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RESEARCH ARTICLE

A Novel Energy Proficient Computing Framework for Green Computing Using Sustainable Energy Sources

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ABSTRACT Numerous green computing applications employ sustainable energy sources to abate redundant energy consumption. Renewable energy sources are vital to improving energy efficiency and should be used optimally. This paper introduces the Energy Proficient Computing Framework (EPCF) in the resource-centric cloud environment. The main objective of the EPCF is to improve the shared efficiency of energy distribution in the computing systems. Renewable energy is distributed among computers according to their running status and the number of calculations available. Traditional k-means clustering separates the states and computations when making this determination. This mapping procedure is repeated throughout the computation until the energy is dispersed without waste. Energy is conserved for the later use if the sources of the leak can be located in advance. As a result, we can conserve and use energy more effectively. In addition, it speeds up calculations and decreases service allocation waiting times. The proposed framework achieves 14.69% less energy cost for the different service al-location rates, 6.34% less energy drain, and 14.4% high efficiency.

INDEX TERMS Renewable energy, energy allocation, green computing, k-means clustering, sustainable energy.

I. INTRODUCTION

Green computing paradigms are emerged for providing environmentally friendly solutions for the application of electronic resources in natural environments. Green communication and computing are disposable/ reusable solutions of electronic applications that reduce its adverse impact on the environment [1]. Another design goal of such paradigms is energy effectiveness and power management. Eco-friendly power allocation and distribution are exploited in these computing environments for reliable outcomes [2]. Such a computing paradigm conserves electricity supply and demand and reduces the quantity of non-disposable toxic wastes [3]. The energy and power management are designed in both dynamic and static manners, particularly green computing models. The static energy optimization operates from the design and fabrication of hardware and circuits compatible with different activities performed by the green computing systems [4]. Contrarily, the dynamic power management optimizes the application execution of the system for preserving its efficiency. Green computing techniques rely on replenishable natural energy sources for performing computations and other system-based operations [5].

The Cloud computing environment provides different service solutions and analytics models for heterogeneous user demands. The computing devices are powered by different energy sources for their seamless operations [5]. The fundamental requirements are the uninterrupted power supply and

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energy drain, the adversary of which results in computation failures and overloading. A cloud data center/ environment is closely packed with numerous servers with independent and stored computing, storage, network, and communication attributes [6]. The operation and utilization of such attributes require seamless energy for reliable operations and a ceaseless power source [7]. Therefore, considering the significance of green computing, renewable energy sources are augmented with the cloud environment envisioned in the recent research approaches [8]. A sustainable energy-dependent power allocation and distribution supports the green cloud computing environment without draining non-renewable energy sources. The cloud workloads are processed using renewable energy sources managed and distributed through specific controllers and smart grid architectures. This helps to balance the energy utilization and allocation effectively across any number of cloud workstations [9], [10].

Energy efficiency is a prime concern in a distributed computing environment as it helps to prolong the lifetime and processing of the computing devices. In a green computing environment, sustainable energy sources are incomparable with conventional energy generating sources [11]. Therefore, the energy generation and distribution from a renewable energy source do not cope with a conventional energy production source. This serves as a drawback in ensuring seamless and uninterrupted power allocation for the cloud-based computing systems [12]. This leads to the ideology of energy conservation and efficiency for improving the computing system performance [13]. In recent years, many energy conservation approaches, harvesting, and efficient allocation for cloud workstations have been introduced. The theme of these approaches is to improve the cloud's computing and energy utilization efficiency for uninterrupted service broadcast for its associated users [14]. As mentioned earlier, dynamic and static energy optimization methods are deployed for the cloud environment for defining the state and computations of the devices and user tasks. Such a non-converging energy conservation approach emphasizes the success of renewable energy-based green computing in cloud environments [15].

In [16], task-centric energy-aware Cloudlet-based Mobile Cloud is developed to improve mobile devices' performance and offload reliably. The scope of this work is to decreases the energy cost and improves the scalability of incoming energy by performing scheduling mechanisms. The throughput is increased concerning varying acquired energy from the sensor device and evaluates the better energy security method.

The energy is consumed by introducing a wavelet decomposition performed by deploying resources in cloud computing and decreasing the noise. In [17], wavelet transform de-noising is used to evaluate the accurate forecasting that decreases unwanted energy usage. From the incoming energy, the noise is reduced by the decomposition method.

The energy cost is reduced by implementing the green geographical load balancing (GreenGLB) online method. It is evaluated by deploying the greedy algorithm to analyze interactive and indivisible workload energy distribution. In [18], the energy is distributed by evaluating the data centers in which energy cost.

Alarifi et al. [19] proposed an energy-efficient hybrid (EEH) framework to sustain the electrical energy and decreases power consumption. Here the scheduling is performed by deploying two methods such as Power Usage Effectiveness (PUE), Data Center Energy Productivity (DCEP). The scope of this work is to decreases the cost of energy usage and improves throughput.

Wu and Wang [20] presented a task processing permutation and voltage supply levels (VSLs) to reduce the processing time energy usage. In this work, the standard heuristic method is developed to promptly process the task in which it deploys the multi-model estimation of distributed (mEDA). The energy consumption is reduced by evaluating a bi-objective genetic algorithm (bGA).

The electric energy is consumed by introducing a tree-based fog computing (TBFC) in [21] to decrease the cloud-based server delay. The processing is performed in fog computing in which it enhances the performances of the system. In this work, the traffic is decreased for the data that is acquired from the sensor.

The Quality of Service is enhanced by implementing an energy-aware model that deploys content filtration and load balancing. In [22], it improves energy consumption and decreases the latency by evaluating the random distribution of energy. The processing is carried out in three categories: neighbors, energy levels, and operational power.

The heuristic algorithm is presented to decreases the computation complexity and reliably enhances energy consumption. In [23], joint consideration, task allocation, green energy scheduling, and NP-hardness are developed to address the latency-sensitive cloud service. For this computation, step scheduling is performed to utilize the energy for pursuing processing.

In a pervasive job, the server energy consumption is processed by deploying the off-line decision-making approach in which the energy is stored in a photovoltaic manner. In [24], the relationship is carried out among the stored energy and renewable energy in which it minimizes the energy from the acquired sensor device.

Energy-efficient load balancing global optimization is developed to perform the task schedule that increases energy consumption. The energy consumption and load balancing are addressed by deploying the task scheduling method in [25]. The processing is evaluated in green computing in which the efficiency of energy is extracted on time.

Alsubhi et al. [26] presented a mobile energy augmentation using cloud computing (MEACC) to minimize load balancing and power consumption. This work addresses the issue that occurs in smart devices such as massive power consumption and inefficient resource utilization. The decision-making model is evaluated to perform to reduce communication costs.

A Scalable and energy-efficiency scheme is proposed in [27] by evaluating three methods, such as zone-based hybrid-placement schemes. The second model deploys the

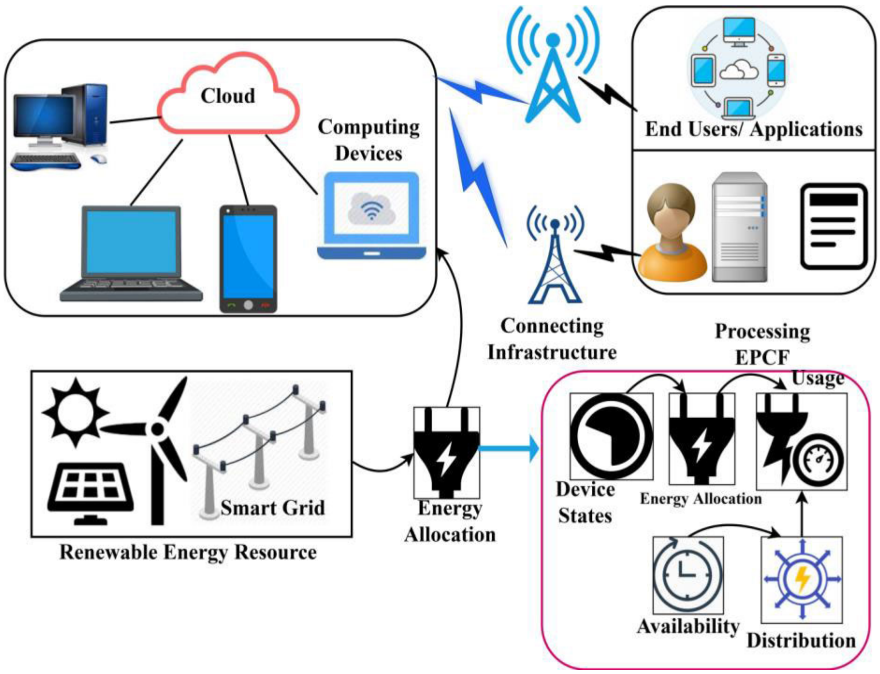

FIGURE 1. Proposed framework in cloud-user environment.

Multi-Stage Weighted Election heuristic (MSWE) whereas, the third method is processed by developing the Minimum Cost Cross-layer Transmission model (MCCT). The objective of this paper is to improve the network lifetime.

In [28], the energy is consumed on mobile cloud computing (MCC), in which it increases the throughput and probability of offloading mechanism. Here two issues are sort out, such as energy consumption and execution delay by developing cloudlet-assisted MCC. The optimization problem is addressed in this work and enhances effectiveness.

Haghighi et al. [29] modeled a K-means clustering to map the incoming task with dynamic consolidation in which it enhances the micro-genetic method. The scope of this proposed work is to minimize energy consumption; in turn, it improves the QoS. Here it deploys the hybrid method that performs on better virtualization technique by introducing the KMGA method.

The rest of the manuscript is arranged as follows: Section II details the Energy Proficient Computing Framework, Section III proposes the Proficient Energy Distribution, and Section IV gives Discussion and Results. Section V draws the Conclusion of the paper.

II. ENERGY PROFICIENT COMPUTING FRAMEWORK

In green computing systems, energy efficiency is improved by decreasing resource computation promptly. It is controlled by predicting the pursuing energy for the particular application and saves for future purposes. Figure. 1 illustrates the framework process in a cloud-user environment.

Renewable energy resources power the cloud environment for performing computations. An energy allocation system performs the allocation of energy based on device states and energy usage. This helps to maintain the balanced distribution and availability of energy for further computations. In the next section, the energy distribution process is discussed.

A. ENERGY DISTRIBUTION

This paper aims to reduce the waiting time and service allocation, increasing reliable energy efficiency. In this work, K-means clustering deploys by mapping the operating state and available computation. The following equation (1a) analyzes energy usage and wastage by verifying with the preceding energy model.

$$\pi' = (e_0 * r_l) + \left(\frac{p_e}{g_a}\right) * \prod\nolimits_{d_i} \left[(\vartheta + l_t) - \left(\delta' * y_u\right)\right] - m' \tag{1}$$

The energy is analyzed by equation the above equation (1a), which is represented as π' in which is energy is acquired from the environment and is termed as $e_0(r_l)$. By equating $(\vartheta + l_t) - \left(\delta' * y_u\right)$ the grouping of energy is used to evaluate resource allocation, which is termed as l_t. The grouping of energy is represented as ϑ in which energy sharing is processed, which is termed as δ'. The energy discovery is referred to as y_u in which it acquired the energy and reduced the wastage, whereas it improves consumption. The analysis is represented as π' the distribution of energy is denoted as d_i which is processed on time, and it is termed as m'.

The energy wastage and usage is represented as w_s and g_a is identified by deploying the preceding energy model that is referred to as p_e. In this analysis, the energy wastage and usage are identified post to this processing. The distribution is evaluated to find the unwanted usage of energy in green computing. It is processed with the energy allocation phase,

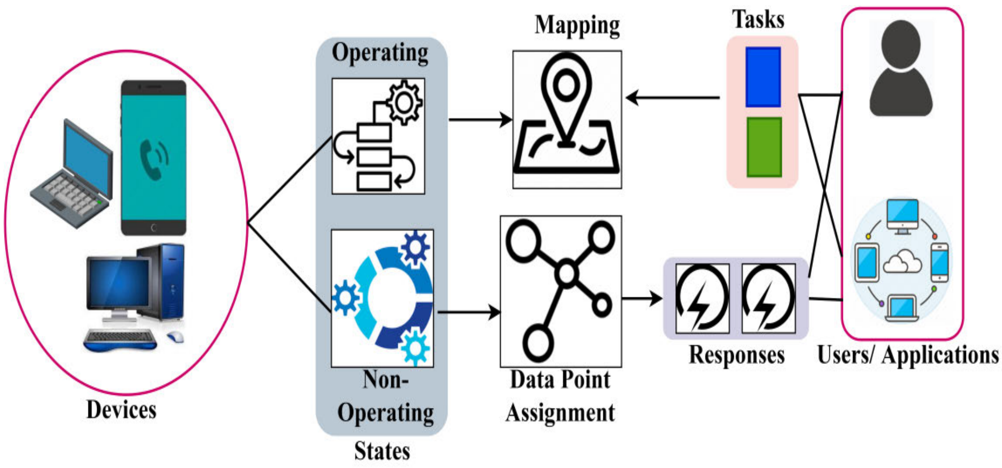

FIGURE 2. State and computation process.

which is computed in the following equation. Here, it acquires the input from the preceding equation's output as an analysis of usage and wastage of energy and produces the result by allocating the energy.

$$l_t = \left[\prod\nolimits_{y_v} (\boldsymbol{e}_0 + \boldsymbol{r}_l) * \left(\frac{e_n + m'}{d_i}\right)\right] + \boldsymbol{\pi}' * (g_a + \boldsymbol{w}_s) - \left(\frac{1}{e_n} + r_l\right) \tag{2a}$$

The energy allocation is computed in the above equation in which it performs the distribution process that is denoted as d_i where it acquires the number of energy that is termed as e_n. By computing $(g_a + w_s) - \left(\frac{1}{e_n} + r_l\right)$ the energy waste and usage are evaluated in which it performs the distribution to the particular green computing. The allocation of energy is used to deploy the better distribution of energy and consume it better. The number of energy is represented as e_n which is acquired from the green computing environment; post to this processing, the following equation (2b) is used to estimate the distribution that acquires the input as the energy and yields the sharing.

$$d_i = \begin{cases} (y_u + e_n) * \left(\frac{e_0}{p_e}\right) + m', \in g_a \\ \sum_{y_u} p_e + e_n * l_t - \pi', \in w_s \end{cases} \tag{2b}$$

In the above equation (2b), the energy is fetched and process on time. Here it computed two derivations such as usage and wastage of energy. The first derivation represents energy usage, and it is represented as $(y_u + e_n) * \left(\frac{e_0}{p_e}\right) + m'$. Here, the preceding energy model deploys to analyze the pursing state of energy usage and allocates the energy in this processing; the usage is monitored. The second derivation evaluates the energy wastage using the preceding model analysis.

By formulating $\sum_{y_u} p_e + e_n * l_t - \pi'$ the energy for computations is acquired and processed, but the analysis is not performed on time, so energy wastage occurs. By integrating equation (2a) and (2b), the following equation is computed: it yields the allocated energy and its usage for the particular application. It is performed to estimate how much energy wastage is evaluated and avoids further processing in green computing.

$$d_i(l_t) = \int \left(r_l * \frac{e_0}{y_u}\right) + \prod\nolimits_{g_a}^{w_s} (m' - \pi') * \left(\frac{ir}{a_0} + p_e * (e_n + r_l)\right) - (m' - \pi') \tag{3}$$

The distribution and allocation of energy are evaluated to calculate the usage and wastage by analysis with the preceding energy processing. Here a timely manner is used to find the usage and wastage of energy and is also associated with the unwanted processing of certain applications. By formulating $\left(\frac{i'}{a_0} + p_e * (e_n + r_l)\right)$ the energy drain occurs if the energy is used for the unwanted application; it must be estimated to satisfy the objective.

B. STATE AND COMPUTATIONS

The energy consumption is used to improve the performance of green computing and sustains energy. Here the energy usage and wastage are computed in which consumption is evaluated by developing the K-means clustering those categories the operating state and available computation. In Figure. 2, the state and computation process for energy distribution is illustrated.

The operating state includes how much energy is processed for the particular application that relies on necessary and unnecessary. The computation describes the availability of energy in green computing, allocated to perform the particular processing. Here the clustering is used to evaluate the state and computation in the following equations.

$$\boldsymbol{\mu}' = \boldsymbol{e}_n * (\boldsymbol{l}_t + \boldsymbol{g}_a) - \boldsymbol{w}_s + \left(\frac{\boldsymbol{m}' + r_{l*e_n}}{\prod_{d_i} e_0}\right) - (\boldsymbol{i}' - \boldsymbol{p}_e) * (\boldsymbol{x}_0 - \boldsymbol{x}') \tag{4a}$$

$$\Delta_0 = \sqrt{\left(\frac{e_0/p_e}{\sum_{l_t e_n}}\right) + (a_0 + w_s) * \left(\frac{y_u + r_l}{m'}\right) + e_0} \tag{4b}$$

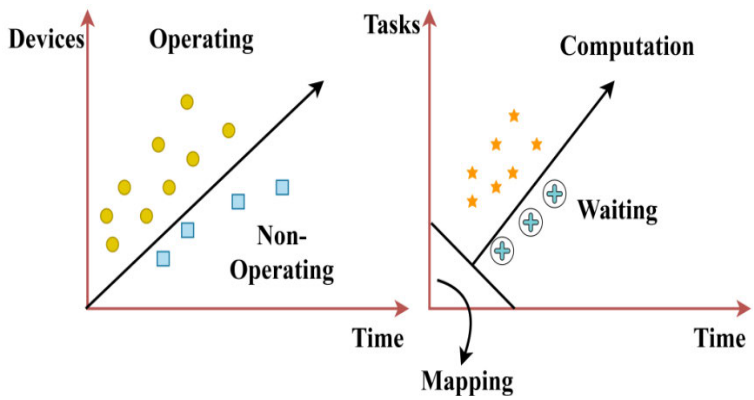

FIGURE 3. Initial representation of states and computations.

In equation (4a) the states are evaluated in which it describes the necessary and unnecessary which is represented as x_0 and x'. It is used to analyze the energy usage by evaluating the preceding processing, and it is denoted as $\left(\frac{m'+r_l*e_n}{\prod_{d_i} e_0}\right) - \left(i' - p_e\right)$. Here, the time is used to discover the application's energy usage by checking with the previous activity and providing the necessary energy to computation. If the application requires lesser energy to process the task means the allocation of energy is provided certainly. The processing is computed by analyzing whether it is necessary to provide particular energy or not to run the application; here, the state is represented as μ'.

Equation (4b) represents the operation computation in which it describes the availability of energy resides or not by deploying this status; the evaluation is performed. Thus, the previous energy model is used to estimate energy availability and processes for green computation. If there is any energy drain occurs, there is a cause of energy wastage to avoid this integration of equation (3) is used. Thus the discovery of energy is processed by examining the allocated energy in the previous state. The operation computation relies on the availability of energy, and it is referred to as Δ_0. The K-means cluster is used along with the EPCF framework for a resource-centric cloud platform by deploying this state and computation.

C. K-MEAN CLUSTERING PROCESS

It is used to partition the acquired energy and computes the distance between the data points that resemble the energy usage and wastage. It is associated with the state and computation of energy to sustain the green computing energy in which the processing is performed on time. The initial representation for states and computations is presented in Figure. 3.

In K-means, the initial step is to select the random data to analyze the cluster's centroid. Here two clusters are used, such as the operating state of the cluster and available computation. So the centroid is used to find efficient energy and consume for pursuing application working. The following equation is used to estimate the objective function in which it decreases the error that is referred to as unwanted usage of energy. It acquires the input as state and computation and provides the output to decreases the energy drain.

$$z_0 = \prod_{m'=1}^{h_0} * \prod_{n'=1}^{h'} \left\| k' - s' \right\|^2 \tag{5a}$$

In the above equation, the objective function is calculated, which is denoted as z_0 The data points of the cluster are termed as $v_0(b_0, b_1)$, the set of cluster centers for the incoming energy is represented as s'. The distance Euclidean distance is detected by analyzing $\left\| k' - s' \right\|$ in which the cluster center is denoted as h_0 that is processed by deploying the objective function. For state and computation processing, the clustering is evaluated as b_0 and b_1. For b_0 the data points are referred to as v_0 and for b_1 the data points are denoted as h' by processing this. It decreases the emerge drain and reduces the upcoming computation. The distance between the two clusters is represented as m' and n'. Post to this objective function, the random selection of centroid is evaluated for the state and computation, which is equated in the following equation.

$$w' = z_0 * \left[\left(\frac{v_0 + s'}{b_0}\right) + \left(\frac{h' + s'}{b_1}\right)\right] + \sum_{k'} \left(\pi' * e_0\right) \tag{5b}$$

The random selection of centroid is to find the centroid for the operating state and available computation in which the closed point is evaluated. In the above equation (5b), the energy necessary to run the application is evaluated. It is termed as w' here the cluster, and its data points are identified by computing the objective function. In Figure. 4, the random selection process of the state and computation is illustrated.

The random selection of cluster centroid is performed to analyze the usage and wastage of energy to run the particular application. Here, the prediction model is used to predict the pursuing usage of energy for the application; for this, the centroid analysis is evaluated.

By formulating $z_0 * \left[\left(\frac{v_0+s'}{b_0}\right) + \left(\frac{h'+s'}{b_1}\right)\right]$ the cluster and its data points are identified in which it selects the cluster

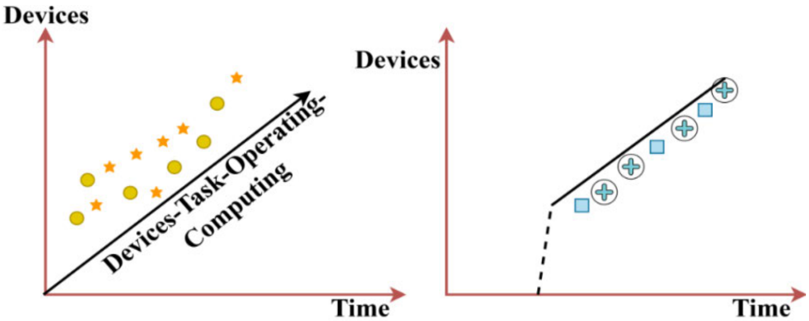

FIGURE 4. Random selection process.

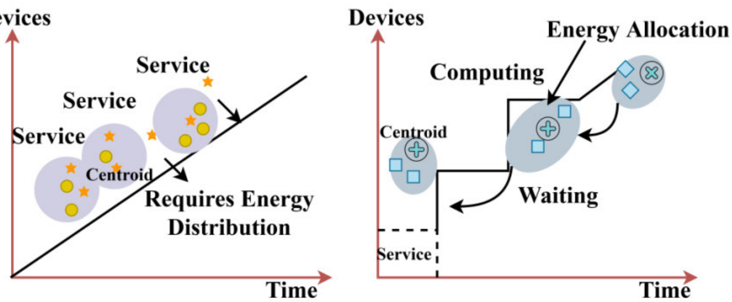

FIGURE 5. Centroid identification for mapping.

center by deploying the objective function. Thus, the random selection of the cluster center is evaluated post to this performance. The Euclidean estimation is used to measure the distance between the centroid and data points for both the clusters. It is computed by using the following equation (5c). It fetches the input from the previous equation output and yields the distance.

$$y_x\left(m', n'\right) = \sqrt{\prod_{t=0}^{\theta_c} \left(m'(t) - n'(t)\right)^2} \tag{5c}$$

The Euclidian distance is analyzed in the above equation by evaluating the cluster's data points and provides the distance between the state and computation. The distance is referred to as y_x in which the initial point to analysis the data points is termed as t here the calculation is estimated for space, and it is represented as e_c. Here, the distance is evaluated from the centroid of the cluster and the data points in which it processes the applications' energy. Thus the distance is calculated in the above equation (5c) post to this update of the centroid is performed. In Figure. 5, the centroid identification process for mapping is illustrated.

It is evaluated for every instance of energy that has been acquired from the sources and consumes to achieve better energy efficiency. So the update of the centroid is computed, and it is identified by evaluating the following equation (6) as follows.

$$\rho_0 = y_x\left(s' + k'\right) * \left(\frac{e_c + e_0(w')}{z_0}\right) + \left[b_0\left(v_0\right) * b_1(h')\right] + \left[m'\left(b_0\right) * n'(b_1)\right] \tag{6}$$

The update of the centroid is calculated in the above equation ρ_0 in which the data points and the center of the cluster are extracted and provides the distance. For every instance of energy acquiring variation, this update of the centroid is performed. The data points for the two cluster are processed, and it is denoted as $b_0\left(v_0\right) * b_1(h')$. The distance between the random clusters is equated as $m'\left(b_0\right) * n'(b_1)$. For every update, the centroid point varies if this happens, then the data point for the cluster differs for the number of iteration steps. So the separate analysis is evaluated by assigning the data points to the cluster for operating state and availability computation in the following equation.

$$C = s'\left(b_0, b_1\right) + \left(\frac{e_0 * z_0}{\prod_{\pi' l_t}}\right) + \left(m', n'\right) * \left(\frac{\mu' + \Delta_0/w_r}{h_0 + h'}\right) + \left(y_x - s'\right) + \rho_0 \tag{7}$$

The data points are assigned to the closest cluster to analyze the state and computation and perform the mapping. The assigning is referred to as in which it acquires the data point from the cluster. The output is the distance between the nearest ranges. By equating $s'\left(b_0, b_1\right) + \left(\frac{e_0 * z_0}{\prod_{\pi' l_t}}\right) + \left(m', n'\right)$ the set of cluster centers is detected, and the distance between the centroid and data points are analyzed. It satisfies by sustaining green computing energy for this analysis of state clusters, and availability computation is performed to identify the data points.

III. PROFICIENT ENERGY DISTRIBUTION

In green computing, the energy allocation is important to provide energy sustainability for pursuing processing for this

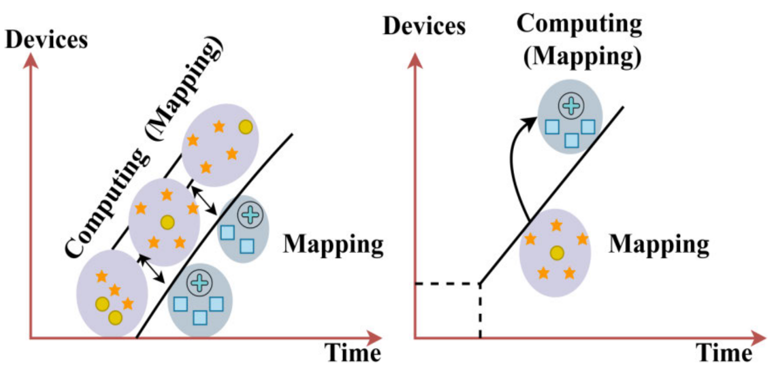

FIGURE 6. Mapping process.

EPCF and the K-means clustering. The assigned data points detect the closest cluster and find the energy necessary to process the forthcoming applications. For this evaluation, the following equation (8a) and (8b) is estimated in which it acquires the update of centroid and process with the Euclidean distance and yields the analysis of data points.

$$\pi'\left(\mu'\left(b_0\right)\right) = \left[\left(i' - p_e\right) * \left(x_0 - x'\right)\right] + \left(\frac{e_0\left(w'\right)}{r_l}\right) * \left(o_f * z_0\right) + \rho_0 \tag{8a}$$

$$\pi'\left(\Delta_0\left(b_1\right)\right) = \sqrt{\left(\frac{\varepsilon_0/p_e}{\sum_{l_t} e_n}\right)} + \left(a_0 + w_s\right) * \left(h_0 + \rho_0\right) \tag{8b}$$

The analysis is performed for the state and computation and identifies the data points and centroid, and it separates the nearest range of energy necessity and provides to the applications. In the operating state, it detects whether it is necessary of higher or lower energy and provides on time in which it performs the update of centroid and transmits o_f. By formulating $\left(\frac{e_0(w')}{r_l}\right) * \left(o_f * z_0\right)$ the energy is transmitted to the application, and it deploys the update of the centroid. Thus, analyzing the cluster's state is evaluated in equation (8a), whereas energy availability is computed in equation (8b). In Figure. 6, the mapping process is illustrated.

The computation of energy availability is evaluated to detect the energy drain; in this clustering, it detects the nearest range of energy availability and unavailability and yields the data point. Here, it detects the amount of energy is used to perform a task, and post to this, it analysis the drain that leads to insufficient energy. The data points update if the centroid changes; in this case, the computation and state common range of energy acquiring and processing are mapped. The following equation (9) is used to evaluate the mapping process for state and computation by deploying the clustering.

$$\alpha_g = a_0\left(e_0 * z_0\right) + \left(\frac{e_0}{x_0 + x'}\right) + \sum\left(y_u + y_x\right) * s' + \left(m' + n'\right) - \rho_0 * \left(k' + v_0\right) \tag{9}$$

The mapping of state and computation is performed to detect the energy necessity and wastage and consume for the forthcoming working process is equated in the above equation. Here the state relates to the identification of necessary and unnecessary, whereas the availability represents the energy is consumed or not. In this, the K-means is used to deploy the EPCF method and perform the mapping with the centroid and the clusters' data points. The mapping is denoted as α_g in which it extracts the closest energy from the cluster and performs the allocation process. Here, the state and computation are mapped by evaluating $\sum\left(y_u + y_x\right) * s' + \left(m' + n'\right)$ in this cluster center and data points are detected, and energy is consumed. Post to this mapping, the efficiency of energy is calculated in the below equation. It acquires the input from the mapped energy from the state and computation cluster and yields sustainable energy.

$$i' = \left(\frac{r_l * z_0}{e_n}\right) + \left(\prod_{s'} k' * \left(v_0 + h_0\right) - y_x + \left(\rho_0 + o_f\right) + l_t * d_i * \left[b_0\left(m'\right) + b_1\left(n'\right)\right]\right) - m' \tag{10}$$

The efficiency is performed by calculating the following equation (10), in this nearest energy that is acquired for the application is computed by deploying the preceding observation. Thus, the distance between the updated centroid and data points is calculated to address the energy drain. The energy drain is sorted out by computing the mapping method in which the state and computation clusters nearest resides energy is tracked. The distribution and allocation of energy is performed by equating $y_x + \left(\rho_0 + o_f\right) + l_t * d_i$ in this, the distance also analyzed and transmitted the consumed energy for the requested applications. Thus, this paper's scope is addressed by deploying K-means clustering, and the energy is sustained by developing the EPCF model.

A. SELF-ANALYSIS

This section discusses the observed output of the proposed EPCF under different varying conditions and metrics.

The computation ratio is varied concerning consuming energy in green computing and analysis sustainability (Figure. 7). Suppose the energy drain decreases, then the computation ratio increases, whereas the energy distribution is processed. Here the comparison is evaluated and estimates the energy drain increases by 10% compared to 100%. The

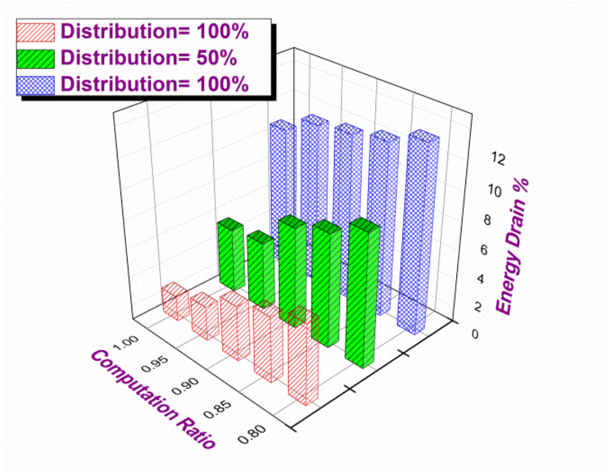

FIGURE 7. Energy drain % analysis.

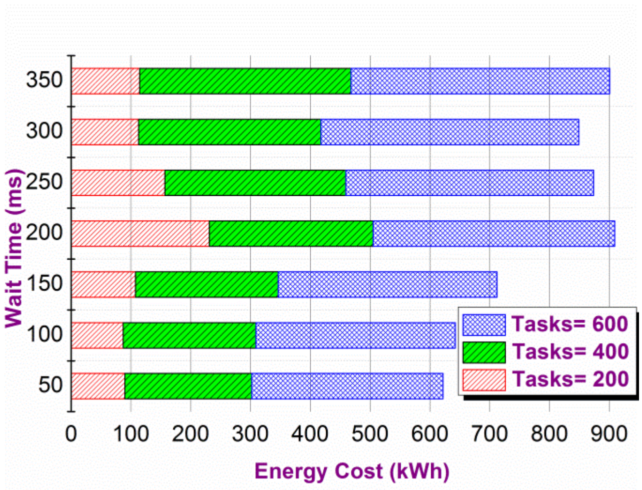

FIGURE 8. Energy cost analysis.

waiting time is varied for the energy cost (Figure. 8), and tasks are assigned to the application and process the energy. The waiting time varies and shows better improvement for energy costs in which tasks are performed on time. Task 600 shows a higher energy cost compare to 200 tasks.

The centroid update is used to improve the energy consumption in which the assigning of data points and clustering is evaluated. Suppose the centroid update increases, the computation ratio decreases. The mapping is performed between the state and computation. The mapping process decreases for the varying centroid update [Figure. 9(a)].

The centroid update is evaluated for the distribution and availability of energy [Figure. 9(b)] in which it enhances the efficiency of energy. Suppose the availability of energy varies from low to high, whereas distribution is processed from high to low value. The energy availability is checked to perform the centroid update, and it deploys the distribution method.

The centroid update is evaluated for the efficiency of the task, allocation, and energy, in Figure. 9(c). The task is assigned to perform in green computing. If the centroid update varies for efficiency and shows the higher value, it compares the task from 200 to 600. Compared to 200 tasks, 600 shows higher efficiency.

The energy distribution is evaluated to decreases the energy drain in which the prediction is not performed accurately. If the prediction is carried out reliably means the distribution is performed optimally. The energy drain increases for varying tasks that deploy from 200-600 compared to 200 tasks 600 shows higher energy drain (Figure. 10).

TABLE 1. Experimental setup.

Parameter	Value
Energy Range	286-534.8kWh
Energy Sources	7
Computing Devices	12
Max. Wait time (ms)	540ms
Tasks	700
Tasks/ Allocation	30-40

IV. PERFORMANCE DISCUSSION

In this subsection, the proposed EPCF performance is discussed using the metrics computation ratio, wait time, service allocation, energy cost, energy drain, and efficiency. The experiment is carried out using the data set information obtained from [30]. The data set is analyzed using a machine of 2.2GHz processing element and 6GB physical memory. The details of the experimental setup are presented in Table 1.

By using this experimental setup, the fore-mentioned metrics are compared along with the existing methods CSRSA [25], SEES [27], and EEHF [19].

A. COMPUTATION RATIO

The computation ratio for the proposed work increases for varying tasks in which the energy is provided to the requested application (Figure. 11). In this processing, the energy usage and wastage are calculated to improve the consumption for further application. The energy is distributed to the end-requestor, and it is computed as $\frac{i'}{a_0} + p_e * (e_n + r_l)$ here the energy drain is analyzed. The energy is acquired and processed on time in which it deploys the state and computation from the sensor. The categorization of this used to discover the energy and mapping is performed between the state and computation process. The K-means clustering is used to evaluate energy grouping with the nearest range and provides the energy if necessary. The allocation of energy is used to achieve better energy efficiency in which the mapping is performed for the cluster. The data points and cluster center is detected, and it is represented as $\left(\frac{v_0+s'}{b_0}\right)+\left(\frac{h'+s'}{b_1}\right)$ here the clusters are selected to identify the energy usage and wastage.

B. WAITING TIME

In Figure. 12, the waiting time is decreased if the energy usage is identified by formulating $\left(\frac{m'+r_l * e_n}{\prod_{d_i} e_0}\right)$ here the number of

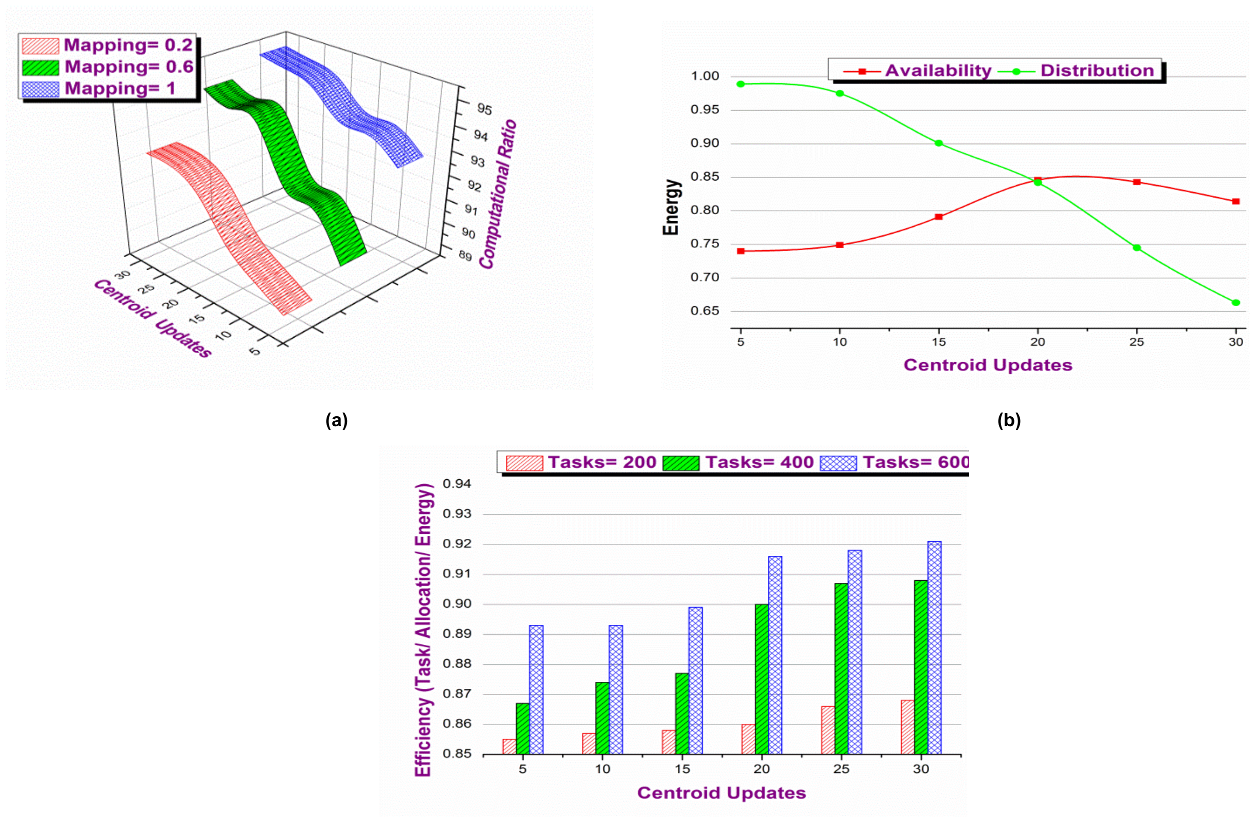

FIGURE 9. Computation ratio, energy (availability and drain), and efficiency for centroid updates.

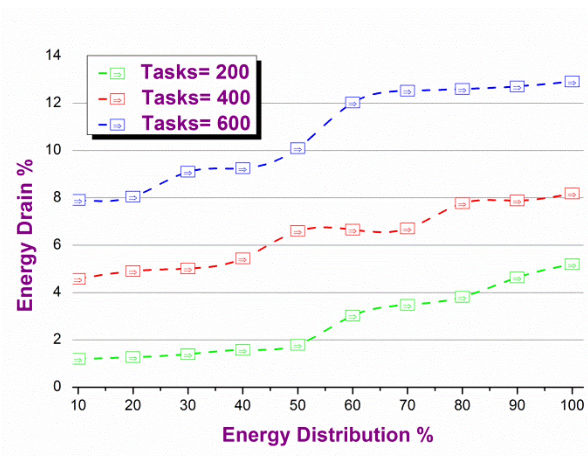

FIGURE 10. Energy drain % analysis for distribution %.

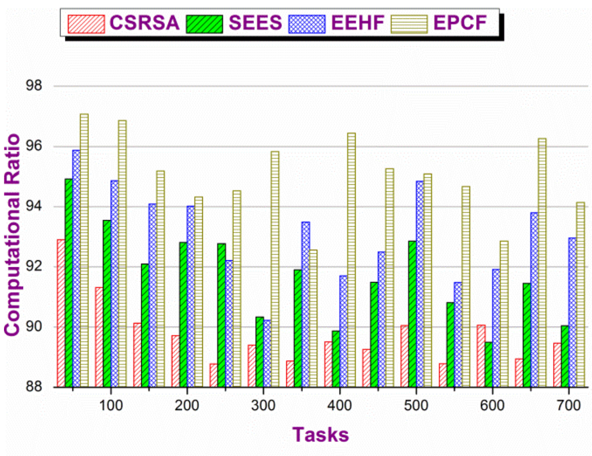

FIGURE 11. Computation ratio analysis.

energy is acquired from the computing and processes the distribution. The energy is distributed in which the cluster centroid is evaluated that detects the data points. Here two clusters are deployed, such as state and computation in which the objective function is calculated for the data points. The processing leads to decreases if the pursuing of energy is analyzed, which is evaluated by computing the prediction method. The analysis is determined by mapping the operation state and availability computation. Here, energy discovery is the initial step that detects the energy necessary for the upcoming processing. By formulating $(y_u + e_n) * \left(\frac{e_0}{p_e}\right)$ the usage of energy is evaluated in which it deploys the distribution of energy. The wastage of energy is analyzed by equating $\sum_{y_u} p_e + e_n * l_t - \pi'$ here the discovery of energy is evaluated in which it predicts the unwanted usage of energy.

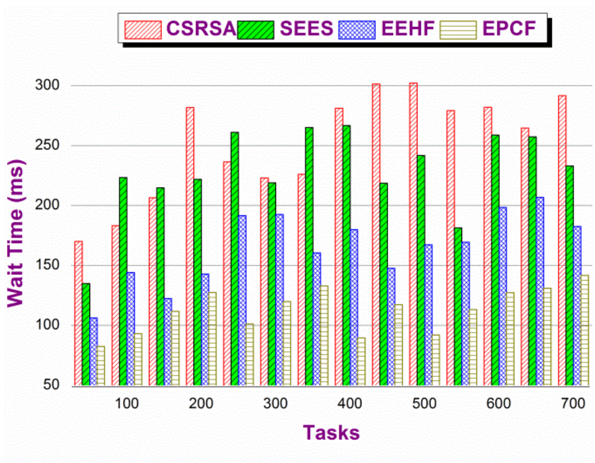

FIGURE 12. Waiting time comparison.

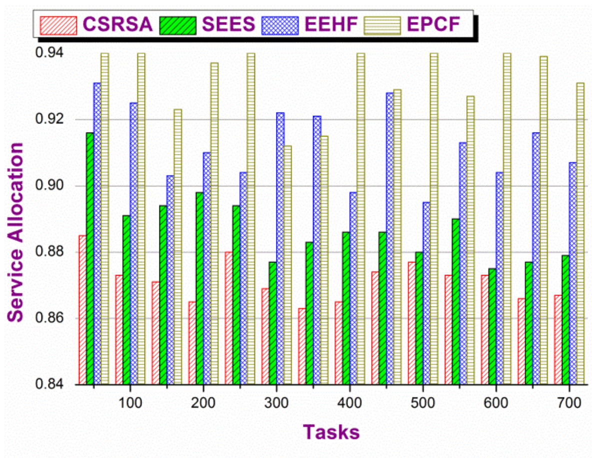

FIGURE 13. Service allocation comparison.

C. SERVICE ALLOCATION

The service allocation is computed for the varying task that provides the energy to the required application in green computing. The energy allocation is used to consume energy and avoids unwanted usage, and it is formulated as $e_n * (l_t + g_a) - w_s$. Here the discovery of energy usage and wastage is analyzed in which the distribution is carried out promptly. For analyzing this, the data points and clusters are detected. It detects the objective function that is denoted as $\prod_{m'=1}^{h_0} * \prod_{n'=1}^{h'} \left\| k' - s' \right\|^2$. The distance between the cluster and data points is detected in which the mapping is performed. Post to the distance calculation, the centroid is selected randomly in which the necessary and unnecessary energy is detected. Here the set of cluster centers is detected in which the data point and the centroid detection are computed. Thus, the state and computation of data points and cluster distance are evaluated, showing higher service allocation (Figure. 13).

D. ENERGY COST

The proposed work decreases the energy cost for varying task and service allocation, where the necessity and un-necessity of energy are evaluated (Figure. 14). Energy cost is decreased if it addresses the processing time, which is associated with the objective function. Here the distance is calculated concerning varying energy, and it is termed as $\left[b_0\left(v_0\right) * b_1(h')\right] + \left[m'\left(b_0\right) * n'(b_1)\right]$. The state and computation cluster is evaluated in which the data points are calculated to consume the energy. The energy cost is decreased by analyzing the centroid in which it detects the usage and unwanted energy for the application. Thus, the distribution of energy is processed by evaluating $\left(\frac{\mu' + \Delta_0/_{w'}}{h_0 + h'}\right)$ in this, it estimates the energy that the application needs to run. Post to this discovery of energy, the cluster center, and data point are evaluated promptly. The grouping is used to improve the efficiency of energy in which it addresses the cost of computation. The energy cost is decreased by update the centroid for every instance.

E. ENERGY DRAIN

In Figure. 15, the energy drain is decreased for the proposed work by comparing it with the existing three methods. The draining of energy is computed if it does not identify the energy in which energy prediction is evaluated. The other case is if the improper energy is identified while predicting the energy drain happens in which the discovery is evaluated. Thus, the iteration of processing the energy is formulated by representing $\sqrt{\left(\frac{e_p p_e}{\delta_{l_+} e_n}\right)^1}$ here the energy is matched with the preceding energy model. The preceding and pursuing energy is matched and derives the efficient processing in which the draining occurs due to objective function. Here, the distance is evaluated for the data points and clusters in which the necessary and unnecessary data is extracted. The acquired energy is extracted and processed on time in which the data points and clustering state and computation is evaluated efficiently. The mapping is computed on deploying the cluster, and it is denoted as $\left(m' + n'\right) - \rho_0 * \left(k' + v_0\right)$.

F. EFFICIENCY

In Figure. 16, the efficiency increases concerning service allocation and energy distribution, and it is computed as $y_x + \left(\rho_0 + o_f\right) + l_t * d_i$. The efficiency is estimated as the tasks allocated for a machine for a single energy distribution instance. Here, the centroid update is evaluated in which the iteration of processing the energy is provided to run the particular applications. Here, both the state and computation of the clustering are evaluated. The distance is calculated to detect the data points. The energy is consumed by deploying the green computing in which it is estimated in the space, and it deploys the available computation cluster. Here the state and computation of the cluster are used to evaluate the nearest range of energy necessary to process. By formulating $\left[\left(i' - p_e\right) * \left(x_0 - x'\right)\right]$ the efficiency of energy is estimated in which the necessary and unnecessary energy is analyzed. Here the distribution of energy is evaluated in which the objective function is used to define the usage and wastage

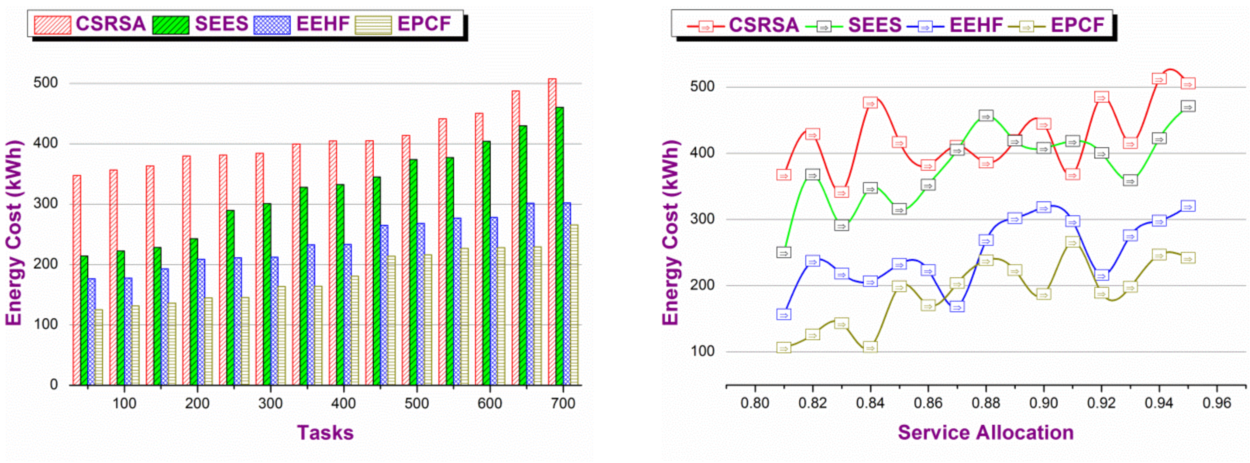

FIGURE 14. Energy cost comparisons.

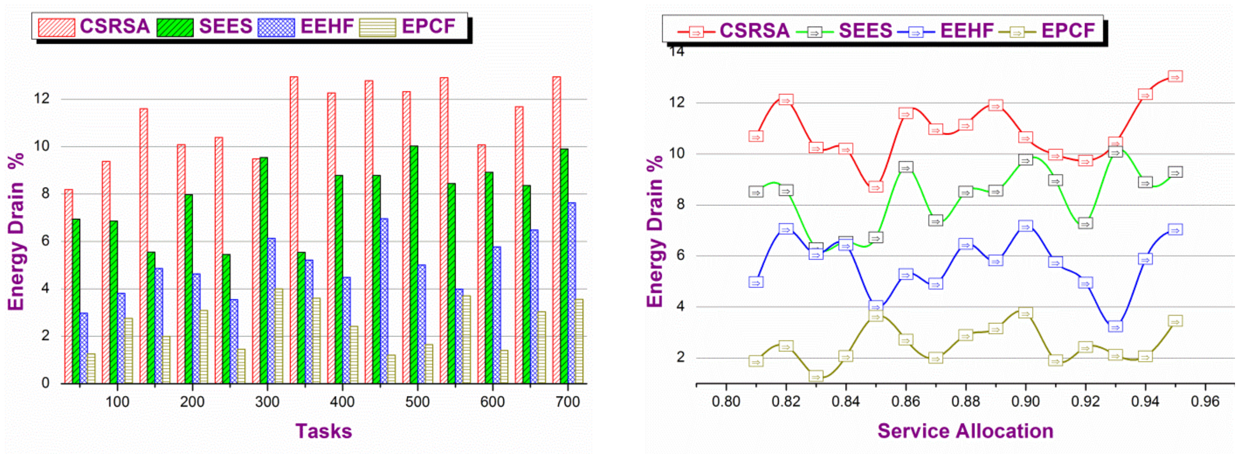

FIGURE 15. Energy drain comparisons.

TABLE 2. Comparisons for tasks.

Metrics	CSRSA	SEES	EEHF	EPCF
Computational Ratio	89.468	90.043	92.961	94.14
Wait Time (ms)	291.695	233.082	182.559	141.641
Service Allocation	0.867	0.879	0.907	0.931
Energy Cost (kWh)	507.726	460.524	302.226	265.464
Energy Drain %	12.944	9.905	7.629	3.563

TABLE 3. Comparisons for service allocation.

Metrics	CSRSA	SEES	EEHF	EPCF
Efficiency (Tasks/ Allocation/ Energy)	0.853	0.861	0.896	0.918
Energy Cost (kWh)	505.684	471.375	320.596	241.986
Energy Drain %	13.05	9.298	7.044	3.453

of energy. The initial step is to predict the pursing energy and provide the application's energy to process on time. The comparison results are presented in Tables 2 and 3 for the tasks and service allocation.

From the above comparisons, it is seen that the proposed EPCF reduces wait time, energy cost, and energy drain by 13.31%, 12.44%, and 6.6%, respectively. Contrarily, it maximizes computation ratio and service allocation by 9.95% and 14%, respectively.

The proposed framework achieves 14.69% less energy cost for the different service allocation rate, 6.34% less energy drain, and 14.4% high efficiency.

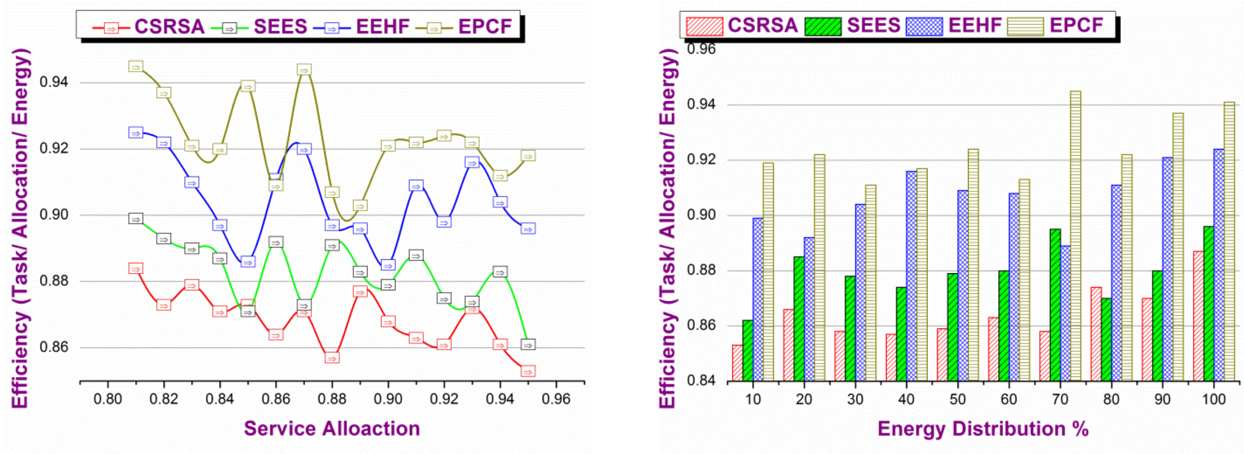

FIGURE 16. Efficiency comparisons.

V. CONCLUSION

Energy proficient computing framework for renewable and sustainable energy-dependent cloud user services is discussed in this article. The design goal of this framework is to improve renewable energy utilization and distribution among cloud computing devices. In this process, the computing devices' states, and the requested computations are identified for energy allocation. Both the state and computations are grouped based on energy availability and distribution, depending upon the previous utilization. This is recurrently performed by identifying the computing and non-computing instances using k-means clustering for reducing unnecessary wait time of the allocated tasks. The unnecessary energy drain is identified for the waiting or distribution instances in the fore-hand, and the mapping is performed. This helps to improve the efficiency of task computation under controlled energy costs. By augmenting the efficiency, the service allocations are performed in a reliable manner for improving the computation ratio.

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