IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Traitement du Signal
Vol. 43, No. 1, February, 2026, pp. 91-102
Journal homepage: http://iieta.org/journals/ts

Appended Virtual Resource Migration Scheme for Application-Specific IoT Backhauled Wireless Sensor Networks

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https://doi.org/10.18280/ts.430107

Received: 12 February 2025
Revised: 21 August 2025
Accepted: 16 October 2025
Available online: 28 February 2026

Keywords:
federated learning, IoT, resource migration, virtualization, Wireless Sensor Networks

ABSTRACT

The Internet of Things (IoT) paradigm is backed by ad-hoc Wireless Sensor Networks (WSN) to provide unremitting connectivity between users and resources. The application demands and service responses are poised through optimal Wireless Sensor (WS) node selection and connectivity accomplishments. To ensure an ideal service quality for IoT users, this article introduces a Demand-appended Virtual Expansion and Migration (DVEM) Scheme. The proposed scheme inherits the virtualization and migration concepts with the advantages of WSN to improve the application response in demand-centric scenarios. In this proposal, the federated learning (FL) paradigm is included to validate decisions on node/ resource expansion (virtualization) and migration. The sensor node connectivity and high demand constraints are accounted for by the federated learning to provide service-oriented decisions on expansion and migration. The process is concurrently repeated for both expansion and migration at different locations to reduce response time with high resource utilization. This proposed scheme improves resource utilization by 13.526% by providing 11.93% of virtualization support to reduce response time by 11.46% for the maximum user demands handled.

1. INTRODUCTION

In the Internet of Things (IoT)-based Wireless Sensor Network (WSN) applications, resource virtualization provides a virtual representation of the physical resources so that multiple applications can run on the same resource without interference [1]. The users profit from the optimum exploitation of resources, reducing the costs for the physical resource owner [2]. Virtualization makes real-time changes of parameters possible, ensuring scalability and flexibility, while abstraction simplifies the deployment and management of complex [3] IoT systems. It will ensure that the reconfiguration of virtual resources en-roots fault handling and load balancing efficiently [4]. Virtualization, hence, ensures that the fundamental principle regarding scalability and flexibility is met. The framework allows load balancing efficiently since the virtual resources can easily be reconfigured [5]. Virtualization also provides energy-efficient operations since it allows energy to be fed only when needed. It thus makes efficient resource management in IoT WSNs feasible [6].

Resource migration is a process of adjusting resources to the changing demands of the user. Processing power, storage, and bandwidth are adjusted correspondingly for optimum performance [7]. Resources are migrated from one node to another to ensure efficiency within the network. Effective management minimizes downtime and loss of data, hence facilitating the delivery of services uninterrupted [8]. The network dynamically responds to varied loads that vary, thus avoiding bottlenecks. Predictive algorithms initiate resource transfers to avoid congestion [9]. The distribution of workload through load balancing across the network avoids overloads on certain nodes. The process allows the network to respond in a dynamic manner due to varying loads [10]. Predictive algorithms of resource needs are helpful in proactively initiating transfers. It ensures resources are at the right place at the right time. Resource migration also facilitates load balancing efficiently across a network [11].

Machine learning (ML) can enhance resource virtualization and migration by analyzing past data to project future network conditions. Such a type of optimization in resource allocation determines the trends of patterns in traffic and resource use and proactively readjusts resources [12, 13]. Fault detection is improved, and it initiates resource migration for the maintenance of stability. It achieves energy efficiency by predicting low-activity times and downsizing resource use to prolong battery life in the case of sensor nodes [14]. Adaptive learning provides optimization based on past experiences in the network. The trends of traffic and resource utilization have been identified through machine learning [15]. Such inference readjusts the resources. Predictive ability in that respect ensures proactive management. That will ensure that resources are available where needed and when required. Machine learning also ensures that the system is energy efficient. These are some of the intelligent methods that enable efficient and adaptive resource management in IoT WSNs [16, 17]. The contributions of the article are:

To discuss different works related to virtualization, resource allocation, utilization, etc., for IoT-WSN and individual networks, with their methodology

To propose a novel demand-appended virtual expansion scheme using federated learning (FL) to improve the decisions on node/ resource expansion and migration, considering the connectivity and application demand factors

To obtain the performance results of the proposed scheme using application response, virtualization rate, migration ratio, response time, and resource utilization metrics

To verify the above-metric performance by providing a comparative analysis with the selected methods disclosed in Section 2

The article's contribution is: Section 2 discusses the related works, followed by the proposed scheme and self-analysis in Section 3. Section 4 presents the experimental scenario and metric-based comparative analysis. In Section 5, the conclusion, limitations, and future scope of the proposal are presented.

2. RELATED WORKS

Hajian et al. [18] developed a load-balancing routing and virtualization mechanism using a Software-Defined Wireless Sensor Network (SDWSN). The SD network is employed here to enhance the flexibility and significance range of the systems. The developed mechanism reduces the energy consumption (EC) level in routing processes. Kim [19] proposed an adaptive multiverse resource allocation algorithm for applications. Wireless network virtualization (WNV) technology is implemented in the algorithm to minimize the traffic during the allocation process. It is used to satisfy the expectation level of the users while performing resource allocation.

Ma et al. [20] designed a virtual machine migration technique for EC optimization. The fundamental tasks are performed according to the availability of the sensor nodes. The destination nodes are calculated for migration, which eliminates the computational cost of further processes. The designed technique decreases the overall EC ratio of the systems. Haris et al. [21] developed an improved version of the study [20] for live virtual machine migration (LVM) in cloud computing (CC). A machine learning based prediction model is implemented to predict the unavailability of the resources. The iteration phrases are evaluated to get optimal data for the migration process. When compared with others, the developed method increases the reliability of the networks.

Tang et al. [22] introduced a digital twin (DT) assisted virtual network function (VNF) migration for SDN-enabled IoT networks. The introduced model uses a deep reinforcement learning (DRL) algorithm to obtain optimal strategies. The introduced model minimizes the overall EC and latency ratio during migration. An enhanced version of the study [21] is proposed by Kumar et al. [23] using a load balancing mechanism. The data analysis reduces the EC level of the networks. The proposed scheme elevates the energy efficiency range of the systems.

Othman et al. [24] introduced an evolutionary multi-objective crowding algorithm (EMOCA) for optimization in virtualized WSNs. The introduced algorithm is used to increase the accuracy level of communication services. The introduced algorithm minimizes the delay and fault ratio of WSNs. Li et al. [25] proposed a survivability mapping strategy for virtual WSNs. It is used to address the link failure rates that are presented in wireless networks. The sensor nodes perform appropriate tasks for the users. The proposed strategy improves the long-term average and decreases the latency range of the networks.

The methods discussed in previous studies [18, 23] perform load balancing with virtualization for managing the increasing demands. Especially, the integration of Wireless Sensor (WS) nodes is designed to meet the computational and response outcomes of IoT, for which virtualization [19, 24] is used. In other methods [20, 21], migration is recommended to handle such issues. However, retaining monotonous service quality through expanding or shrinking virtual resources is tedious due to load balancing. To address these problems, a novel Demand-appended Virtual Expansion and Migration (DVEM) scheme is proposed in this article. The proposed scheme is different from afore afore-mentioned methods/ techniques by handling the virtualization and migration from a resource-user perspective. The nature of the WSN nodes is designed to provide connectivity-based expansion and migration. Specifically, the indirect constraints of the sensor nodes, such as energy and mobility, are effectively balanced by deciding migration or expansion, or both stipulations, in any WSN backhauled IoT scenarios. Therefore, the motivation is initialized from the resource-constrained nature and the maximum support of the sensor nodes deployed in a demand-populated application/ service scenario.

3. PROPOSED DEMAND-APPENDED VIRTUAL RESOURCE EXPANSION-MIGRATION SCHEME

The proposed scheme is designed to increase the duration of application support based on user and resource connectivity inputs. The connected users and resource services and network processing are required from the IoT-based wireless sensor nodes (WSN), i.e., the elements of a WSN, namely the processing unit, sensing unit, power unit, and communication unit that are observed in random time intervals. The proposed scheme is presented in Figure 1.

The actual goal of this proposed scheme is to reduce the battery drain, power drops, power consumption, network routing, network speed, transmission media, network topology, scalability, and fault tolerance in analyzing individual resource constraints of detected applications. The challenging task is the virtualization and migration of discrete resource constraint-detected applications with the previous knowledge of resource constraints. The application requirements are stored as records from the previously identified instances.

3.1 Users and resources connectivity analysis

The appropriate demands of the applications are identified through wearable sensor nodes over the IoT platform. The observations from WSNs are classified as individual and groups of users and resources based on their nodes' connectivity. In this model, the battery drain is detected as an instance of wrong observations of node availability, node death, and node energy level.

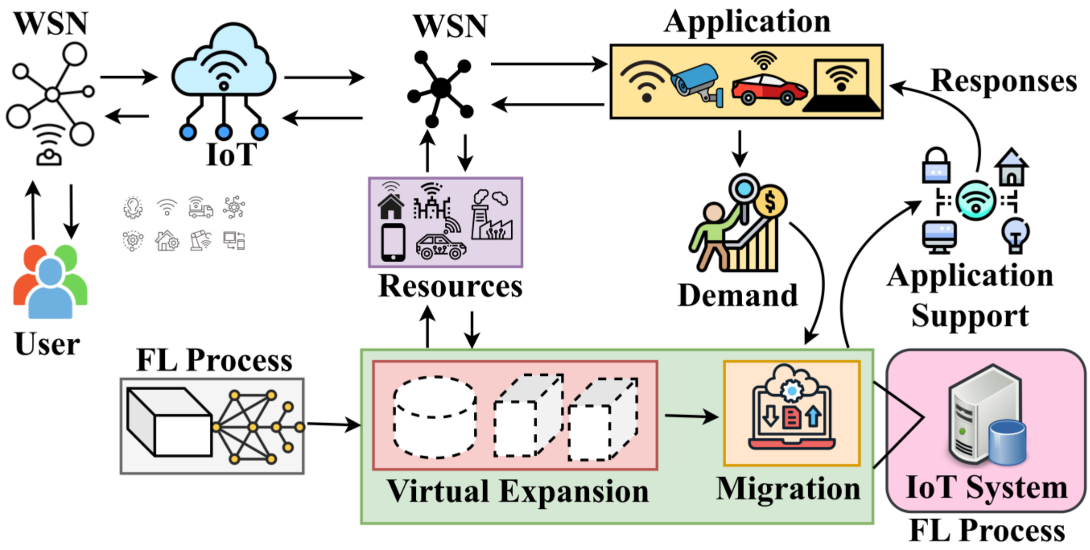

Figure 1. Proposed Demand-appended Virtual Expansion and Migration (DVEM) scheme

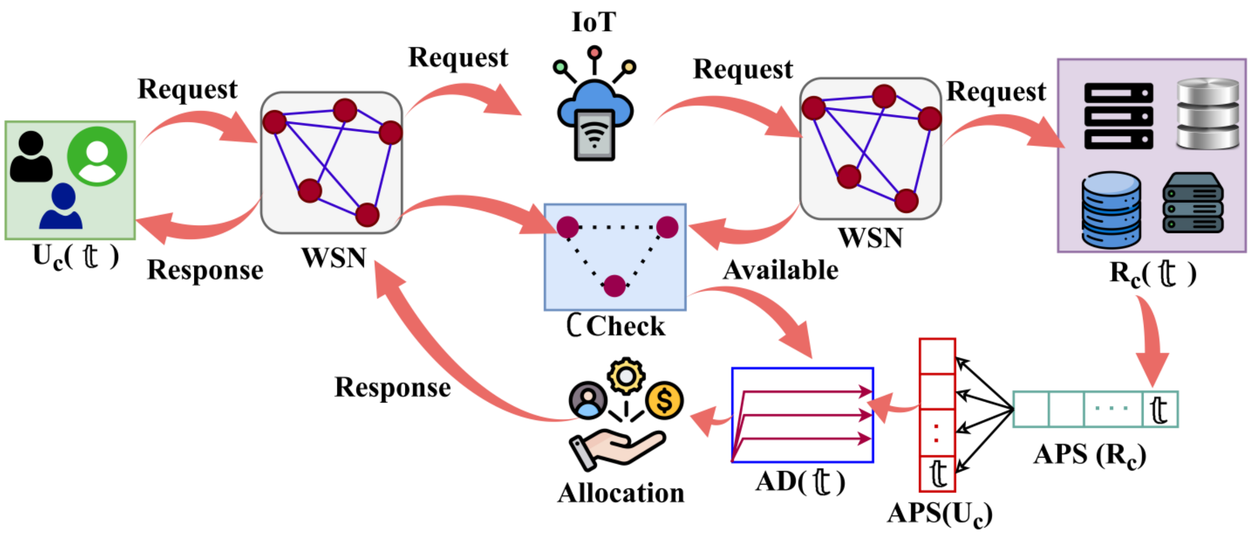

Figure 2. Application demand modeling before virtualization

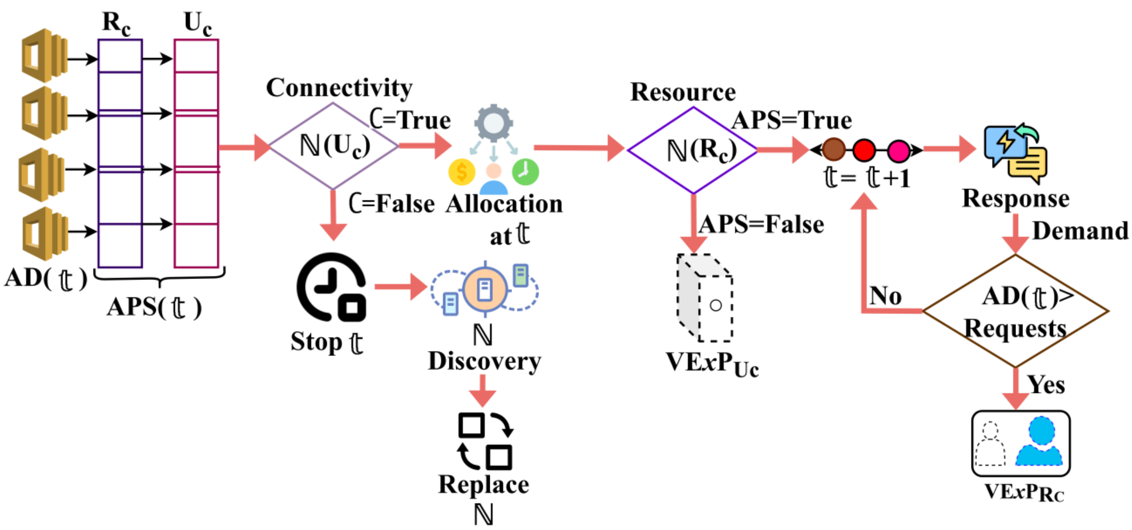

Figure 3. Virtual expansion decision process

Initial Modeling of user and resource connectivity, the variable $U_c(\mathbb{t})$ and $R_c(\mathbb{t})$ signifies the sequence of users and resources connectivity detected in a given time interval, such that the application demands $AD(\mathbb{t})$ is given as:

$$AD(\mathbb{t}) = U_c(\mathbb{t}) - \mathbb{E} * R_c(\mathbb{t}) \tag{1}$$

$$arg \min_{\mathbb{t}} \sum \mathbb{E}(\mathbb{t}) \forall\, U_c(\mathbb{t}) + R_c(\mathbb{t}) \quad (2)$$

In the above Eqs. (1) and (2), $\mathbb{E}$ is the error-causing factor, and the objective of reducing the impacting factors using the constraint $\forall\, U_c(\mathbb{t}) + R_c(\mathbb{t}) \in AD(\mathbb{t})$ is defined. The connectivity is observed from two instances, such as users (U_c) and resources (R_c). Therefore, the total connectivity is expressed as $\complement = U_c + R_c$ such that the resource connectivity is detected between the user connectivity. Where $\mathbb{N}$ symbolizes the number of nodes in a particular network, then $U_c = (\mathbb{N} \times \complement) - R_c$ is a single-node observation that is classified cluster node. Eqs. (1) and (2), the application demand at any interval $\mathbb{t}$ is computed, for which the objective of error minimization is set. The error confining condition in Eq. (2) considers the user connectivity and their demand for resources. This computation relies on precise requests and responses between the service providers and users. For a balanced response, the target of $\mathbb{E}$ is to be satisfied as defined above. Let $APS(U_c)$ and $APS(R_c)$ represent the application support/ response for all connected users and resources observed from $\mathbb{N}$ in different time intervals, and $\mathbb{E}$ are detected in all R_c that is formulated as:

$$APS(U_c) = \mathbb{N} * U_c : U_c(\mathbb{t}) + R_c(\mathbb{t}), \forall\, \mathbb{E} = 0 \quad (3)$$

And,

$$APS(R_c) = \frac{R_c}{\mathbb{N}} : \mathbb{E} - U_c(\mathbb{t}) + R_c(\mathbb{t}), \forall\, \mathbb{E} \neq 0 \quad (4)$$

As per Eqs. (3) and (4), the application responses observed from both connectivity are represented as $(\mathbb{N} \times U_c)$ and $\left(\frac{R_c}{\mathbb{N}}\right)$ are mapped to identify the application demands based on resource constraints. Now, based on the application support as in the above equation, Eq. (1) is rewritten as:

$$AD(\mathbb{t}) = APS(U_c) - APS(R_c) = [\mathbb{N} * U_c : U_c(\mathbb{t}) + R_c(\mathbb{t})] - \left[\frac{R_c}{\mathbb{N}} : \mathbb{E} - U_c(\mathbb{t}) + R_c(\mathbb{t})\right] \quad (5)$$

For the above-expanded application demands, the continuous $APS(U_c) \in \complement$ is validated on facing the first resource connectivity as in Eq. (5). This validation is performed to identify influencing factors based on virtual expression to the migration process using the FL process. Eq. (5) considers the user request and response-based demand update such that the influence of $\mathbb{E}$ through retained response or failed requests is identified. If the identification is true, then the imbalance between U_c and R_c requires additional migration/ virtualization support. The application demand modeling is illustrated in Figure 2.

The initial modeling of the $AD(\mathbb{t})$ is defined using the maximum request and response in $\mathbb{t}$. Being a conventional, pervasive access-based platform, IoT provides $U_c(\mathbb{t})$ satisfaction with $R_c(\mathbb{t})$. However, the $\mathbb{N}$ is the deciding factor for $AD(\mathbb{t})$ such that $APS(U_c) :\equiv APS(R_c)$ under $R_c(\mathbb{t})$ allocation. This $\mathbb{E}$ is defined (identified) by the energy-drain/node unavailability between successive /random $\mathbb{t}$ if $AD(\mathbb{t})$ is true. Therefore, the initial demand model relies on the $\complement$ check for the $\mathbb{N}$ that defines $APS(U_c)$ and $APS(R_c)$ such that $\mathbb{E}$ is true/false (Refer to Figure 2).

The virtual expression to migration is performed using the available users and resources through FL. For this process, the sequence of node connectivity for all the resources $\mathbb{N} \in R_c$ is expressed as:

$$\mathbb{N}(R_c) = \left(1 - \frac{U_c}{\mathbb{N}}\right) U_{c_{i-1}} + \frac{R_c}{\mathbb{N}} \sum_{i=1}^{\mathbb{t}} \left(1 - \frac{R_c}{\mathbb{N}}\right)^{i-1} R_{c_{i-1}} \quad (6)$$

In Eq. (6), $U_{c_{i-1}}$ is the previous knowledge of the connected user's service information and t_s is the previous data of connected resource services and their responses using WSNs in the IoT environment. Therefore, based on the services of connected nodes, $AD(\mathbb{t}) = APS(U_c) - APS(R_c)[1 - \mathbb{N}(R_c)]$ is the outcome without influencing factors. The node connectivity plays a vital role in defining the resource availability between users and service providers. Based on migration/ overload, the connectivity feature varies for which $\mathbb{I}$ assessment is made. Besides the connectivity problem over the resource allocation is validated to confine the error in response. The virtual expression $(VE \times P_{U_c})$ and $(VE \times P_{R_c})$ for connected users and resources in the first stage is expressed as:

$$VExP_{U_c} = \sum_{i \in \mathbb{t}} [\mathbb{N}(R_c) \times U_c(\mathbb{t}) + R_c(\mathbb{t})]_i - APS(U_c).\mathbb{t} \quad (7)$$

$$VExP_{R_c} = \sum_{i \in \mathbb{t}} \mathbb{N}(R_c)_i \{ [1 - \mathbb{N}(U_c)_i] \times APS(U_c)\}_i - APS(R_c).\mathbb{t} \quad (8)$$

Based on Eqs. (7) and (8), the virtual expression is based on the application support observed from the IoT system for the consecutive process. In this initial proposed modeling process, the computation of $VE \times P_{U_c}$, $VE \times P_{R_c}$, $APS(U_c)$ and $APS(R_c)$ are the serving inputs for the FL process. The consecutive support from the application helps to easily identify the error occurrence by checking node availability, node inactivity, and node energy level between the connected nodes. The need for a virtual expansion decision is presented in Figure 3.

There are two possible cases for expanding the virtualization process: $(VE \times P_{U_c})$ and $\left(VE \times P_{R_c}\right)$. The decisions on these possibilities are verified under connectivity, resource, and demand cases. If $\complement$ = true, then the allocation is performed at $\mathbb{t}$ provided APS is true in increasing the allocation sequences. If the response tallies AD $(\mathbb{t})$ modeled, then $VE \times P_{R_c}$ is the expansion demand. In the case of resource condition, if APS is false, then $VE \times P_{U_c}$ is the virtual expansion required (Figure 3). This FL process is discussed in the section below.

3.2 Federated Learning process for virtualization

In the virtualization process, FL is used for identifying the correctness of battery energy, node availability, and node energy, and detecting energy-drained nodes. In this model, the number of nodes and instances may vary based on the service requests and responses. For instance, the FL process performs two types of modeling, namely sequence migration and battery drain identification. In the migration process, the no-node availability, no-node energy, and the occurrence of dead nodes are identified using a virtual expression. In this proposed model, the connectivity inputs for node migration are based on the connected users and resources in different time intervals. The resource constraint of $U_c(\mathbb{t}) + R_c(\mathbb{t}) \in \complement$ is processed based on their application demands and the occurrence of migration.

In the grouping process, the user and resource connectivity and the time instances are differentiated independently by using the virtualization concept. The virtualization process is performed for both connectivity, after which the IoT system FL process is used to migrate the current node. The virtualization output sequence $\mathbb{V}_{\mathbb{t}}$ is expressed using Eqs. (9) - (10) as:

$$\mathbb{V}_{\mathbb{t}} = \mathbb{N}(U_c)_{\mathbb{t}} - \mathbb{N}(R_c)_{\mathbb{t}} - APS(U_c)_{\mathbb{t}-1} \quad (9)$$

$$\mathbb{M}_{\mathbb{t}} = \mathbb{N}(R_c)_{\mathbb{t}} + APS(U_c)_{\mathbb{t}-1} - APS(R_c)_{\mathbb{t}-2} \quad (10)$$

The virtualization processes generate two outputs, namely appendable and removable or taken away from the instances. In Eq. (10), $\mathbb{M}$ signifies the migration sequence that is represented as $(\mathbb{M}_1 \; to \; \mathbb{M}_{\mathbb{t}})$. Here, the grouping is pursued through virtual expression based on the impacting factors present in WSNs. The resource constraint of $\mathbb{t} \in \mathbb{V}$ must not be equal to $\mathbb{t} \in \mathbb{M}$ is the best decision for appropriate grouping. If the occurrence of resource connectivity is the initial service, then migration is performed using application support. In this model, the associated virtual expression and migration are dependable such that $U_c = \{U_c \cup APS(R_c)\}$ and $R_c = \{\mathbb{V}_{\mathbb{t}} \cap APS(R_c)\}$ is grouped independently to improve the IoT system. The FL process for virtualization is illustrated in Figure 4. In Figure 4, illustrated above, the resource and user-case validations using FL are presented. In both cases, $\mathbb{t}$ is the AD mapping time common to U_c and R_c. Under both instances of the verification is a common form $\mathbb{M}_1 \; to \; \mathbb{M}_t$ such that $\mathbb{C}$ decides if it is to be virtualized between the user and IOT or IOT and resources. In the $\mathbb{N}(R_c)_{\mathbb{t}}$, to $[\mathbb{V}_{\mathbb{t}} \cap APS(R_c)]$ occurs between $\mathbb{t}$ and $(\mathbb{t}-1)$ whereas $[U_c \cup APS(R_c)]$ occurs between $(\mathbb{t}-1)$ and $(\mathbb{t}-2)$. These sequence reductions follow the continuous allocation across various $\mathbb{t}$. The common sequences are free from $\mathbb{V}_{\mathbb{t}}$ whereas the remaining are virtualized.

The common sequences are free from $\mathbb{V}_{\mathbb{t}}$ whereas the remaining are virtualized. Therefore, from the virtualized sequence, the training is iterated to ensure FL decisions satisfy the constraints in $(VExP_{U_c})$ and $(VE \times P_{R_c})$. The FL system is distributed to account for two different sets of inputs $(\mathbb{t}, R_c, U_c)$ and $(AD, R_c, \mathbb{t})$. The R_c and $\mathbb{t}$ are the connecting factors to decide if U_c is required or AD is detected. If $U_c \geq AD$, then new requests are input, failing which requires a migration. Depending on the outputs in $(\mathbb{t}+1)$ and its continuous intervals, the resource allocation or user demand (pending) is computed. In the allocation case, the demand acceptance for processing is high, whereas in the pending case, the migration recommendations are. Therefore, the training is performed for resource and user cases separately using $\mathbb{V}_t$ observed under classified Eqs. (8) and (9) respectively. This update is made in all the $(\mathbb{t}+2)$ interval to ensure $\mathbb{I}$ is less. The aggregation is performed from the WS node inputs, such as connectivity, energy level, and response provided. The change in any of the above requires a training update to enhance the accuracy of computations. The migration of the initial allocation is performed, from which the nodes are alone grouped for further processing. After the dependable process, the application support of a single user is compared with the set of users based on $APS(R_c)$. In this process, the $APS(R_c)$ and the node migration serves as the input for the training set in different $\mathbb{t}$ instances that are classified under resource constraints. First, the virtual expression is represented using a non-linear matrix representation, where the i and j in the matrix symbolize the row and column vectors based on the resource and user connectivity. If R_c and $U_c(\mathbb{t}) + R_c(\mathbb{t})$ represents the training set for migration, i.e., if $VE \times P_{U_c} < VE \times P_{R_c}$, then the matrix 1 value is 1. Instead, if $VE \times P_{U_c} > VE \times P_{R_c}$ is true, then the inverted values are used to represent the inverted matrix. From the matrix representation, the new sequence of node availability is further distinguished and grouped under the virtualization concept, where $\mathbb{t} \in U_c$. In this model, the node's dead occurrence due to high power consumption, battery drain, and other reasons is identified.

Based on the above matrix representation, the resource constraints of $VE \times P_{U_c} > VE \times P_{R_c}$ is marked as "1" whereas $VE \times P_{U_c} < VE \times P_{R_c}$ is marked as "0" for the add-on process. If the presence of 1 is detected in any particular node, then the migration is recommended through the FL process. Hence, the classification of connected resources from connected users initiates the virtualization and migration process as in Eqs. (9) and (10). Now, the resource constraints based on their application demands are verified using the FL process and the nodes from the initial allocation. The FL process of user and resource connectivity validation occurs in the proposed model for reducing battery drain. In this process, the application support is decided for the dependable process based on the above matrix representation.

3.3 Migration process

In the migration process, the above-mentioned training set $\mathbb{T}$ serves as the input for the appendable process with the extracted resource connectivity required for accurate migration. In the initial retrieval process, the migrated WSNs are segregated for correlation verification. In this verification, if there is any battery drain or power drops occur, then $VE \times P_{U_c}$ is computed as in Eqs. (7) and (8). Instead, for $VE \times P_{R_c}$, the resource constraint sequence is updated, and the nodes are migrated. Here, the FL process and migration are different from the IoT system, as expressed in:

$$\mathbb{V}_{\mathbb{t}} = \mathbb{T} \times (U_c(\mathbb{t}) + R_c(\mathbb{t}))_i + APS(R_c)_{\mathbb{t}-1} + \mathbb{E}(\mathbb{t}) \quad (11)$$

And,

$$\mathbb{V}_{\mathbb{t}} = APS(U_c)_{\mathbb{t}-1} + \mathbb{T} \times R_{c_{\mathbb{t}}} \quad (12)$$

The above Eqs. (11) and (12) formulate the occurrence of resource connectivity in different time intervals, and the intermediate occurrence of user connectivity in resource connectivity observation leads to high EC and battery drain. In this model, the U_c in R_c satisfies $\mathbb{V}_{\mathbb{t}} = 0$ is the previous solution for individual users, where the migration for U_c leads to zero. The equations presented in Eqs. (11) and (12) are different from those of Eq. (9) with the accumulation of resource connectivity and resource constraint factors. Depending on U_c and R_c, the imbalance modifies the $\mathbb{V}_t$ aided by the FL process. In the process, $\mathbb{V}_t \cap APS\ (R_c)$ and $U_c \cup APS\ (R_c)$ are the two computations to categorize $\mathbb{V}_t$ for resource allocation. Hence, this influencing factor is not considered in the virtualization process. In both the connectivity processing, the error-causing factors are increased before the node is migrated, as:

$$\mathbb{M}_{\mathbb{t}} = \sum_{i=1}^{\mathbb{t}} \mathbb{T}\big(U_c(\mathbb{t})\big) + R_c(\mathbb{t})_{i-1} - \left[\frac{R_c}{\mathbb{N}} : \mathbb{E} - APS(R_c)_{\mathbb{t}-1} + APS(R_c)_{\mathbb{t}-2}\right] \quad (13)$$

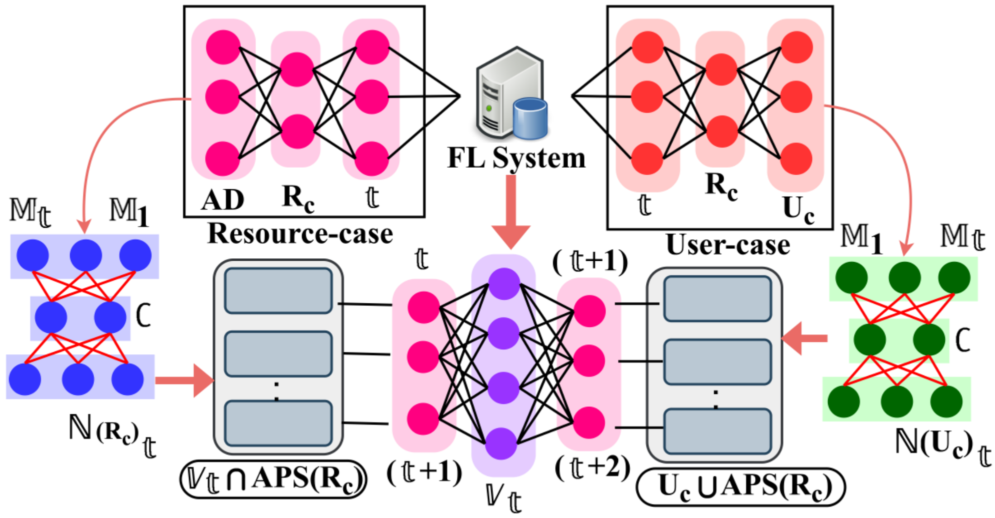

Figure 4. Virtualization process using federated learning

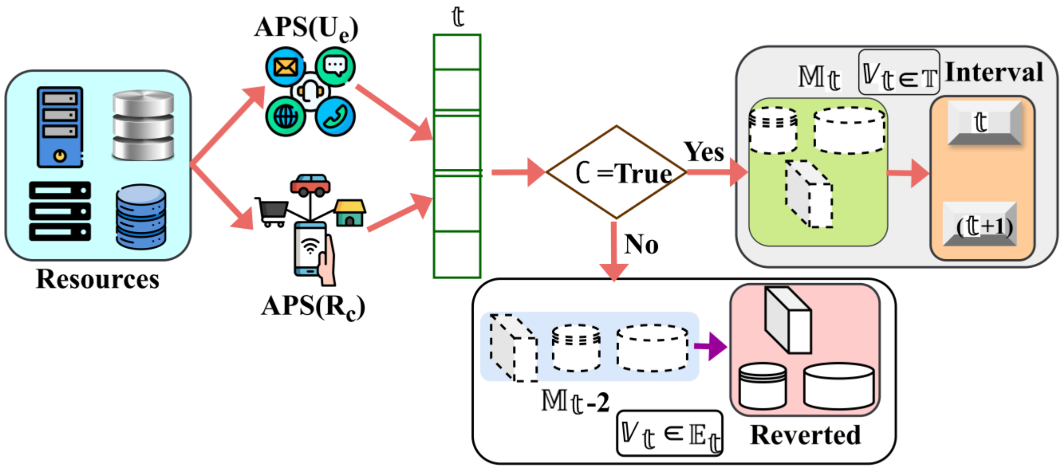

Figure 5. Migration process illustration

The migration process is illustrated in Figure 5 above for $\mathbb{V}_{\mathbb{t}} \in \mathbb{E}_{\mathbb{t}}$ and $\mathbb{V}_{\mathbb{t}} \in \mathbb{T}$ cases. The first case concerns the varying user demands that overflow the available resources. The alternating case concerns the varying $\mathbb{N}$ state in various $\mathbb{t}$. Using the available sequences, the FL classification is used to satisfy $\mathbb{V}_1 = 0$ for both U_c and R_c under $(VE \times P_{R_c})$ and $(VE \times P_{U_c})$ respectively. Therefore, the reverse migration in $\mathbb{M}_{\mathbb{t}-2}$ is performed if $AD(\mathbb{t}) \leq$ user demand and $APS(U_c) :\equiv APS(R_c)$ is true. Contrarily, if the case fails $\mathbb{C}$, then $\mathbb{M}_{\mathbb{t}}$ is reversed until $\mathbb{N}$ (new) is available. This case is active until the user is served with a new $\mathbb{N}$ between IoT and R_c. In this scheme, the battery drain is addressed in either user or resource connectivity and grouped under connected users, and resources are migrated in the previous allocations. The WSNs' influencing factors identification is given as follows:

$$\mathbb{E} = \mathbb{N} \times \mathbb{T} - APS(R_c) * \left(VExP_{R_c}\right) + \mathbb{M}_{\mathbb{t}}(\mathbb{T}) - \left(\frac{\mathbb{V}_{\mathbb{t}}}{\mathbb{N}}\right)\mathbb{C} + APS(U_c)_{\mathbb{t}} + APS(R_c)_{\mathbb{t}} \tag{14}$$

Eq. (14) computes the occurrence of battery drain, high EC, and other influencing factors in WSNs. This identification of impacting factors is used to process the following requests and responses with the probability of migration in either user or resource connectivity. In this model, if $\mathbb{E} = 0$, then the neighbor node is visited for further resource allocation. Similarly, if the condition of $VE \times P_{U_c} > VE \times P_{R_c}$ is satisfied by the particular node, then $\mathbb{E} = 0$. Another $\mathbb{E}$ based assessment is defined in Eq. (14), considering the $\mathbb{N}$ and $APS(U_c)$. In the redefining phase of $\mathbb{M}(\mathbb{T})$, the change in $\mathbb{V}_t$ identifies its impact on performance degradation. This equation is provided to verify the objective satisfaction throughout the virtualization and migration processes. Resource virtualization is performed in $\mathbb{V}_t$ is categorized as presented in Eqs. (8) and (9). The U_c and R_c demands finalize the migration based on the connectivity. This refers to the two-fold decisions of $\mathbb{V}_t$ and R_c based allocations such that the FL identifies the synchronous $\mathbb{t}$ for AD and U_c. In this case, the migration for reducing $\mathbb{E}$ is the target based on which virtualization (increasing/ decreasing) is mode. The FL decisions are made for opting for virtualization/ migration based on the response generated and resource allocations. The FL's training update maximizes the chances of $\mathbb{E} = 0$ that eventually balances the migration and virtualization functions. Therefore, the migration is not performed, which means the virtual expression of allocated resources is observed for all node data. This observation of resource connectivity is valid until it satisfies the user's application demands. Instead, the occurrence of influencing factors continuously migrates both connected users and resources until it is stabilized either for users or resources.

3.4 Self-analysis

Based on the discussions above, a few self-analysis process is discussed below. In the analysis presented in Figure 6, the $\mathbb{E}$ from U_c and $\mathbb{N}$ are considered.

In the proposed scheme, FL identifies the three possibilities for $\mathbb{E}$ under $\mathbb{C}$. This includes $\mathbb{C}=0(least)$, $\mathbb{C}=1(high)$, and $0<\mathbb{C}<1$ that replicates the $\mathbb{E}$. The $\mathbb{E}$ is accounted for from $R_c\ and\ U_c$ under distinguishable $\mathbb{t}$. The FL separates $[\mathbb{V}_{\mathbb{t}} \cap APS(R_c)]$ and $[U_c \cup APS(R_c)]$ to identify and migrate $\mathbb{E}$ in both ends. This process is repeated until $AD(\mathbb{t})$ is satisfied by the applications to ensure that maximum resource allocations are performed. Besides, the $\mathbb{C}$ variations are precisely identified to decide if the augmentation of $\mathbb{M}_{\mathbb{t}}$ is mandatory in satisfying $AD(\mathbb{t})$ (Figure 6). Following this $APS(U_c)$ and $APS(R_c)$ for the same time intervals is analyzed in Figure 7.

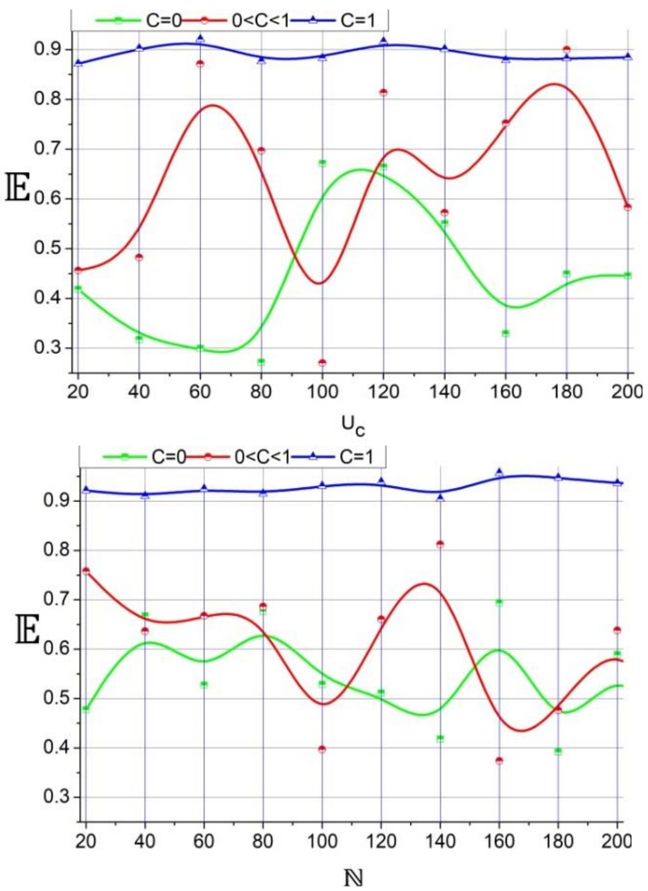

Figure 6. $\mathbb{E}$ from U_c and $\mathbb{N}$

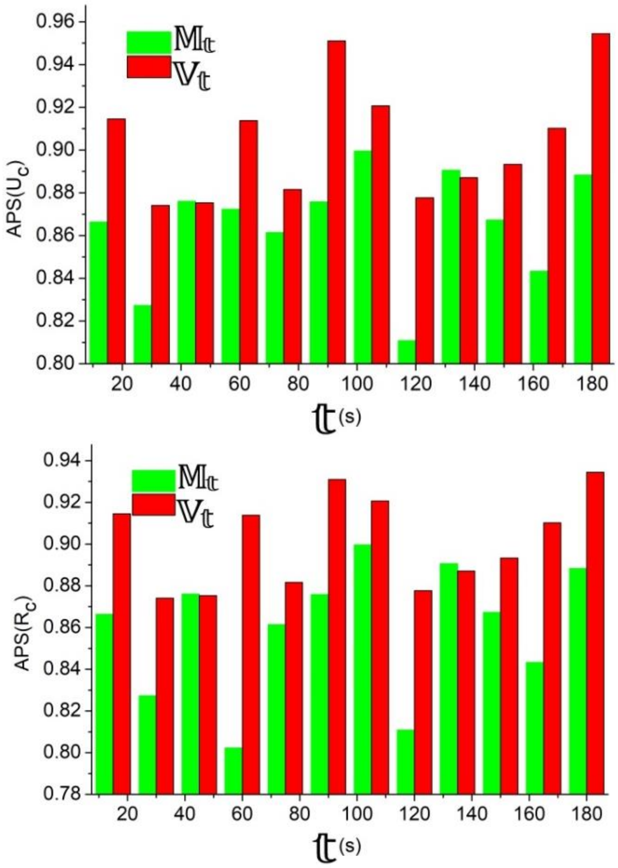

Figure 7. $APS(U_c)$ and $APS(R_c)$ analysis

The $APS(U_c)$ and $APS(R_c)$ analysis presented in the above Figure 7 is required to ensure $\mathbb{N}$ allocation/reallocation along with $\mathbb{t}$. This ensures maximum resource utilization in any $\mathbb{t}$ for which R_c satisfies $AD(\mathbb{t})$. Besides, the U_c demands are met in $\mathbb{t}$ that does not exceed to $(\mathbb{t}+1)$ interval. The FL addresses the problem of $\mathbb{E}$ by identifying $VE \times P_{U_c} > VE \times P_{R_c}$ such that the mapping is optimal. If the IoT platform provides an optimal allocation through $\mathbb{V}_{\mathbb{t}}$ then $\mathbb{M}_{\mathbb{t}}$ is also concurrently satisfying the appended $AD(\mathbb{t})$. Thus, the processes are expected to be concurrent as aligned by the virtualization and migrations recommended by the FL. In the following analysis, $VE \times P_{U_c}$ and $VE \times P_{R_c}$ are considered in the same $\mathbb{t}$ as in Figure 7.

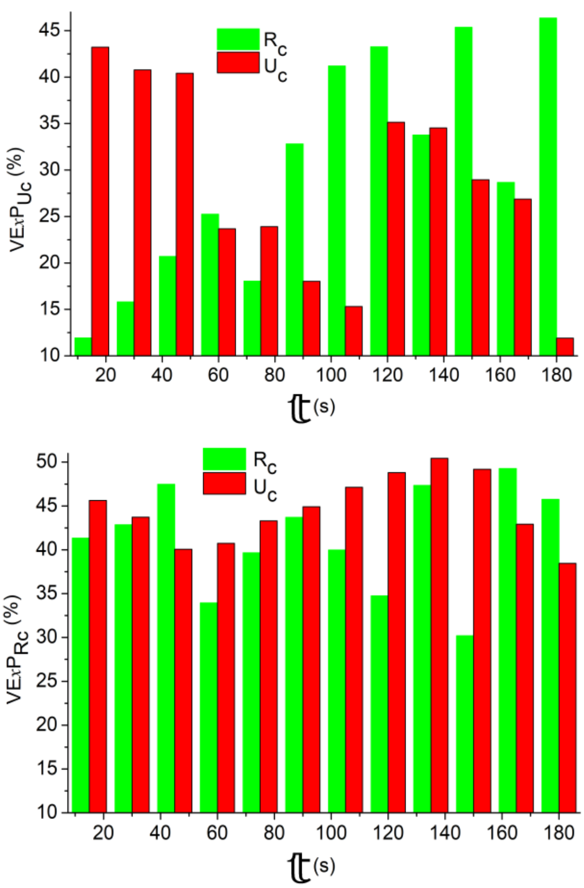

Figure 8. Analysis of $VE \times P_{R_c}$ and $VE \times P_{U_c}$

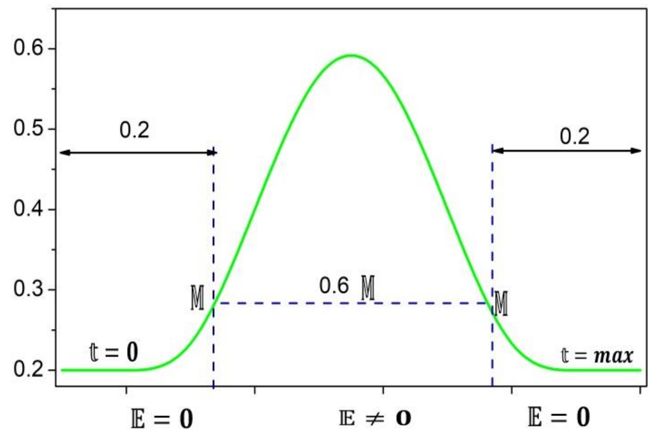

Figure 9. p-value assessment

The analysis presented in Figure 8 above showcases the $VE \times P_{R_c}$ and $VE \times P_{U_c}$ rates for different $\mathbb{t}$. As $\mathbb{t}$ increases, the appendable $\mathbb{V}_{\mathbb{t}}$ and $\mathbb{M}_{\mathbb{t}}$ varies with new demands and resource availability. The optimal case is the $\mathbb{M}_{\mathbb{t}}$ that ensures high resource utilization, and suppresses $\mathbb{C}$. In the proposed scheme, the FL is independent of R_c and U_c processes such that the successive resource allocations in $\mathbb{t}, (\mathbb{t}-1)$, and $(\mathbb{t}-2)$ are prominent in deciding the appendability of $\mathbb{V}_{\mathbb{t}}$ and $\mathbb{M}_{\mathbb{t}}$. Therefore, the successive verifications of $\mathbb{C}$ and distinguishable $\mathbb{E}$ are useful in maximizing utilization. The p-value assessment for $\mathbb{M}$ chance under $\mathbb{E} = 0$ and $\mathbb{E} \neq 0$ cases is presented in Figure 9.

The p-value assessment for $\mathbb{M}$ chances under $\mathbb{E} = 0$ and $\mathbb{E} \neq 0$ is considered. If the objective of $\mathbb{E}$ minimization fails, the chances of migration and resource virtualization are high. Therefore, considering two consecutive intervals for $\mathbb{t} = 0$ to $\mathbb{t} = 0.2$, the increasing and decreasing demands are considered. The rest of the interval is conventional to satisfy $U_c = R_c$ condition. The FL is also trained using this case for multiple intervals, such that $\mathbb{V}_t$ (classified) defines the case of $APS\ (R_c)$ for the maximum request demands. This reduces the chances of migration satisfying the objective of $\mathbb{E} = 0$ (Figure 9).

4. RESULTS AND DISCUSSION

The results and discussion are elaborated using application response, virtualization rate, migration ratio, response time, and resource utilization metrics. These metrics are obtained from a specific simulation scenario designed using the Contiki Cooja simulator. The scenario is plotted with 240 wireless sensor nodes with an initial energy of 50J; the node virtualization/ expansion occurs if the energy drops below 5J. The energy utilization patterns of the WS nodes rely on listening, transmission, receiving, sensing, processing, and sleep actions. The receiving and transmission power is nearly 60% of the initial energy.

This is the initial setting for the experimental analysis and is modified based on the network size, node placement, and network dynamics. The features match the real-time applicability of sensor nodes for any application application. The user count is 200, and the resource server is 10, handling 70-80 requests/ service interval. The interval time for a user lasts between 30s and 180s. The user demand ranges between 100 and 1500 from the above user count, experiencing a service response from 100 to 400 per service interval. Besides, the users, sensor nodes, and resources are connected using 20 intermediate stations that are stationary. The intermediate stations refer to the fixed access points, communication tower, and base stations. The nodes refer to the intermediate wireless bridges that interact with users and base stations supporting mobility. If the nodes can be from user/ resource providers and that targets seamless connectivity for resource sharing. Based on multiple dynamic hops and neighbour discovery sequences, the connectivity is retained. Therefore, for both dynamic and static users, the node placement and its dynamicity are considered. Besides, the IoT network offers high bandwidth-based communications, due to which interference and network slicing issues are less. To verify and validate the scalability of the proposed method, the number of users and their requests are varied. The application of $\mathbb{M}$ and virtualization is balanced to sustain the varying users' support. Depending on the FL decisions, scalable user support by sustainable $\mathbb{N}$ is achieved. The metrics from the simulation outcomes are compared with T-TRAA [19], EMOCA [24], and F-SVNE [25] methods. The baseline methods selected for comparative analysis rely on the similarity of virtualization for load handling in IoT-WSN environments. These methods target resource allocation and management using possible virtualizations. In the other process, connectivity (link) based solutions are also provided for request and response optimization in these methods. Besides, task separation and functional modifications of the nodes are used to redefine the resource management. The link-based computations and resource management are also defined in the proposed method, and therefore, more similar methods are used in this comparative assessment.

4.1 Application response

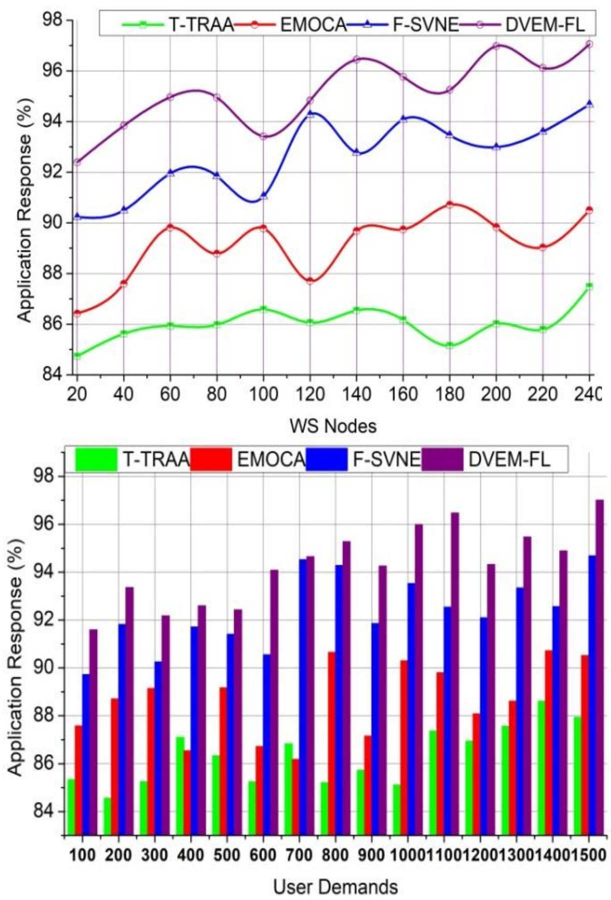

Figure 10. Application response

The proposed scheme is implemented to achieve high application response (Figure 10) based on the user and resource connectivity in the WSN backhauled IoT. The error-causing factors are identified with less response, and migration is the best decision. The resource constraint-based WSN migration is performed between the network topology and application interfaces that are identified from the virtualization concept for reducing high response time. Identifying which node is stabilized in a particular service interval is identified for wide application support. The influencing factors of WSNs are identified with the previous allocation for reducing service and response time. Hence, a high application response is achieved.

4.2 Virtualization rate

In this scheme, the requests from users and responses from applications are exchanged over the application interface to improve resource allocation with a reduced migration ratio. The high virtualization rate is achieved using the wireless sensor nodes. The high response time and migration ratio take place in IoT systems, leading to complexity in application support that is reduced using the resource constraints of $\forall\, U_c(\mathfrak{t}) + R_c(\mathfrak{t}) \in AD(\mathfrak{t})$. In this article, the previous utilization is compared with the present allocation for identifying demand changes and thereby increasing resource allocation. Therefore, the battery drain identified nodes are taken for performing accurate migrations in this proposed model, which results in less response time. Hence, the resource constraints are continuously modified based on the user demands to satisfy a high virtualization rate (Figure 11).

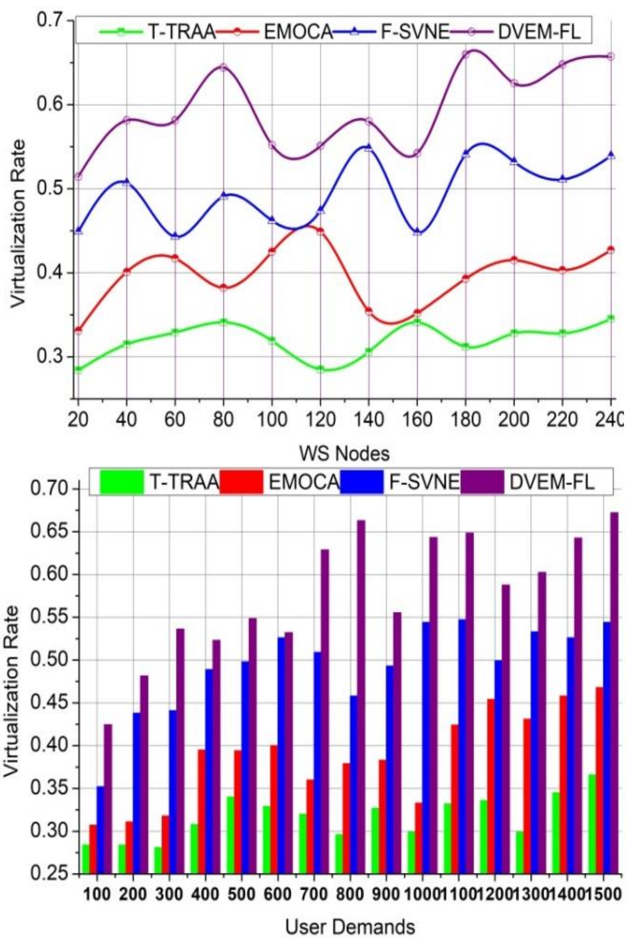

Figure 11. Virtualization rate

4.3 Migration ratio

The user and resource connectivity from the IoT system is analyzed to provide services to all the nodes through wireless sensors with better migration. The identification of error-causing factors in WSNs, the appendable and removable nodes, is differentiated from the migration process. The connected users and resources-based services and network processing are obtained from the IoT system to increase resource utilization.

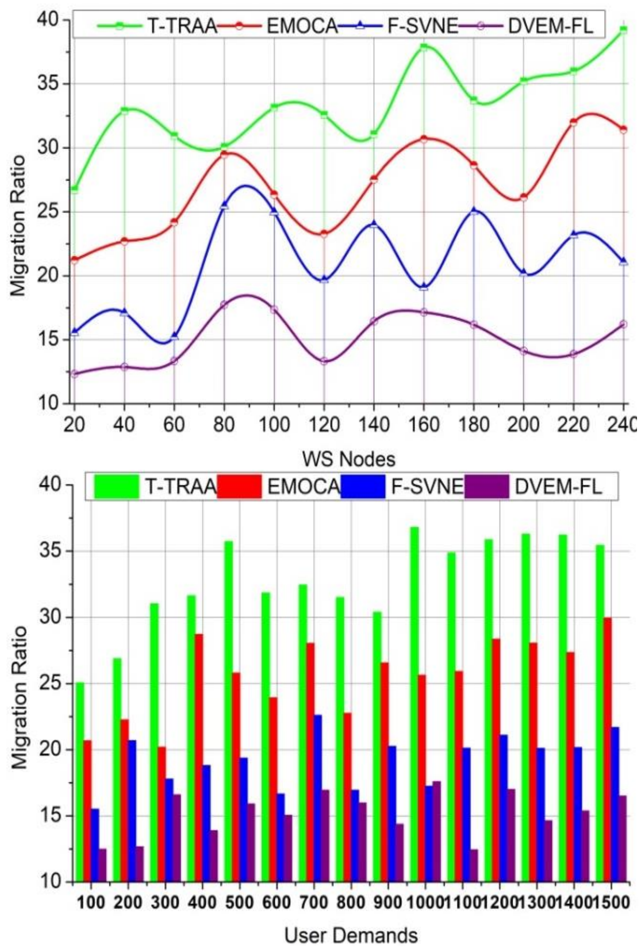

Figure 12. Migration ratio

In this model, the battery drain is detected as an instance of false observations of node availability, node energy drain, and node energy level. The virtualization and migration process jointly provide the output of maximum or minimum resource allocation with its least possible error occurrence. Therefore, the IoT system continuously processing requests and responses with a lower migration rate is the best decision (Figure 12).

4.4 Response time

The connected users and resources are served with the number of nodes from which the optimal one is selected using the FL. Hence, the node availability, power consumption, energy level, and node drain are identified based on the application support, and accurately identify whether the particular node is stable at the time of the virtualization process. In this case, this virtualization ratio is computed to identify error-influencing factors in WSNs based on application demands using the FL process. From the instance, the possibility of virtual expression is identified to satisfy the continuous node data processing based on application demands, and to reduce the migration rate. The virtual expression in the IoT system is identified from the node data analysis without battery drain. The reduction of application demand changes and response time is represented in Figure 13.

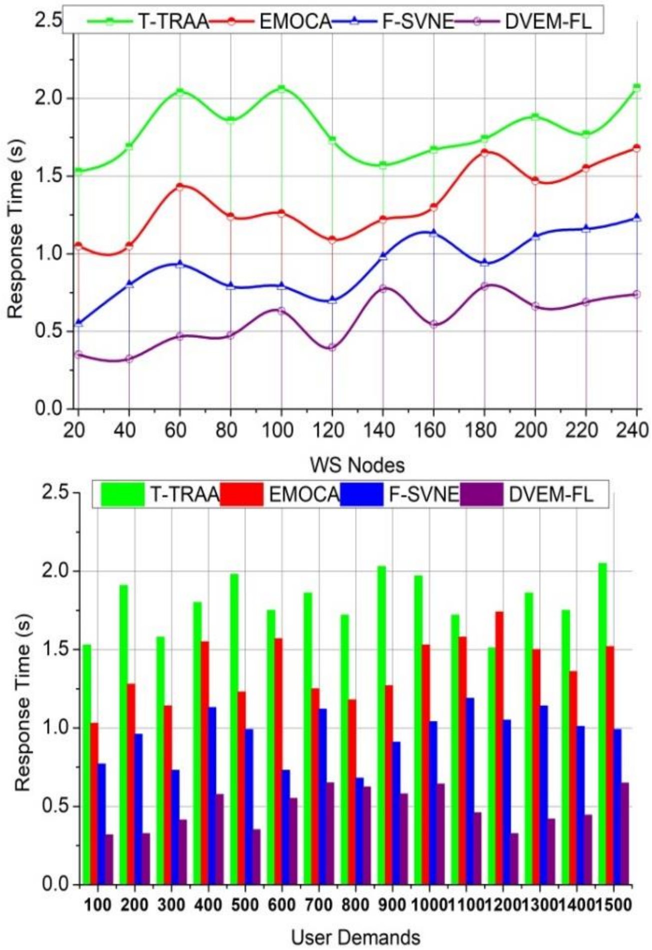

Figure 13. Response time

4.5 Resource utilization

High resource utilization is achieved through processing individual users and a set of users and resources in different service intervals. The extended support from applications helps to easily identify the impacting factors in WSNs through node availability, node drain, and node energy level verification between the application interfaces. The FL process is used to compute accurate virtualization and migration ratios for all the resources in the IoT system to prevent errors. Therefore, the extended application support is provided based on the connected users and resources, service intervals, and processing rate. Hence, high resource utilization is achievable using this scheme, as illustrated in Figure 14. The comparative analysis results are presented in Tables 1 and 2 for the different WS nodes and user demands.

The proposed scheme improves application response, virtualization rate, and resource utilization by 12.34%, 11.01%, and 13.06% respectively. This scheme reduces the migration ratio and response time by 14.35% and 11.1% respectively.

The proposed scheme improves application response, virtualization rate, and resource utilization by 11.93%, 10.64%, and 13.526% respectively. This scheme reduces the migration ratio and response time by 12.51% and 11.46% respectively.

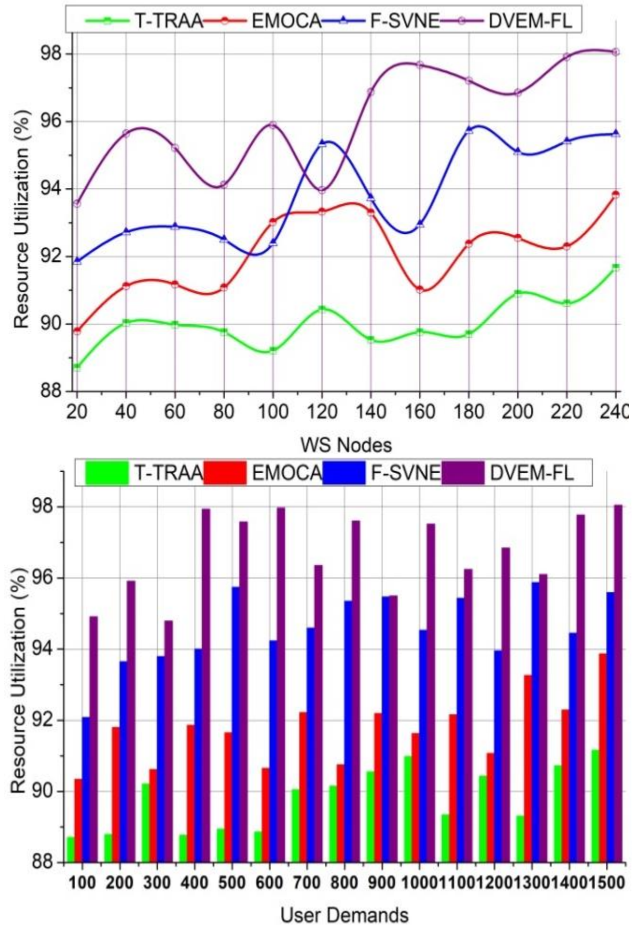

Figure 14. Resource utilization

Table 1. Comparative analysis results for Wireless Sensor (WS) nodes

Metrics	T-TRAA	EMOCA	F-SVNE	DVEM-FL
Application Response (%)	87.48	90.5	94.67	97.052
Virtualization Rate	0.345	0.427	0.539	0.6571
Migration Ratio	39.2	31.42	21.07	16.213
Response Time (s)	2.07	1.68	1.23	0.739
Resource Utilization (%)	91.67	93.83	95.63	98.063

Table 2. Comparative analysis results for user demands

Metrics	T-TRAA	EMOCA	F-SVNE	DVEM-FL
Application Response (%)	87.94	90.52	94.68	97.013
Virtualization Rate	0.366	0.468	0.544	0.6722
Migration Ratio	35.44	29.94	21.68	16.506
Response Time (s)	2.05	1.52	0.99	0.649
Resource Utilization (%)	91.16	93.87	95.59	98.048

5. CONCLUSION

The demand-appended virtual expansion and migration scheme is introduced in this article, exclusive to WSN backhauled IoT. In this scheme, the continuous requests and responses from the connected users and resources are mapped continuously. The virtual expression is verified from the connected resources under connectivity and high demand constraints, and a high response time is identified using the FL process. The application support with failed utilization or high response time in connected resources is addressed using the FL decisions. If expansion and migration processes are not concurrent, the node replacement and resource reallocation processes are initiated. This proposed scheme improved resource utilization by 13.06% by providing 11.01% virtualization support to reduce response time by 11.1% for the maximum sensor nodes deployed. This proposed scheme is reliable for high user/ demand dense environments, whereas the complication relies on node replacement solutions recommended. Rather, the concept is to be extended for rechargeable WSNs to ensure sustainable and prolonged application support for different categories of users. Thus, future work focuses on a similar scenario with rechargeable nodes along an energy harvesting feature. This is expected to stabilize the connectivity for the node, user, and resource groups irrespective of the distance and demand densities.

REFERENCES

[1] Almurisi, N., Tadisetty, S. (2022). Cloud-based virtualization environment for IoT-based WSN: Solutions, approaches and challenges. Journal of Ambient Intelligence and Humanized Computing, 13(10): 4681-4703. https://doi.org/10.1007/s12652-021-03515-z

[2] Babu, M.V., Sekaran, R., Kannan, S., Ravi, V. (2023). CE2RV: Commissioned energy-efficient virtualization for large-scale heterogeneous wireless sensor networks. International Journal of Communication Systems, 36(9): e5480. https://doi.org/10.1002/dac.5480

[3] Liu, B., Han, C. (2022). Research on wireless network virtualization positioning technology based on next-generation agile IoT technology. Journal of Interconnection Networks, 22(4): 2150029. https://doi.org/10.1142/S0219265921500298

[4] Ghaseminya, M.M., Eslami, E., Shahzadeh Fazeli, S.A., Abouei, J., Abbasi, E., Karbassi, S.M. (2025). Advancing cloud virtualization: A comprehensive survey on integrating IoT, Edge, and Fog computing with FaaS for heterogeneous smart environments. The Journal of Supercomputing, 81(14): 1303. https://doi.org/10.1007/s11227-025-07799-2

[5] Shamsan, A.H., Faridi, A.R. (2022). A conceptual architecture for integrating software defined network and network virtualization with internet of things. International Journal of Electrical and Computer Engineering, 12(6): 6777-6784. https://doi.org/10.11591/ijece.v12i6.pp6777-6784

[6] Sun, M., Zhou, Z., Wang, X., Wu, Y., Huang, Z. (2023). Optimizing service redeployment in migration-oriented IoT networks. IEEE Internet of Things Journal, 10(17): 15537-15552. https://doi.org/10.1109/JIOT.2023.3264498

[7] GSR, Y., MN, T., K, V. (2024). A literature study and performance gaps on Centralized server-based load balancing and routing strategies under cloud-IoT-WSN. Australian Journal of Electrical and Electronics Engineering, 21(2): 138-160. https://doi.org/10.1080/1448837X.2024.2309424

[8] Cavdar, M.C. (2022). Resource optimization of multi-purpose IoT wireless sensor networks with shared monitoring points. Doctoral dissertation, Bilkent University. https://www.proquest.com/openview/38af04fdc78a6d01fdf6f07d96ff307c/1?pq-origsite=gscholar&cbl=2026366&diss=y.

[9] Kumar, N., Kumar, S. (2022). A salp swarm optimization for dynamic resource management to improve quality of service in cloud computing and IoT environment. International Journal of Sensors Wireless Communications and Control, 12(1): 88-94. https://doi.org/10.2174/2210327911666210126122119

[10] Li, Q., Kumar, P., Alazab, M. (2022). IoT-assisted physical education training network virtualization and resource management using a deep reinforcement learning system. Complex & Intelligent Systems, 8: 1229-1242. https://doi.org/10.1007/s40747-021-00584-7

[11] Rao, M.R., Sundar, S. (2024). Enhancement in optimal resource-based data transmission over LPWAN using a deep adaptive reinforcement learning model aided by novel remora with lotus effect optimization algorithm. IEEE Access, 12: 76515-76531. https://doi.org/10.1109/ACCESS.2024.3406749

[12] Chakour, I., Mhammedi, S., Daoui, C., Baslam, M. (2024). Unlocking QoS potential: Integrating IoT services and Monte Carlo Control for heterogeneous IoT device management in gateways. Computer Networks, 238: 110134. https://doi.org/10.1016/j.comnet.2023.110134

[13] Feng, H., Shu, Z., Taleb, T., Wang, Y., Liu, Z. (2022). An aggressive migration strategy for service function chaining in the core cloud. IEEE Transactions on Network and Service Management, 20(2): 2025-2039. https://doi.org/10.1109/TNSM.2022.3231186

[14] Jeyaraj, R., Balasubramaniam, A., MA, A.K., Guizani, N., Paul, A. (2023). Resource management in cloud and cloud-influenced technologies for internet of things applications. ACM Computing Surveys, 55(12): 1-37. https://doi.org/10.1145/3571729

[15] Shi, Y., Yi, C., Wang, R., Wu, Q., Chen, B., Cai, J. (2023). Service migration or task rerouting: A two-timescale online resource optimization for MEC. IEEE Transactions on Wireless Communications, 23(2): 1503-1519. https://doi.org/10.1109/TWC.2023.3290005

[16] Kaaniche, K., Othmen, S., Alfahid, A., Yousef, A., Albekairi, M., El-Hamrawy, O.I. (2024). Enhancing service availability and resource deployment in IoT using a shared service replication method. Heliyon, 10(3): e25255. https://doi.org/10.1016/j.heliyon.2024.e25255

[17] Liu, F., Yu, H., Huang, J., Taleb, T. (2023). Joint service migration and resource allocation in edge IoT system based on deep reinforcement learning. IEEE Internet of Things Journal, 11(7): 11341-11352. https://doi.org/10.1109/JIOT.2023.3332421

[18] Hajian, E., Khayyambashi, M.R., Movahhedinia, N. (2022). A mechanism for load balancing routing and virtualization based on SDWSN for IoT applications. IEEE Access, 10: 37457-37476. https://doi.org/10.1109/ACCESS.2022.3164693

[19] Kim, S. (2022). Adaptive multiservice resource allocation algorithm with wireless network virtualization. IEEE Access, 10: 51515-51524.

https://doi.org/10.1109/ACCESS.2022.3174056
[20] Ma, Z., Ma, D., Lv, M., Liu, Y. (2023). Virtual machine migration techniques for optimizing energy consumption in cloud data centers. IEEE Access, 11: 86739-86753. https://doi.org/10.1109/ACCESS.2023.3305268
[21] Haris, R.M., Barhamgi, M., Nhlabatsi, A., Khan, K.M. (2024). Optimizing pre-copy live virtual machine migration in cloud computing using machine learning-based prediction model. Computing, 106: 3031-3062. https://doi.org/10.1007/s00607-024-01318-6
[22] Tang, L., Li, Z., Li, J., Fang, D., Li, L., Chen, Q. (2024). DT-assisted VNF migration in SDN/NVF-enabled IoT networks via multiagent deep reinforcement learning. IEEE Internet of Things Journal, 11(14): 25294-25315. https://doi.org/10.1109/JIOT.2024.3392574
[23] Kumar, S., Cengiz, K., Vimal, S., Suresh, A. (2022). Energy efficient resource migration based load balance mechanism for high traffic applications IoT. Wireless Personal Communications, 127(1): 385-403. https://doi.org/10.1007/s11277-021-08269-7
[24] Othman, R.A., Darwish, S.M., Abd El-Moghith, I.A. (2023). A multi-objective crowding optimization solution for efficient sensing as a service in virtualized wireless sensor networks. Mathematics, 11(5): 1128. https://doi.org/10.3390/math11051128
[25] Li, S., Yan, Y., Ji, Y., Peng, W., Wan, L., Zhang, P. (2023). Survivability mapping strategy for virtual wireless sensor networks for link failures in the Internet of Things. Electronics, 12(11): 2498. https://doi.org/10.3390/electronics12112498