 14.38%, 8.25%, and 9.15% individually. Besides the energy utilization and delay are lowered by 11.27% and 10.59% correspondingly (Table 4).

Table 4. Comparative analysis results for # users

Metrics	MQDS	LPM-LSTM	QM-FF+PSO	HES3
Resource Allocation (%)	70.02	81.59	88.25	94.357
Energy Conservation (J)	4.2	9.31	15.27	19.145
Energy Utilization (J)	363.79	261.17	154.71	82.998
Delay (ms)	2400.5	1837.1	1258.4	668.098
Scheduling Rate (Demand/ Resource)	10.11	25.92	43.17	58.499

Table 5. Comparative analysis results for # resources

Metrics	MQDS	LPM-LSTM	QM-FF+PSO	HES3
Resource Allocation (%)	72.26	81.54	89.72	94.315
Energy Conservation (J)	5.72	11.78	14.57	18.921
Energy Utilization (J)	361.4	264.22	179.21	99.27
Delay (ms)	2257.2	1680.4	1089.2	526.014
Scheduling Rate (Demand/ Resource)	11.44	25.12	44.03	57.523

For the varying resources proposed scheme improves resource allocation, energy conservation, and scheduling rate by 13.14%, 7.25%, and 8.88% individually. Besides the energy utilization and delay are lowered by 10.5% and 11.44% correspondingly (Table 5).

6. CONCLUSION

In this article, the hybrid energy saving and scheduling scheme for QoS enhancement in IoT is introduced and discussed. The proposed scheme is supported using federated learning for classifying energy and delay-based constraints. The classified constraints are suppressed using optimal resource sharing and allocations based on the user demands. In this process, the local decisions are performed using distributed federated learning process for preventing unnecessary energy consumption/ wastage. Besides the local decisions on resource sharing and allocation are performed by addressing the maximum and minimum wait times for different user demands. Considering the pervasive nature of the network, adaptable decisions of scheduling and resource allocations are performed. Precisely the goal is to improve resource sharing and request responses avoiding energy failures and high response delays. The learning process recurrently identifies the chances of energy failures and delay improvements through user demand satisfaction and constraint analysis. Therefore, for the varying resources proposed scheme improves energy conservation by 7.25%, and reduces delay by 11.44%. The future work is planned to incorporate multi-objective improvements based on allocation constraints and offloading issues due to request-to-response mapping. In particular, the high-density factors and their influence on QoS retention are also planned to be considered.

REFERENCES

[1] Hou, D., Lin, C.C., Katal, A., Wang, L. (2020). Dynamic forecast of cooling load and energy saving potential based on Ensemble Kalman Filter for an institutional high-rise building with hybrid ventilation. Building Simulation, 13: 1259-1268. https://doi.org/10.1007/s12273-020-0665-7

[2] Xie, C.C., Hua, Q.Z., Zhao, J.Z., Guo, R.J., Yao, H.Y., Guo, L.X. (2022). Research on energy saving technology at mobile edge networks of IoTs based on big data analysis. Complex & Intelligent Systems, 8: 3943-3952. https://doi.org/10.1007/s40747-022-00735-4

[3] Dong, Y.Q., Fan, P.Y., Letaief, K.B. (2020). Energy harvesting powered sensing in IoT: Timeliness versus distortion. IEEE Internet of Things Journal, 7(11): 10897-10911. https://doi.org/10.1109/JIOT.2020.2990715

[4] Abbas, M.T., Grinnemo, K.J., Eklund, J., Alfredsson, S., Rajiullah, M., Brunstrom, A., Caso, G., Kousias, K., Alay, Ö. (2022). Energy-saving solutions for cellular Internet of Things–A survey. IEEE Access, 10: 62073-62096. https://doi.org/10.1109/ACCESS.2022.3182400

[5] Shah, S., Jadeja, A., Doshi, N. (2022). An analytical survey of energy efficiency in IoT paradigm. Procedia Computer Science, 210: 283-288. https://doi.org/10.1016/j.procs.2022.10.151

[6] Wu, F. (2021). An energy-saving transmit method between Internet of Things device and base station under fading channel. Wireless Personal Communications, 119: 1231-1249. https://doi.org/10.1007/s11277-021-08259-9

[7] Lekidis, A., Katsaros, P. (2021). Energy characterization of IoT systems through design aspect monitoring. International Journal on Software Tools for Technology Transfer, 23: 765-781. https://doi.org/10.1007/s10009-020-00598-5

[8] Zhang, W., Yue, M. (2021). The application of building energy management system based on IoT technology in smart city. International Journal of System Assurance Engineering and Management, 12: 617-628. https://doi.org/10.1007/s13198-021-01054-6

[9] Abu-Baker, A., Alshamali, A., Shawaheen, Y. (2021). Energy-efficient cluster-based wireless sensor networks using adaptive modulation: Performance analysis. IEEE Access, 9: 141766-141777. https://doi.org/10.1109/ACCESS.2021.3118672

[10] Zhao, L., Qu, S.C., Zeng, J.H., Zhao, Q.Y. (2020). Energy-saving and management of telecom operators' remote computer rooms using IoT technology. IEEE Access, 8: 166197-166211. https://doi.org/10.1109/ACCESS.2020.3022641

[11] Luo, S.Q., Chen, X., Zhou, Z., Yu, S. (2021). Fog-enabled joint computation, communication and caching resource sharing for energy-efficient IoT data stream processing. IEEE Transactions on Vehicular Technology, 70(4): 3715-3730. https://doi.org/10.1109/TVT.2021.3062664

[12] Ansere, J.A., Kamal, M., Gyamfi, E., Sam, F., Tariq, M., Mohammed, A. (2020). Energy efficient resource optimization in cooperative Internet of Things networks. Internet of Things, 12: 100302. https://doi.org/10.1016/j.iot.2020.100302

[13] Wang, K. (2021). Energy-efficient resource allocation optimization algorithm in industrial IoTs scenarios based on energy harvesting. Sustainable Energy Technologies and Assessments, 45: 101201. https://doi.org/10.1016/j.seta.2021.101201

[14] Sun, J.S., Zhu, T., Wozniak, M. (2022). Intelligent spacing selection model under energy-saving constraints for the selection of communication nodes in the Internet of Things. Mobile Networks and Applications, 27: 628-636. https://doi.org/10.1007/s11036-021-01828-z

[15] Bomgni, A.B., Sindjoung, M.L.F., Tchibonsou, D.K., Velempini, M., Myoupo, J.F. (2022). NESEPRIN: A new scheme for energy-efficient permutation routing in IoT networks. Computer Networks, 214: 109162. https://doi.org/10.1016/j.comnet.2022.109162

[16] Hsu, C.W., Hsu, Y.L., Wei, H.Y. (2020). Energy-efficient edge offloading in heterogeneous industrial IoT networks for factory of future. IEEE Access, 8: 183035-183050. https://doi.org/10.1109/ACCESS.2020.3029253

[17] Imran, Iqbal, N., Kim, D.H. (2022). IoT task management mechanism based on predictive optimization for efficient energy consumption in smart residential buildings. Energy and Buildings, 257: 111762. https://doi.org/10.1016/j.enbuild.2021.111762

[18] Orsini, G., Posdorfer, W., Lamersdorf, W. (2021). Saving bandwidth and energy of mobile and IoT devices with link predictions. Journal of Ambient Intelligence and Humanized Computing, 12: 8229-8240. https://doi.org/10.1007/s12652-020-02557-z

[19] Nguyen, D.C., Ding, M., Pathirana, P.N., Seneviratne, A., Li, J., Poor, H.V. (2021). Federated learning for Internet of Things: A comprehensive survey. IEEE Communications Surveys & Tutorials, 23(3): 1622-1658. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9415623.

[20] McMahan, H.B., Moore, E., Ramage, D., Hampson, S., Aguera y Arcas, B. (2017, April). Communication-efficient learning of deep networks from decentralized data. In International Conference on Artificial Intelligence and Statistics, pp. 1273-1282. http://proceedings.mlr.press/v54/mcmahan17a/mcmahan17a.pdf.

[21] Castillo-Atoche, A., Vázquez-Castillo, J., Osorio-De-La-Rosa, E., Heredia-Lozano, J.C., Viñas, J.A., Cetina, R.Q., Estrada-López, J.J. (2021). An energy-saving data statistics-driven management technique for bio-powered indoor wireless sensor nodes. IEEE Transactions on Instrumentation and Measurement, 70: 1-10. https://doi.org/10.1109/TIM.2021.3063187

[22] Tong, Z., Cai, J.H., Mei, J., Li, K.L., Li, K.Q. (2022). Dynamic energy-saving offloading strategy guided by Lyapunov optimization for IoT devices. IEEE Internet of

Things Journal, 9(20): 19903-19915. https://doi.org/10.1109/JIOT.2022.3168968
[23] Qi, N., Miridakis, N.I., Xiao, M., Tsiftsis, T.A., Yao, R.G., Jin, S. (2020). Traffic-aware two-stage queueing communication networks: Queue analysis and energy saving. IEEE Transactions on Communications, 68(8): 4919-4925. https://doi.org/10.1109/TCOMM.2020.2988278
[24] You, X.D., Sun, D.W., Lv, X.Q., Gao, S., Buyya, R. (2022). MQDS: An energy saving scheduling strategy with diverse QoS constraints towards reconfigurable cloud storage systems. Future Generation Computer Systems, 129: 252-268. https://doi.org/10.1016/j.future.2021.11.025
[25] Li, D., Lan, M., Hu, Y. (2022). Energy-saving service management technology of Internet of Things using edge computing and deep learning. Complex & Intelligent Systems, 8: 3867-3879. https://doi.org/10.1007/s40747-022-00666-0
[26] Feng, L., Zhou, Y., Liu, T., Que, X.Y., Yu, P., Hong, T., Qiu, X.S. (2021). Energy-efficient offloading for mission-critical IoT services using EVT-embedded intelligent learning. IEEE Transactions on Green Communications and Networking, 5(3): 1179-1190. https://doi.org/10.1109/TGCN.2021.3072140
[27] Liu, Y.T., Zhang, X.N., Zeng, Z.H., Yu, S. (2024). FedEco: Achieving energy-efficient federated learning by hyperparameter adaptive tuning. IEEE Transactions on Cognitive Communications and Networking, 10(6): 2311-2324. https://doi.org/10.1109/TCCN.2024.3408416
[28] Liaq, M., Ejaz, W. (2024). Computational offloading and delay minimization for UAV-aided edge federated learning. In ICC 2024-IEEE International Conference on Communications, Denver, CO, USA, pp. 1292-1297. https://doi.org/10.1109/ICC51166.2024.10622696
[29] Samikwa, E., Di Maio, A., Braun, T. (2024). DFL: Dynamic federated split learning in heterogeneous IoT. IEEE Transactions on Machine Learning in Communications and Networking, 2: 733-752. https://doi.org/10.1109/TMLCN.2024.3409205
[30] Wang, Y., Yang, K., Wan, W.X., Zhang, Y.T., Liu, Q. (2021). Energy-efficient data and energy integrated management strategy for IoT devices based on rf energy harvesting. IEEE Internet of Things Journal, 8(17): 13640-13651. https://doi.org/10.1109/JIOT.2021.3068040
[31] Chen, H., Qin, H., Chen, W.M., Li, N., Wang, T., He, J.X., Yang, G.L., Peng, Y. (2023). BMS: Bandwidth-aware multi-interface scheduling for energy-efficient and delay-constrained gateway-to-device communications in IoT. Computer Networks, 225: 109645. https://doi.org/10.1016/j.comnet.2023.109645
[32] Kaur, R., Schaye, C., Thompson, K., Yee, D.C., Zilz, R., Sreenivas, R.S., Sowers, R.B. (2021). Machine learning and price-based load scheduling for an optimal IoT control in the smart and frugal home. Energy and AI, 3: 100042. https://doi.org/10.1016/j.egyai.2020.100042
[33] Kim, J., Park, K., Yang, H., Ha, S. (2021). Adaptive run-time scheduling of dependent services for service-oriented IoT systems. Design Automation for Embedded Systems, 25: 265-295. https://doi.org/10.1007/s10617-021-09253-x
[34] Abdul-Qawy, A.S.H., Nasser, A.B., Guroob, A.H., Saad, A.M.H.Y., Alduais, N.A.M., Khatri, N. (2021). TEMSEP: Threshold-oriented and energy-harvesting enabled multilevel SEP protocol for improving energy-efficiency of heterogeneous WSNs. IEEE Access, 9: 154975-155002. https://doi.org/10.1109/ACCESS.2021.3128507
[35] Li, Y., Zhao, X.H., Liang, H. (2020). Throughput maximization by deep reinforcement learning with energy cooperation for renewable ultradense IoT networks. IEEE Internet of Things Journal, 7(9): 9091-9102. https://doi.org/10.1109/JIOT.2020.3002936
[36] Mahmoudi, Y., Zioui, N., Belbachir, H. (2022). A new quantum-inspired clustering method for reducing energy consumption in IOT networks. Internet of Things, 20: 100622. https://doi.org/10.1016/j.iot.2022.100622
[37] Kang, J., Kim, J., Kim, M., Sohn, M. (2020). Machine learning-based energy-saving framework for environmental states-adaptive wireless sensor network. IEEE Access, 8: 69359-69367. https://doi.org/10.1109/ACCESS.2020.2986507
[38] Joshi, U., Kumar, R. (2022). Reinforcement learning based energy efficient protocol for wireless multimedia sensor networks. Multimedia Tools and Applications, 81: 2827-2840. https://doi.org/10.1007/s11042-021-11387-w
[39] Savazzi, S., Nicoli, M., Rampa, V. (2020). Federated learning with cooperating devices: A consensus approach for massive IoT networks. IEEE Internet of Things Journal, 7(5): 4641-4654. https://doi.org/10.1109/JIOT.2020.2964162