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# Resource provisioning model for executing realistic workload in heterogenous internet of things environment

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**ABSTRACT**

Resource provisioning considering scientific or realistic workload in a heterogeneous internet of things (IoT) environment presents significant challenges in terms of execution time and energy consumption. These challenges arise due to the dynamic nature of scientific or realistic-time workloads and the diverse characteristics of IoT devices. In this study, we propose a resource provisioning model that takes into account the dynamic and real-time nature of IoT workloads in a heterogeneous environment. The model aims to allocate computational resources effectively, considering the real-time demands of IoT applications while optimizing execution time and energy consumption. Three scientific workloads have been used to evaluate the proposed model. The results have been compared with the existing models. The results show that the proposed model attains better performance in terms of reducing time and energy consumption for the execution of workload tasks.



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## 1. INTRODUCTION

A heterogeneous internet of things (IoT) environment refers to a system where diverse devices, technologies, and platforms come together to create interconnected networks and enable a wide range of IoT applications. In this environment, a variety of IoT devices with different capabilities, such as sensors, actuators, and controllers, coexist [1]. These devices can vary in terms of computational power, memory capacity, communication protocols, and energy constraints [2]. The communication infrastructure supporting the heterogeneous IoT environment includes a mix of technologies such as Wi-Fi, Bluetooth, Zigbee, and cellular networks, allowing devices to connect and communicate seamlessly [3]. The heterogeneity in device types and communication technologies poses both challenges and opportunities in terms of interoperability, data management, and system integration [4]. However, it also enables the deployment of IoT solutions that cater to specific use cases and application requirements, leveraging the strengths of different devices and technologies [5]. Resource provisioning in a heterogeneous IoT environment is the process of efficiently allocating and managing computational resources to support the diverse devices and applications within the system [6].

With a wide range of devices, each having unique capabilities and requirements, resource provisioning becomes crucial for ensuring optimal performance and utilization. This involves assessing the capabilities of IoT devices in terms of their computational power, memory capacity, energy constraints, and communication capabilities [7]. Based on this assessment, resources can be allocated accordingly to meet the specific needs of different devices and applications. Resource provisioning considering realistic workload in a heterogeneous IoT environment is a critical aspect of ensuring optimal performance and responsiveness. In this context, resource provisioning involves dynamically allocating and managing computational resources based on the real-time demands of IoT applications and devices [8]. Realistic workload monitoring plays a key role in this process, as it enables continuous tracking of the workload and performance metrics of IoT applications and devices. By analyzing factors such as data processing requirements, communication patterns, latency constraints, and resource utilization in real-time, resource provisioning algorithms can make informed decisions about resource allocation [9]. These algorithms dynamically adjust the allocation of computational resources, scaling up or down as needed to match the changing workload. This dynamic allocation ensures that resources are efficiently distributed to meet the real-time demands of IoT applications, while also optimizing resource utilization and minimizing response times. By considering realistic workload in resource provisioning, the heterogenous IoT environment can effectively adapt to changing demands and deliver reliable and responsive IoT services [10].

Resource provisioning considering realistic workload in a heterogeneous IoT environment poses significant challenges in terms of execution time and energy consumption [11]. Addressing these challenges is crucial to ensure efficient and sustainable operation of IoT applications. One of the key challenges is the dynamic nature of realistic workload in IoT environments [12]. Workload patterns can fluctuate rapidly, leading to unpredictable resource demands. Resource provisioning mechanisms must be capable of quickly adapting to these changes to meet real-time execution requirements. This involves continuously monitoring the workload, predicting future resource needs, and dynamically adjusting resource allocations in response. Optimizing execution time is another critical aspect. Real-time applications often have strict latency requirements, and delays in resource provisioning can lead to missed deadlines and degraded performance. Efficient scheduling algorithms are needed to allocate resources in a way that minimizes execution time, ensuring timely processing of real-time tasks. Energy consumption is a significant concern in resource provisioning for IoT environments [13]. IoT devices are often resource-constrained and operate on limited battery power. Inefficient resource allocation can lead to unnecessary energy consumption, reducing the overall system lifetime and increasing operational costs [14].

Resource provisioning algorithms should aim to minimize energy usage by intelligently allocating resources based on workload characteristics and device capabilities. To address these challenges, resource provisioning algorithms need to strike a balance between meeting real-time execution requirements and optimizing energy consumption. This requires sophisticated optimization techniques, such as dynamic voltage and frequency scaling (DVFS) [15], task consolidation [16], and load balancing [17], to achieve efficient resource allocation. Furthermore, considering energy-aware scheduling policies and incorporating energy models for IoT devices can help guide resource provisioning decisions that minimize energy consumption while meeting realistic workload demands. Overall, resource provisioning considering realistic workload in a heterogeneous IoT environment requires careful consideration of execution time and energy consumption. By developing intelligent resource provisioning algorithms that dynamically adapt to workload changes and optimize resource allocation, it is possible to achieve efficient and sustainable operation of IoT applications in terms of both execution time and energy consumption. Hence, in this work we propose a model which provides the execution of the scientific or realistic workload in heterogenous IoT environment consuming less time and energy.

## 2. LITERATURE SURVEY

In this section, survey on various research work for executing workload in heterogenous Internet of Things environment has been conducted. Jangu and Raza [18], they have presented an efficient algorithm which mainly focusses on executing the tasks of the workload on the basis of the priority and deadline. In this algorithm, the have proposed an improved jelly-fish searching optimizer (IJFA) to execute the tasks. This algorithm considers various parameters such as virtual machines, size of the task and speed of the virtual machine before allocating the resources for the execution. The IJFA has been experimented using small and large real-time workloads. For evaluating their algorithm, they have used the quality-of-service (QoS) parameters. The results show that the proposed algorithm attains better resource utilization and reduces the cost for execution when compared with the existing works. Nayagi *et al.* [19], they have proposed called as fault-tolerant aware (FTA) to reduce the energy and cost during the execution of the workload. They have used the DVFS method in their work and proposed a novel model. The results show that the proposed model attains better result in reducing the energy when compared with the other workload execution methods. Prakash *et al.* [20], they have proposed a model called as parent to child (P2C) which executes the workload in the given deadline. This work considers the node dependency of the workload. In this work, they use the resources efficiently to provide better resources for the execution of the workload tasks in the given deadline. For evaluating their model, they have used five scientific applications which are represented using the directed-acyclic-graphs and executed them in the WorkflowSim simulator. The results show that the proposed P2C method reduces the time for the execution by considering the parent to child nod dependencies.

Adhikari and Gianey [21], in this work, they have proposed a model which considers the task offloading of the workload to the edge environment for better and fast execution. This work main focus was to reduce the energy consumption during the execution of the tasks of the workload. The tasks of the workload are given resources on the basis of their requirement. The results show that the proposed model reduces the energy-consumption by 41% to 62%. Tian *et al.* [22], they have proposed an algorithm called predictive energy-consumption scheduling (PECS), which considers at which frequency a task will come after the execution of the previous task. Their main focus was to execute the tasks of the workload in the given deadline. To allocate the tasks better resources they have proposed a matrix called as extracellular matrix (ECM) which will predict the amount of energy a task will consume. Using the results of the matrix, the resources are allocated for the execution. Finally, a strategy is made to execute tasks of the workload in the given deadline. The results show that the proposed PECS algorithm reduces energy by 13.33% and 48.28% when compared with two existing resource efficient workload execution methods.

## 3. MODEL

In Figure 1, the architecture of the proposed model has been given. In an edge-cloud environment where the workload is distributed across the edge, middle layer (edge servers), and the cloud, the execution of the workload typically follows a multi-tiered architecture. The workload is divided into different tasks or components, and each component is executed at the appropriate layer based on its requirements and the available resources. In this execution model, the workload is distributed and executed across multiple layers based on the specific requirements of each task. The edge layer focuses on real-time and time-sensitive tasks, the middle layer handles intermediate processing and collaboration, and the cloud layer deals with resource-intensive and non-real-time tasks. This tiered architecture enables efficient utilization of resources, reduces network congestion, improves response time, and optimizes the overall performance of the system in an edge-cloud environment.

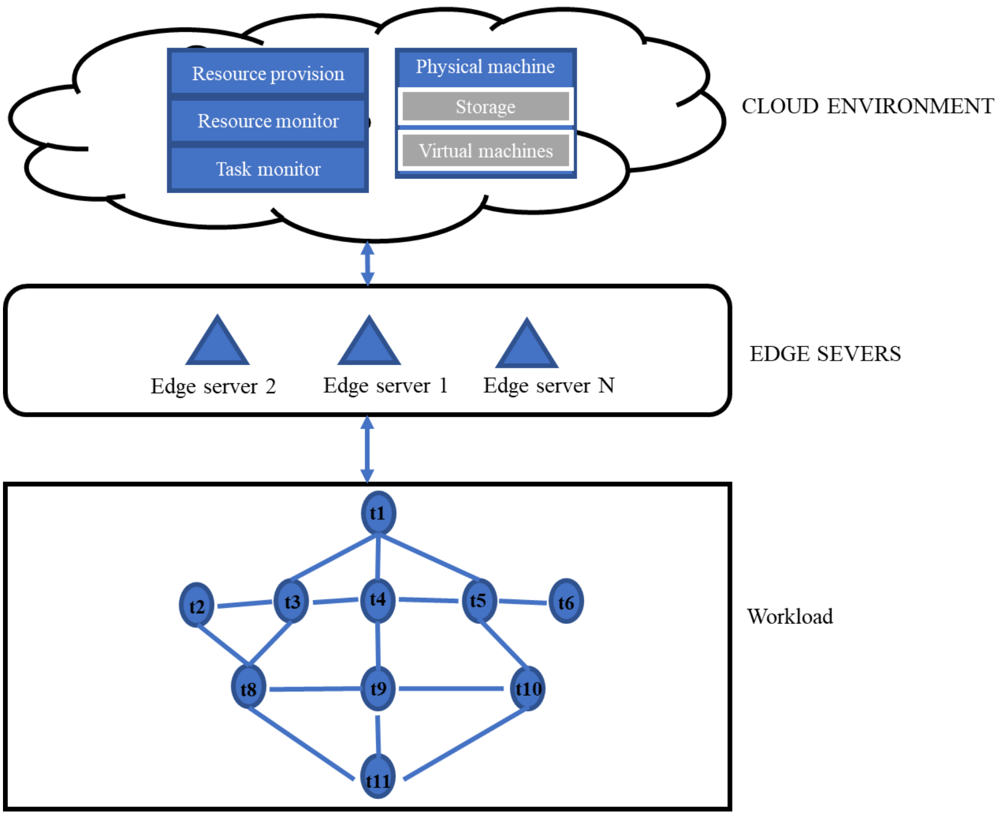


Figure 1. Architecture of proposed heterogenous IoT environment

### 3.1. Workload representation

For building a model in a heterogenous IoT environment, which consider realistic workload, in this work, the tasks of the workload which contain various activities such as data collection, processing, analysis and communication are characterized using the directed-acyclic-graph (DAG). In the DAG, the tasks are represented as $X$. The $X$ is represented using the given:

$$X(K, D) \tag{1}$$

the task $X$ comprises of various set of tasks which is represented using $K$. The set of tasks refers to a collection or group of individual activities or operations that need to be performed to accomplish a specific goal or objective. Further, the set of tasks may have more tasks, i.e., subtasks. These subtasks in this work are represented using the $D$. When representing a set of tasks with subtask dependencies in a DAG, it is important to capture the hierarchical relationships between tasks by organizing them into parent and child nodes. The $K$ and $D$ are represented using the (2) and (3).

$$K = \{K_1, K_2, \dots, K_n\} \tag{2}$$

$$D = \{(K_q, K_r)|K_q, K_r \in K\} \tag{3}$$

Where, $K_q$ is the parent node and $K_r$ is the child node. In the context of a scientific or realistic workload which is represented using DAG, the QoS parameters has to be defined to ensure that the execution of the workload meets the specific performance and reliability requirements. Hence, in this work, the QoS has been defined for each task on the basis of the virtual machine (VM). Further, in this work, to capture the characteristics and requirements of the data flow which has to be communicated between the tasks, the edge parameters have been defined. The QoS-aware computational time for the $K_q$ is represented using $S(K_q)$ and the data flow between the parent node $K_q$ and child node $K_r$ is represented using $E(K_q, K_r)$. Further, the precedent task of the parent node $K_q$ is attained by using the (4).

$$S(K_q) = \{K_q|(K_q, K_r) \in D\} \tag{4}$$

While the primary focus in this section is to represent the scientific or realistic workload in the form of DAG. The DAG helps to define the dependencies and sequencing of tasks. The incoming tasks of the DAG can provide valuable insights for analysis, optimization, and resource allocation in certain scenarios. Hence, in this work, the incoming tasks have been defined which is represented as $K_{\leftarrow}$. The $K_{\leftarrow}$ for a given scientific or realistic task of the workload is represented using the (5).

$$F(K_{\leftarrow}) = \emptyset \tag{5}$$

Similar to the incoming tasks, the outgoing tasks can also help for analysis, optimization, and resource allocation in certain scenarios. Hence, in this work, the incoming tasks have been defined which is represented as $K_{\rightarrow}$. The $K_{\rightarrow}$ for a given scientific or realistic task of the workload is represented using the (6).

$$\nexists K_q \in K: K_{\rightarrow} \in F(K_q) \tag{6}$$

### 3.2. Execution model for workload processing

In this section, the executional model for the processing the scientific or realistic workload has been presented. The heterogenous IoT environment comprises of the physical machine (PM), VMs, internet and users. These set of interconnected devices and systems vary in terms of their capabilities, characteristics, and functionalities. In such an environment, different types of IoT devices, protocols, platforms, and technologies coexist, creating a complex ecosystem. In a heterogeneous IoT environment, these components interact and collaborate to enable various IoT functionalities, such as data collection, processing, communication, and user interactions. The internet serves as the backbone, connecting the physical and virtual machines and facilitating the flow of data and services between them. In this work, we consider a heterogenous IoT environment where there various PM are defined as $I$. The $I$ is expressed as (7).

$$I = \{I_1, I_2, I_3, \dots, I_o\} \tag{7}$$

Where, $o$ represents the PMs which exist in the heterogenous IoT environment. PM in a heterogeneous IoT environment can have different parameters and characteristics that define their capabilities and capacities. These parameters help define the capabilities and limitations of the PM in the IoT environment. They play a crucial role in resource provisioning, workload management, and decision-making processes related to task allocation, data processing, and system optimization. By considering these parameters, IoT systems can make informed decisions regarding resource allocation, load balancing, and optimization strategies based on the specific requirements and characteristics of each PM. In this work, the different parameters for the PM have been defined using $I_l$. Also, for each PM, $I_l \in I$. The $I_l$ is expressed as (8).

$$I_l = \{st_l, n_l, q_l^{\uparrow}, o_l, (g_l, w_l), V_l\} \tag{8}$$

Where, $st_l$ represents the storage-size, $n_l$ represents the processing-capacity, $q_l^{\uparrow}$ represents the maximum level of energy, $o_l$ represents the maximum amount of data that can be transmitted over a network within a given time frame, $(g_l, w_l)$ represents the voltage-level and frequency-level respectively and $V_l$ represents the VM which exist inside PM. The $(g_l, w_l)$ is expressed as (9);

$$(g_l, w_l) = \{(g_l^1, w_l^1), (g_l^2, w_l^2), \ldots, (g_l^{\uparrow}, w_l^{\uparrow})\} \tag{9}$$

further, the $V_l$ is expressed as (10);

$$V_l = \{v_{l,1}, v_{l,2}, \ldots, v_{l,|V_k|}\} \tag{10}$$

each VM in the PM is expressed as (11);

$$v_{l,m} = \{g_{l,m}, n_{l,m}, st_{l,m}\} \tag{11}$$

where, $g_{l,m}$ represents the VM frequency-level, $n_{l,m}$ represents VM storage-capacity and $st_{l,m}$ represents storage-size. The VM in this work can shift between the PM depending on the task requirement.

### 3.3. Energy consumption modeling for physical machines

Energy consumption modeling for PM in heterogenous IoT environments involves quantifying and predicting the amount of power or energy consumed by these PMs during operation. This modeling helps in understanding and optimizing energy usage, enabling more efficient resource allocation, energy management, and sustainability in IoT systems. Hence, in this section, we propose a model which helps to reduce the energy-consumption during the execution of the scientific or realistic workloads. To process or execute each task of the workload, energy is consumed. Consider a PM which is processing a task, in this scenario, the PM consumes energy which can be defined as $t_l$ and the maximum energy consumed by the PM can be defined as $i_l$. Ali *et al.* [23], they have presented a model to evaluate the energy-consumption of PM. Using this model, the energy consumed by each PM can be expressed as (12):

$$I_l = t_l * q_l^{\uparrow} * z_l^u + (1 - t_l) * q_l^{\uparrow} * \left(\left(g_l^{\uparrow}\right)^3\right)^{-1} * (g_l)^3 \tag{12}$$

where, $t_l$ represents the maximum consumption of energy by the PM, $q_l^{\uparrow}$ represents the maximal level of energy of the PM, $z_l^u$ represents whether the PM is executing a task or in idle state and $z_l^u \in \{1,0\}$, $g_l$ represents the CPU-frequency at a given time frame $u$ and $g_l^{\uparrow}$ represents the CPU-maximum frequency. From all these parameters, the energy-consumption can be reduced by optimizing the parameters and the energy consumption can be evaluated by the (13):

$$\mathcal{E} = \sum_{j=1}^{o} \int_{\mathrm{xt}}^{\mathrm{yt}} \left(t_l * q_l^{\uparrow} * z_l^u + (1 - t_l) * q_l^{\uparrow} * \left(\left(g_l^{\uparrow}\right)^3\right)^{-1} * (g_l)^3\right) dt \tag{13}$$

where, $g_l$ as well as $z_l^u$ are time-dependent as they change depending on the time frame $u$ and depending on the task of the workload.

### 3.4. Optimization model for task scheduling in heterogenous IoT environment

Various PMs and VMs are required for scheduling and executing the scientific or realistic workload tasks in the heterogenous IoT environment. Consider a PM which consists of different VMs represented as $v_{l,m}$

which is used for executing the scientific or realistic workload tasks represented as $K_q^r$. For execution of these tasks, a mapping-relationship among the $v_{l,m}$ as well as $K_q^r$ has to be defined. The mapping-relationship is defined as $y_{q,lm}^r$ in this work. The $y_{q,lm}^r$ is expressed as (14).

$$y_{q,lm}^r = \begin{cases} 0, & if\ K_q^r \text{ is not mapped to } v_{l,m} \\ 1, & \text{otherwise} \end{cases} \tag{14}$$

The task $K_q^r$ which needs to be executed might have various data-dependency. Hence, the data-dependency for each task can be expressed as (15);

$$gK_{q,lm}^r + KK_{qk}^r \leq st_{q,lm}^r, \quad \forall f_{qk}^r \in F_j \tag{15}$$

where, $gK_{q,lm}^r$ represents the time taken for completing the execution of $K_q^r$, $KK_{qk}^r$ represents the time consumed for transmitting data between the tasks $K_q$ and $K_r$ and $st_{k,lm}^r$ represents the storage-size. After execution of $K_q^r$ in $v_{l,m}$, the time consumed for execution of $K_k^r$ is expressed as (16);

$$gK_r = \max_{K_q^r \in U_r} \{gK_{q,lm}^r\} \tag{16}$$

the $K_q^r$ has to be executed in the given time frame. Hence, optimal resources have to be provided to execute the $K_q^r$ in that time frame. The time frame for the execution of the $K_q^r$ is expressed as (17).

$$gK_r \leq e_r, \quad \forall x_r \in X \tag{17}$$

Consider a scenario where a PM is executing a task in the VMs and another task arrives to the PM having higher priority. Then in this scenario, the other task has to be given some resources or VMs. This issue can be expressed as;

$$g_l^{\uparrow} - \sum_{m=1}^{|V_l|} g_{l,m} \geq 0, \quad \forall i_l \in I \tag{18}$$

$$n_l - \sum_{m=1}^{|V_l|} n_{l,m} \geq 0, \quad \forall i_l \in I \tag{19}$$

the constraints presented in the (15)-(19) have to be addressed and resolved for reducing the energy-consumption and providing optimal resources for the execution of $K_q^r$. Hence, to resolve these constraints, the given equation is used;

$$\text{Min} \sum_{l=1}^{o} \int_{\text{xt}}^{\text{yt}} \left( t_l * q_l^{\uparrow} * z_l^u + (1 - t_l) * q_l^{\uparrow} * \left( \left(g_l^{\uparrow}\right)^3 \right)^{-1} * (g_l)^3 \right) dt \tag{20}$$

where, $o$ represents the size of PMs which exist in the heterogenous IoT environment, $xt$ represents the time at which the execution started, $yt$ represents the time at which the execution ended. Also, $g_l$ as well as $z_l^u$ are time-dependent as they change depending on the time frame $u$ and depending on the task of the workload. This model main aim is to provide optimal resources for the execution of the tasks of the workload. Hence, to achieve this the following equation is used;

$$\text{Max} \left( \sum_{j=1}^{n} \sum_{k=1}^{|U_r|} cpu_q^r * \mathcal{T}_k^r \right) / \left( \sum_{l=1}^{o} g_l^{\uparrow} * \mathcal{A}_l \right) \tag{21}$$

where, $n$ represents the workload-size of $X$, $|U_j|$ represents the task-size of the $X$, $cpu_q^r$ represents the CPU-frequency for the $K_q^r$, $\mathcal{T}_q^r$ represents the completion of the workload execution, $o$ represents the size of PMs which exist in the heterogenous IoT environment and $\mathcal{A}_l$ represents the state (idle or active) of the PM. Furthermore, task scheduling is said to be a NP-Hard problem. Hence, to solve this, the proposed model executes the $K_q^r$ using the flow presented in the Figure 2. The proposed model attains better performance in terms of execution time and energy consumption when compared with the existing works which has been discussed in the next section.

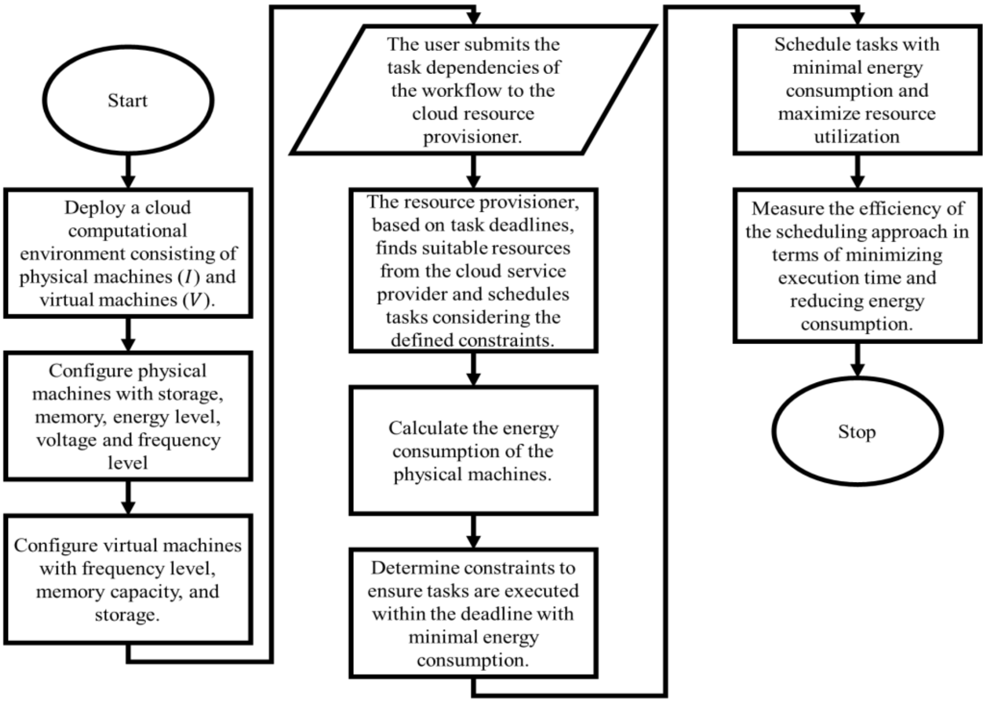


Figure 2. Flow for the workload task scheduling

## 4. RESULTS AND DISCUSSION

### 4.1. Experimental setup

In this section, the results obtained during the experimentation have been discussed. The experiments have been conducted on a Windows 10 operating system containing 8 GB RAM and 500 GB of harddisk. The experiments have been conducted using CloudSim. The experiments have been performed based on execution time, power sum, average power, and energy consumption required by the resources for the execution of the tasks of the scientific workloads. Host and VM sizes are heterogeneous. Three scientific workload cybershake [24], inspiral [25], and SIPHT [26] have been considered for evaluating the proposed model and comparing it with the existing works. The proposed model has been compared with the EMS model [27].

### 4.2. Execution time

The execution time has been evaluated in this section. The proposed model has been evaluated by considering three scientific workloads. Further, the results have been compared with the existing EMS model. The results for the execution time have been given in the Figures 3-5 for the cybershake, inspiral, and SIPHT workloads. The results show that the proposed model has attained 79.16%, 83.32%, and 51.46% better performance for the cybershake, inspiral, and SIPHT workloads respectively.

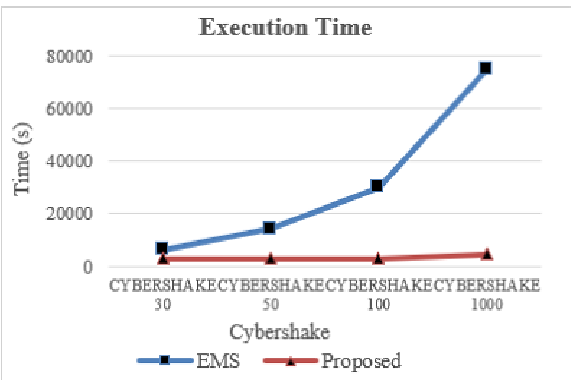


Figure 3. Execution time for cybershake workload

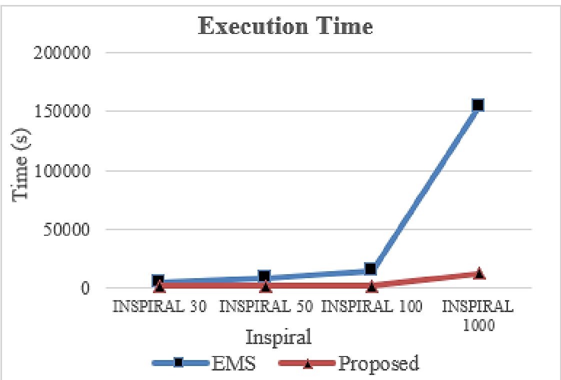


Figure 4. Execution time for inspiral workload

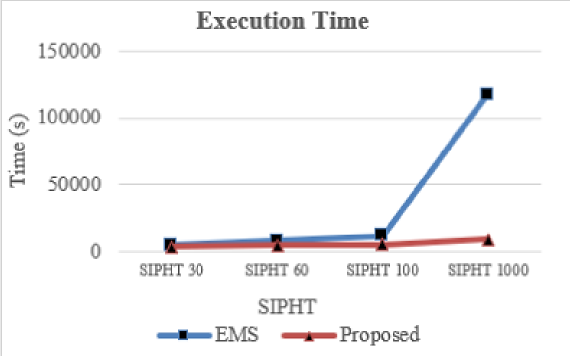


Figure 5. Execution time for SIPHT workload

### 4.3. Energy consumption

The energy consumption has been evaluated in this section. The proposed model has been evaluated by considering three scientific workloads. Further, the results have been compared with the existing EMS model. The results for the energy consumption have been given in the Figures 6-8 for the cybershake, inspiral, and SIPHT workloads. The results show that the proposed model has attained 24.35%, 44.85%, and 29.18% better performance for the cybershake, inspiral, and SIPHT workloads respectively.

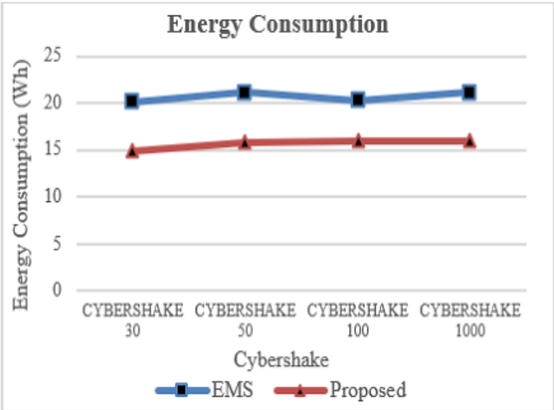


Figure 6. Energy consumption for cybershake workload

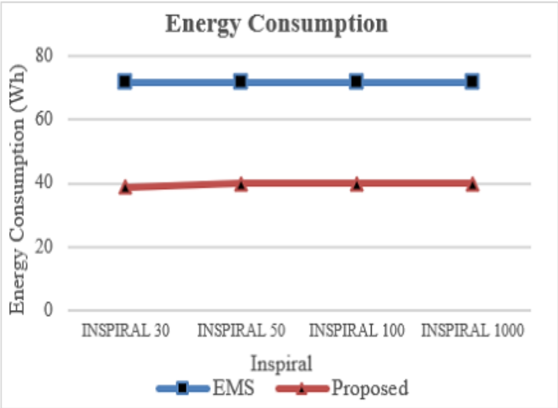


Figure 7. Energy consumption for inspiral workload

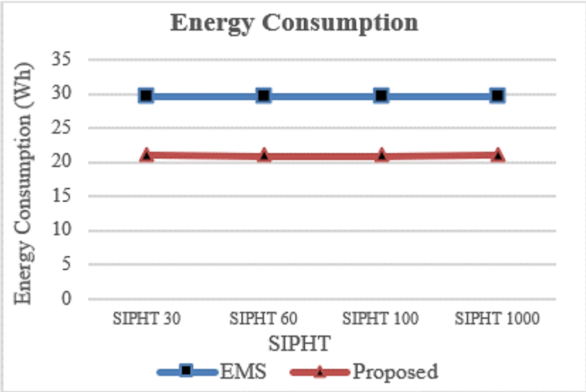


Figure 8. Energy consumption for SIPHT workload

## 5. CONCLUSION

Resource provisioning for scientific or realistic workload in a heterogeneous IoT environment poses significant challenges related to execution time and energy consumption. The dynamic nature of workloads and the diverse characteristics of IoT devices require efficient resource allocation strategies. In this study, we have proposed a resource provisioning model that specifically addresses these challenges. The model takes into account the dynamic and realistic nature of IoT workloads, aiming to allocate computational resources effectively while optimizing execution time and energy consumption. To evaluate the effectiveness of the proposed model, we conducted experiments using three scientific workloads and compared the results with existing models. The evaluation focused on performance metrics such as execution time and energy consumption. The results of the evaluation indicate that the proposed model outperforms existing models in terms of reducing both time and energy consumption for the execution of workload tasks. This demonstrates the efficacy of the proposed resource provisioning model in meeting the real-time demands of scientific workloads while optimizing resource utilization and energy efficiency. The findings of this study contribute to the field of resource provisioning in heterogeneous IoT environments, providing insights and practical guidelines for designing efficient resource allocation mechanisms. By effectively managing resource allocation in real-time, the proposed model enables improved performance and energy efficiency in scientific or realistic workload scenarios. Future research could explore the integration of security mechanisms and privacy-preserving techniques into the resource provisioning model. This would ensure that sensitive data and resources are adequately protected in the provisioning process.

## REFERENCES


[1] T. Lynn, P. T. Endo, A. M. N. C. Ribeiro, G. B. N. Barbosa, and P. Rosati, "The internet of things: definitions, key concepts, and reference architectures," *Palgrave Studies in Digital Business and Enabling Technologies*. Springer International Publishing, pp. 1–22, 2020, doi: 10.1007/978-3-030-41110-7_1.

[2] A. Gerodimos, L. Maglaras, M. A. Ferrag, N. Ayres, and I. Kantzavelou, "IoT: communication protocols and security threats," *Internet of Things and Cyber-Physical Systems*, vol. 3, pp. 1–13, 2023, doi: 10.1016/j.iotcps.2022.12.003.

[3] Y. He *et al.*, "Cross-technology communication for the internet of things: a survey," *ACM Computing Surveys*, vol. 55, no. 5, pp. 1–29, May 2022, doi: 10.1145/3530049.

[4] M. Noaman, M. S. Khan, M. F. Abrar, S. Ali, A. Alvi, and M. A. Saleem, "Challenges in integration of heterogeneous internet of things," *Scientific Programming*, vol. 2022, pp. 1–14, Aug. 2022, doi: 10.1155/2022/8626882.

[5] I. Zhou *et al.*, "Internet of things 2.0: concepts, applications, and future directions," *IEEE Access*, vol. 9, pp. 70961–71012, 2021, doi: 10.1109/ACCESS.2021.3078549.

[6] M. Etemadi, M. Ghobaei-Arani, and A. Shahidinejad, "Resource provisioning for IoT services in the fog computing environment: An autonomic approach," *Computer Communications*, vol. 161, pp. 109–131, Sep. 2020, doi: 10.1016/j.comcom.2020.07.028.

[7] K. Raghavendar, I. Batra, and A. Malik, "A robust resource allocation model for optimizing data skew and consumption rate in cloud-based IoT environments," *Decision Analytics Journal*, vol. 7, p. 100200, 2023, doi: 10.1016/j.dajour.2023.100200.

[8] A. Mijuskovic, A. Chiumento, R. Bemthuis, A. Aldea, and P. Havinga, "Resource management techniques for cloud/fog and edge computing: an evaluation framework and classification," *Sensors*, vol. 21, no. 5, pp. 1–23, Mar. 2021, doi: 10.3390/s21051832.

[9] J. Santos, T. Wauters, B. Volckaert, and F. De Turck, "Resource provisioning in fog computing: from theory to practice†," *Sensors (Switzerland)*, vol. 19, no. 10, p. 2238, May 2019, doi: 10.3390/s19102238.

[10] R. Jeyaraj, A. Balasubramaniam, A. K. M.A., N. Guizani, and A. Paul, "Resource management in cloud and cloud-influenced technologies for internet of things applications," *ACM Computing Surveys*, vol. 55, no. 12, pp. 1–37, 2023, doi: 10.1145/3571729.

[11] K. Kaur, A. Singh, and A. Sharma, "A systematic review on resource provisioning in fog computing," *Transactions on Emerging Telecommunications Technologies*, vol. 34, no. 4, Apr. 2023, doi: 10.1002/ett.4731.

[12] H. U. Atiq, Z. Ahmad, S. K. U. Zaman, M. A. Khan, A. A. Shaikh, and A. Al-Rasheed, "Reliable resource allocation and management for IoT transportation using fog computing," *Electronics*, vol. 12, no. 6, p. 1452, Mar. 2023, doi: 10.3390/electronics12061452.

[13] J. Fang, Y. Chen, and S. Lu, "Energy-efficient resource provisioning strategy for reduced power consumption in edge computing+," *Applied Sciences (Switzerland)*, vol. 10, no. 17, p. 6057, Sep. 2020, doi: 10.3390/app10176057.

[14] S. Sorrell, "Reducing energy demand: a review of issues, challenges and approaches," *Renewable and Sustainable Energy Reviews*, vol. 47, pp. 74–82, 2015, doi: 10.1016/j.rser.2015.03.002.

[15] M. G. Jordan, G. Korol, T. Knorst, M. B. Rutzig, and A. C. S. Beck, "Energy-aware fully-adaptive resource provisioning in collaborative CPU-FPGA cloud environments," *Journal of Parallel and Distributed Computing*, vol. 176, pp. 55–69, 2023, doi: 10.1016/j.jpdc.2023.02.009.

[16] S. Hashemifar and A. Rajabzadeh, "HPCDF: optimal service provisioning in iot fog-based environment for QoS-aware delay-sensitive application," *ArXiV*, 2023, doi: 10.48550/arxiv.2301.12522.

[17] D. Kanellopoulos and V. K. Sharma, "Dynamic load balancing techniques in the IoT: a review," *Symmetry*, vol. 14, no. 12, p. 2554, 2022, doi: 10.3390/sym14122554.

[18] N. Jangu and Z. Raza, "Improved jellyfish algorithm-based multi-aspect task scheduling model for IoT tasks over fog integrated cloud environment," *Journal of Cloud Computing*, vol. 11, no. 1, 2022, doi: 10.1186/s13677-022-00376-5.

[19] D. S. Nayagi, G. G. Sivasankari, V. Ravi, K. R. Venugopal, and S. Sankar, "Fault tolerance aware workload resource management technique for real-time workload in heterogeneous computing environment," *Transactions on Emerging Telecommunications Technologies*, vol. 34, no. 3, 2023, doi: 10.1002/ett.4703.

[20] V. Prakash, S. Bawa, and L. Garg, "Multi-dependency and time based resource scheduling algorithm for scientific applications in cloud computing," *Electronics (Switzerland)*, vol. 10, no. 11, p. 1320, 2021, doi: 10.3390/electronics10111320.

[21] M. Adhikari and H. Gianey, "Energy efficient offloading strategy in fog-cloud environment for IoT applications," *Internet of Things (Netherlands)*, vol. 6, p. 100053, 2019, doi: 10.1016/j.iot.2019.100053.

[22] S. Tian, W. Ren, Q. Deng, S. Zou, and Y. Li, "A predictive energy consumption scheduling algorithm for multiprocessor heterogeneous system," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 2, pp. 979–991, 2022, doi: 10.1109/TGCN.2021.3131323.

[23] S. A. Ali, M. Ansari, and M. Alam, "Resource management techniques for cloud-based IoT environment," in *Internet of Things (IoT): Concepts and Applications*, Cham: Springer International Publishing, 2020, pp. 63–87.

[24] "Cybershake Dataset," *Peagasus*, 2011. https://pegasus.isi.edu/workflow_gallery/gallery/cybershake/index.php (accessed Jun. 02, 2023).

[25] "Inspiral Dataset," *Peagasus*, 2011. https://pegasus.isi.edu/workflow_gallery/gallery/ligo/index.php (accessed Jun. 02, 2023).

[26] "Sipht Dataset," *Peagasus*, 2011. https://pegasus.isi.edu/workflow_gallery/gallery/sipht/index.php (accessed Jun. 02, 2023).

[27] B. Hu, Z. Cao, and M. C. Zhou, "Energy-minimized Scheduling of real-time parallel workflows on heterogeneous distributed computing systems," *IEEE Transactions on Services Computing*, vol. 15, no. 5, pp. 2766–2779, Sep. 2022, doi: 10.1109/TSC.2021.3054754.


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