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A Robust Smart Grid-Aware Cloud Computing Framework for Sustainable Energy Management

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Abstract

The growing use of renewable energy as a part of a smart grid infrastructure has raised new challenges relating to the coordination of the computational workload scheduling and the availability of intermittent energy in a distributed cloud infrastructure. The traditional cloud scheduling systems do not work with knowledge of the current pattern of renewable generation and thus the people have to rely more on the non-renewable grid energy and the intensity of carbon emissions is also high. In order to overcome this drawback, the current study is a proposal of a Smart Grid-Aware Cloud Computing Framework, with an embedded Grid-Aware Adaptive Scheduling Algorithm to dynamically schedule the execution of the computational workload of renewable-sustainable cloud nodes. The suggested framework incorporates the knowledge of renewable availability, estimation of sustainability threshold, and migration control with carbon awareness into the scheduling of tasks. Experimental evaluation conducted under heterogeneous workload demand and renewable generation conditions demonstrates improved Renewable Utilization Ratio of 0.79 compared to 0.66 achieved by reinforcement learning–based adaptive scheduling methods. The proposed framework further reduces normalized computational energy consumption to 0.81 and lowers carbon emission index to 0.52, while maintaining acceptable scheduling latency of 1.07 under renewable-aware workload migration. These findings suggest that the introduction of renewable conscious scheduling tools in cloud infrastructures can make the execution performance in smart grid settings to be greatly more sustainable.

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1. Introduction

The high pace of digitalization of the modern energy infrastructure has created a new level of complexity in the operational conditions of the contemporary power distribution systems. With the development of electrical grids into more and more of the so-called cyber-physical ecosystems, the traditional boundaries between computing platforms and energy networks are becoming more indistinct. It has become anticipated that smart grids can be managed together with cloud enabled control, enabling the acquisition, processing, and predictive decision-making of mass data, with two-way energy flow and real-time sensing capabilities [1]. It is not only technological but also structural as the energy provisioning model is becoming more adaptive, intelligence-driven, and can dynamically respond to changing supply-demand environments.

At the same time, the spread of renewable generation units, most of which are photovoltaic installations, has made it increasingly evident that flexible management architectures are required, which are able to coordinate distributed energy resources without undermining grid stability and sustainability targets [2]. Cloud computing is one of the core enablers in this dynamic environment, which can be used to scale monitoring and optimization of grid operations based on distributed analytics and control that is mediated by virtualization [3].

1.1 Current Trends

In recent times, there has been an explosion in the use of cloud-native energy platforms that combine Internet of Things (IoT) devices and real time data pipelines to allow predictive load balancing and demand-response coordination [4]. New models are adopting greater amounts of machine learning and deep reinforcement learning approaches to optimize the dispatch of energy under unpredictable environmental and consumption circumstances [5].

Moreover, the development of virtualization technologies has made it easy to implement energy-conscious resource scheduling models in geographically dispersed microgrids [6]. Mechanisms of edge-assisted cloud orchestration are also becoming more popular to minimize communication latency in grid control applications with time-constraint [7]. Such developments suggest that there is a paradigm change to hybridized energy-computing environments in which computational intelligence has a direct impact on grid-level sustainability measurements [8].

1.2 Existing Research Gaps

Regardless of these developments, the current body of literature has a number of limitations to its methodology. A significant part of the existing research is more centered on computational optimization in isolated cloud conditions instead of sufficiently considering grid-dependent operation constraints [9]. Likewise, a majority of smart grid management systems do not have incorporated systems of synchronizing the allocation of computational resources and actual availability of renewable energy in real time [10].

Moreover, the sustainability based performance indices, e.g., energy efficiency, minimization of carbon footprint, and use of renewable, tend to be defined as secondary optimization constraints, but not decision variables [11]. Research gap: There is still a significant gap in research in the establishment of common architectures that are capable of aligning the distribution of the computational workload with the dynamics of energy-generation [12].

1.3 Problem Statement

The combination of the cloud-based computational infrastructures and the smart grid systems presents a multidimensional coordination issue of resources, where energy use, related to the cloud activities, can unconsciously offset sustainability benefits attained with the integration of renewables. The traditional workload scheduling models used in the clouds generally respond unconditionally to the grid-level energy conditions that results in poor use of the green resources of energy and high operational emissions [13].
As a result, a grid aware cloud computing framework is required to implement the ability of dynamically matching the computational demand and the availability of renewable energy in order to attain sustainable energy management throughout the distributed infrastructures [14].

1.4 Motivation and Need for study

This study is inspired by the fact that the modern data-driven energy ecosystems have increasing mismatch between computational scalability demands and environmental sustainability goals. With the growing use of large-scale cloud services to support smart grid analytics, the energy demands associated with them are also growing [15]. In the absence of smart orchestration systems to co-ordinate computational loads and renewable generation cycles the resultant energy consumption can be counterproductive to larger decarbonization efforts in the power system [16].
The current strategies tend to be based on the static provisioning plans or heuristic methods of scheduling, which cannot respond to real-time grid dynamics and renewable intermittency [17]. Also, the lack of anticipatory assimilation among the cloud resources control and the energy-generation prediction inhibits the performance of the contemporary models of sustainable computing [18]. The need to resolve these drawbacks brings about the formulation of an adaptive approach that can be used to utilize grid-level intelligence to distribute workloads and make energy conscious decisions.

1.5 Research Objectives

The main aims of the research are to develop a smart grid-sensitive cloud computing system to manage sustainable energy, to provide the dynamical matching between renewable energy availability and the workload distribution in the computational devices, to increase the energy usage efficiency by adaptive scheduling systems, and to reduce the number of carbon emissions as a result of the large scale cloud computing.

1.6 Scope of the Work

The proposed research area includes the creation of a unified system of cloud-grid orchestration that will support real-time coordination between distributed computing resources and renewable energy systems. The proposed methodology aims at the optimization of smart grid systems on the concept of sustainability without modifying the current power distribution infrastructures [19].

1.7 Novelty and Contribution

In contrast to the traditional cloud optimization models, which do not depend on energy-generation trends, the given structure adds a grid-aware decision layer that is able to incorporate measures of renewable availability in computational workload scheduling operations. The suggested energy intelligence/cloud resource orchestration coupling is a new step towards environmentally adaptive computing ecosystems [20].

1.8 Method Overview and Limitation

The suggested framework takes into consideration real-time grid telemetry at the cloud scheduling modules via predictive analytics and workload migration policies energy-conscious. The system is meant to enhance the efficiency of the utilization of energy by dynamically matching the execution of tasks with the renewable generation cycles without compromising on the service level performance.

Despite the fact that the suggested framework shows the potential of sustainability-based workload orchestration, the efficiency of this framework might be affected by the presence of real-time grid telemetry data and its accuracy. Moreover, the enormous scale implementation in heterogeneous infrastructures can add overheads on communication that can be further optimized in the subsequent implementation.

The expected results of this research are less energy wastage in cloud computing, increased use of renewable in intelligent grids, and better sustainability indices in distributed computational setups.

The remainder of this paper is structured as follows. Section 2 reviews related work in smart grid–integrated cloud computing. Section 3 describes the proposed system architecture and methodological framework. Section 4 presents experimental evaluation and performance analysis. In Section 5, sustainability implications are discussed and in Section 6, conclusions are made.

2. Literature Review

The increased interdependency of both smart energy systems and the large-scale computing systems has elicited immense research intensity in recent years. A unique piece of work has emerged as a literature at the intersection of the smart grid technologies, cloud computing, renewable integration, and energy-aware workload management. All these contributions are directed to the objective of streamlining the operational efficiency, scalability and sustainability of the existing power systems. However, the extent to which the management of computer resources is missioned towards real time grid intelligences is broad with the existing frameworks. In that regard, the present section recounts the recent developments, which relate to the seamless incorporation of smart grids related to the energy management, cloud-based scheduling, demand response mindful of renewable sources, and grid coordination on a hybrid cloud foundation.

2.1 Smart Grid–Integrated Energy Management Systems

The creation of smart grid systems has significantly changed the way energy used to be distributed traditionally as it has enabled real time monitoring, coordinations of distributed generation and adaptive load controls. Over the past years, grid intelligence keeps on being driven further by grid-sensitive technologies and supervisory control systems, which utilize communication and technology to assist in fine-grained control of electrical networks [21]. These systems may also dynamically respond to the fluctuations in demand and can integrate renewable energy such as solar and wind energy into the current grid systems [22].

Several recent papers have pointed out the importance of devolved control systems in gaining operational stability in distributed energy systems. Indicatively, adaptive load-balancing algorithms have been proposed in order to remove voltage instability, which arises when the renewable generation is intermittent [23]. On the same note, predictive scheduling approaches on the basis of real-time consumption have shown enhanced veracity in microgrid operations through predicting the demand peaks and managing energy dispatch in line with such predictions [24]. Nonetheless, even though these solutions will help increase grid responsiveness, they are frequently independent of the issue of computational infrastructure. Consequently, the power to maintain extensive monitoring and analytics systems is often not included in sustainability metrics [25].

2.2 Cloud Computing in Energy-Aware Grid Environments

Cloud computing technologies have reached the point of necessity to manage the enormous amounts of operation data that are produced by smart grid networks. Their predictive analytic, fault detection and demand forecasting can be conducted at scale by utility with unprecedented speed [26]. Recent research in this field has found virtualization-based resource management models in order to optimize the distribution of computational workload among geographically distributed data centres [27].

Moreover, containerized cloud-based systems have been used to implement real time energy management services that can coordinate distributed energy resources using centralized orchestration platforms [28]. Hybrid cloud-edge architecture is also becoming popular because it enables grid operations with a high degree of latency to be performed locally but leave computationally demanding tasks to remote servers [29].

Nevertheless, the majority of energy management frameworks that are enabled by clouds are still largely concerned with computational efficiency and not sustainability. The performance measurements including throughput and latency are usually used to make workload scheduling decisions without regard to the availability of renewable energy at the grid level [30].

2.3 Renewable Integration and Demand-Response Optimization

The incorporation of renewable energy sources into smart grids brings in the added complexity of the fact that these sources can vary in their output nature. To overcome this need, demand-response programs have been established to control the amount of energy consumed by the consumers depending on the state of supply [31]. In these programs, real-time pricing cues, or automatic control measures are usually used to promote energy use in times of elevated renewable generation [32].

The works of recent have delved into machine learning-based prediction, which aims at forecasting the output of renewable sources and managing demand-response scheduling accordingly [33]. These methods have already demonstrated potential in minimizing grid congestion and an increase in the renewable use rate. Also reinforcement learning models have been used to adapt load distribution across the microgrids dynamically based on the varying energy availability [34].

However, the computational structures needed to run these predictive models do not necessarily run on a cycle of renewable generation. Such mismatch between the provision of energy and the computational demand prevents a high sustainability potential of smart grid ecosystems [35].

2.4 Energy-Aware Workload Scheduling in Cloud Systems

In order to reduce harmful effects of large-scale data centers, scientists have suggested that energy-conscious workload scheduling strategies can be employed where the use of power is considered when allocating resource among the strategies. As an illustration, methods of task migration have been devised to move the computational loads to servers that run in lower levels of energy consumption [36]. Equally, green-conscious planning models strive to match the activities of a data center with green energy supply times [37].

In more recent times, multi-objective optimization models have been proposed to bring a trade off between service-level agreements and sustainability indicators, including carbon emission reduction and renewable energy use [38]. These models use predictive analytics in estimating the future state of energy and scale down the workload of the computer as needed.

Most of these frameworks however are based on simplistic assumptions on energy availability and do not include real-time grid telemetry in scheduling, however. Consequently, they are not very effective in the dynamic smart grid setup [39].

2.5 Hybrid Cloud–Grid Orchestration Frameworks

An emerging research has started to explore integrated architectures that can be used to integrate cloud computing platforms and smart grid intelligence to achieve a better sustainability. The purpose of these hybrid structures is to coordinate the distribution of computational work loads with the patterns of renewable energy generation through the power of predictive analytics and distributed control systems [40].

The results of the first implementations have proven the possibility to coordinate cloud operations with grid-scale energy conditions, which resulted in the enhanced use of renewable resources and lowered operating emissions. However, the current models are usually not scalable and necessitate huge communication overhead to synchronize the grid sensors with the cloud orchestration modules in real-time.

Moreover, some hybrid structures do not support their responsiveness to abrupt variations in renewable production or demand trends because of a lack of adaptive workload migration policies. This drawback highlights the importance of more open architectures that will allow to incorporate predictive energy intelligence in the cloud scheduling mechanisms without affecting computational performance.

2.6 Research Gap Identification

Though some significant advancement in the merging of smart grid intelligence and cloud-based computational framework can be seen in the reviewed studies, there are a number of unaddressed challenges that remain in the same implementations. One of the most important points that come out in the literature is that smartest grid optimization models are more oriented towards optimization of grid-side performance indicators, including load balancing, dispatch efficiency, and demand-response coordination. Conversely, cloud-based sustainability models tend to focus on minimizing energy use in computations by virtualization or task migration approaches without including real-time information on energy availability by the grid environment.

Moreover, the scheduling strategies based on renewability are often not based on dynamic orchestration of workloads through continuous grid telemetry, and they are based on static assumptions of provisioning or predictive estimates. Consequently, the computational tasks that are being implemented in cloud environments are very rarely correlated with the real cycles of renewable generation or even grid-scale energy situations. Such a mismatch causes poor exploitation of green energy resources and restricts the total sustainability value of cloud-based smart grid systems.

The limitations of these studies in comparison with some of the latest state-of-the-art studies are summarized in Table 1, which shows that there are no integrated frameworks that can align the allocation of cloud workloads with the availability of renewable energy in real time. These results highlight the need to develop a standardized smart grid-sensitive cloud computing architecture, which is dynamically scalable to change computing demand based on the dynamics of supply-demand in distributed energy systems.

Table 1: Comparative Literature Gap Analysis of Smart Grid–Integrated Cloud-Based Sustainable Energy Management Frameworks

	Ref. No.	Title / Focus Area	Methodology / Tools Used	Key Findings	Limitations / Gaps Identified	Relevance to the Current Study
1	Barros et al. / 2025 / [15]	Edge–Cloud Continuum for Smart Grids using Deep Q-Learning (grid-side energy management)	Edge–cloud architecture; Deep Q-Learning for control policy	Demonstrates adaptive energy management under dynamic grid conditions; improves control responsiveness	Focuses on grid control more than cloud workload sustainability; limited discussion on carbon-aware cloud scheduling and end-to-end cloud resource orchestration	Supports the RL-driven control layer idea; highlights need to couple grid intelligence with cloud compute decisions
2	Singhal et al. / 2023 / [16]	Energy-aware load balancing using cloud & fog (smart grid workload distribution)	Cloud–fog framework; load-balancing heuristics; sensing-driven decisions	Shows improved workload distribution and responsiveness for smart grid services	Sustainability treated mainly as energy efficiency; lacks explicit renewable-aligned scheduling and grid-supply-aware compute migration	Closely matches cloud/fog + grid services; exposes the gap your study targets: grid-aware sustainable cloud orchestration
3	Singh et al. / 2025 / [18]	Cloud-integrated AI platform for EV charging + microgrid management (real-time optimization)	Scalable cloud AI platform; optimization for EV/microgrid coordination	Demonstrates scalable real-time optimization; practical direction toward resilience	Strong EV/microgrid emphasis; cloud scheduling is not explicitly tied to renewable availability or data-center sustainability metrics	Provides evidence for cloud-integrated real-time optimization; motivates extending toward renewables-aware compute–grid coupling
4	IEEE Trans. Cloud	Cloud-edge orchestrated power dispatching (DER	Cloud-edge orchestration for dispatch; DER	Demonstrates effectiveness of orchestrated dispatch	Primarily dispatch-oriented; less attention to cloud energy consumption, carbon impact,	Anchors the “cloud-edge + grid dispatch” base; your study extends it to sustainability-

	Computing / 2023 / [3]	dispatch coordination)	coordination mechanisms	across distributed resources	and compute–energy co-optimization	aware cloud workload control
5	Saleem et al. / 2023 / [6]	IoT + Cloud for Demand Side Management (smart grid DSM)	IoT sensing, cloud analytics, DSM strategies	Shows improved DSM with connected sensing and cloud services	Limited treatment of cloud sustainability and carbon-aware scheduling; often assumes cloud resources as "always available"	Useful for DSM integration and data pipeline design; gap aligns with your focus on sustainable cloud operations
6	Abedin et al. / 2025 / [22]	Cloud-based computational resources for dispatch optimization (smart energy networks)	Cloud-based optimization for dispatch factor; computational acceleration	Highlights the benefit of cloud compute in improving dispatch optimization	Optimizes dispatch but not holistic sustainability; lacks integrated framework linking compute placement to renewable cycles	Strong link to "cloud-assisted grid optimization"; supports your argument for grid-aware cloud scheduling decisions
7	Alharbey et al. / 2024 / [29]	Digital twin for smart grid performance (sustainability + security + efficiency)	Digital twin concept; integrated evaluation dimensions	Demonstrates value of digital twins for monitoring, prediction, and grid performance enhancement	Often conceptual; compute-energy tradeoffs and deployment-level scheduling policies are not deeply operationalized	Helps justify model-driven orchestration and real-time telemetry coupling; your study can operationalize scheduling inside the twin-driven loop
8	Abbas et al. / 2023 / [35]	Energy-proficient green computing using sustainable energy sources (green cloud)	Sustainable energy-powered compute framework; green computing strategies	Connects computing sustainability with energy sources; offers green computing direction	Usually cloud-centric without smart-grid telemetry integration; limited grid-aware orchestration and real-time coupling	Complements your sustainability objective; your contribution is to make it grid-aware and responsive via smart grid telemetry

However, the considered literature shows the increasing overlap between energy systems and computational infrastructures. Although both the smart grid management and cloud resource optimization have made tremendous advancements separately, the aspect of combining the two towards workload orchestration with sustainability has not been well investigated. This study aims to fill this gap by suggesting a smart grid-sensitive cloud computing architecture to dynamically match the computational load and the renewable energy supply to support sustainable energy management.

3. Methodology

Unlike the current cloud-focused approaches to scheduling where energy availability is perceived as a volatile or fixed constraint, the given methodology presents the grid-aware mechanism of computational orchestration that can dynamically align the execution of the workload with the actual patterns of the renewable energy generation. The innovation of the given approach is that sustainability-based decision intelligence is placed on the cloud resource management layer through grid-responsive adaptive scheduling algorithm. Using the nonstop energy telemetry of renewable sources that are spread, the framework allows an active task relocation and workload redistribution according to the supply-demand dynamics, and not standard performance-based metrics. It is the interactions of this perspective that allow an ecologically responsive computing process in smart grid ecosystems, and as a result, transposes the inherent disconnect between computation scalability and utilization of renewable energy that architectures manifest today.

3.1 System Architecture and Framework Design

The suggested Smart Grid Conscious Cloud Computing Framework (SG-CCF) is presumed to dynamically manage the allocation of the computing load to the real-time availability of the renewable energy to the distributed smart grid settings. The existing orchestration systems tend to be concentrated on the computational power not making any consideration on the grid-level energy dynamics, which result in the ineffective utilization of renewable resources [16]. In an effort to address this shortcoming, the current framework combines smart grid telemetry and cloud scheduling modules by way of a grid-responsive orchestration layer.

The system architecture includes three interconnected layers, namely (i) renewable generation layer, (ii) smart grid telemetry acquisition layer, and (iii) cloud workload scheduling layer. These elements communicate with each other via a bilateral communication interface, which is able to synchronize the execution of workload with real time energy supply situations, as illustrated in Figure 1. The architectural plan is an extension of cloud-edge coordinated dispatching schemes as in [3] because sustainability-oriented decision variables are incorporated into the cloud resource management procedure. Similar concepts of adaptive energy management with reinforcement learning assistance have been studied in [4], but their combination with renewable-conscious workload migration has not been studied extensively.

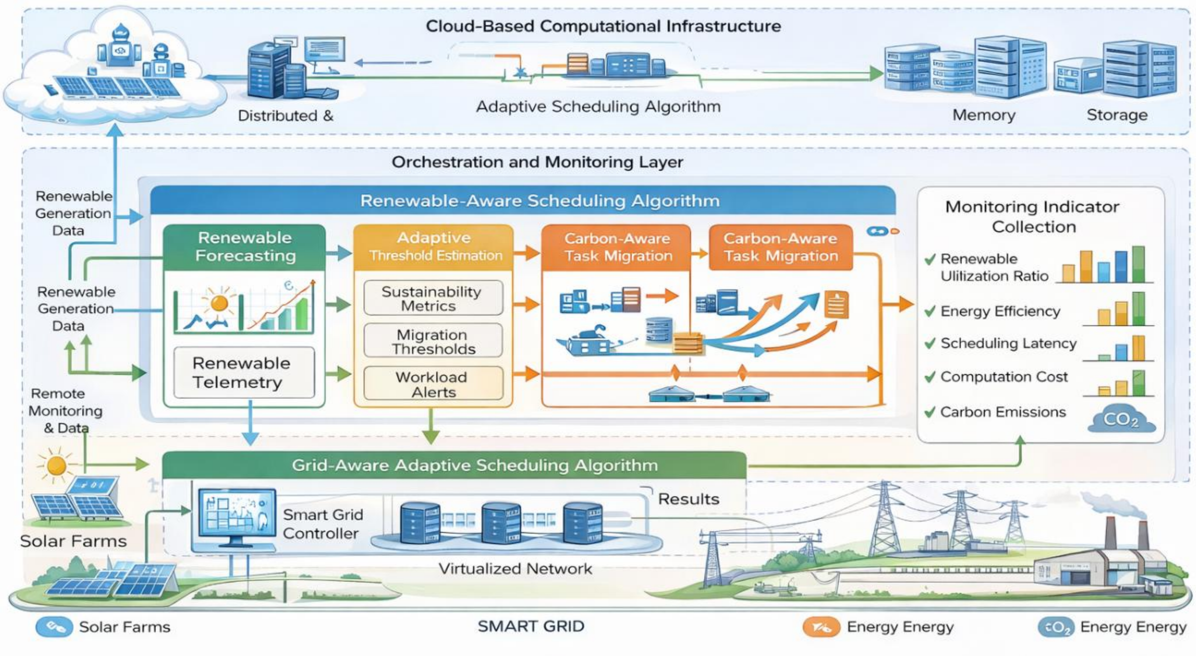

Figure 1: System architecture of the proposed Smart Grid-Aware Cloud Computing Framework integrating renewable generation data with cloud workload orchestration.

The renewable energy generation at any given time instant t is represented as (1):

$$G_r(t) = \sum_{i=1}^{N} P_i(t) \cdots (1)$$

Where

$G_r(t)$ denotes total renewable power available at time t, $P_i(t)$ represents the power generated by the i^{th} distributed energy resource (DER), and N denotes the number of active renewable nodes within the grid network [22]. Similarly, the aggregate computational workload demand in the cloud environment is defined as (2):

$$W_c(t) = \sum_{j=1}^{M} L_j(t) \cdots (2)$$

Where,

$W_c(t)$ represents total workload demand at time t, $L_j(t)$ denotes the workload intensity associated with the j^{th} computational task, and M represents the number of active tasks within the scheduling queue [34]. An energy-demand coupling coefficient is defined to measure the compatibility between the supply available of renewable energy and the demand that can be calculated as (3):

$$\alpha(t) = \frac{G_r(t)}{W_c(t)} \cdots (3)$$

Where, α(t) is the level of synchronization of renewable energy supply and the workload demand. Greater α(t) means that there are good conditions to perform computational tasks through the renewable energy resources, and lower means that it depends on the auxiliary grid supply [40].

This coefficient is an important decision variable to be used in the future scheduling activities in the proposed orchestration structure.

3.2 Data Acquisition and Preprocessing Framework

The implementation of the suggested SG-CCF model depends on the heterogeneous telemetry, which is received at the distributing renewable generation units, smart grid

monitors, and cloud infrastructure surveillance systems. It is common knowledge that one of the successful methods of managing energy at the demand side of smart grids is the integration of IoT-enabled metering devices with cloud analytics platforms [6]. The data of renewable generation such as solar irradiance, wind velocity and DER power production are obtained at the nearby grid-connected generation units at frequent sampling intervals.
The demand-side load profiles are being gathered on the basis of advanced infrastructure of smart meters that ensure the recording of consumption statistics in residential and commercial segments. Simultaneously, cloud infrastructure monitoring, including CPU usage, memory usage, duration of tasks performed, and queue time, is received by means of virtualized monitoring agents that run in containerized setups. Other cloud-based computation monitoring schemes have equally been applied in the context of energy conscious scheduling at cloud systems that are integrated into smart grids [36].
The energy used by the computational activity in the cloud is approximated as (4):

$$E_c(t) = \sum_{j=1}^{M} P_j(t) \,.\, T_j(t) \cdots (4)$$

Where
$E_c(t)$ denotes total computational energy consumption at time t, $P_j(t)$ represents the power consumption of the j^{th} cloud task, and $T_j(t)$ denotes execution time of the corresponding task [7].

The renewable utilization ratio is computed as (5):

$$U_r(t) = \frac{G_r(t)}{G_r(t) + E_f(t)} \cdots (5)$$

Where, $U_r(t)$ represents renewable energy utilization at time t, and $E_f(t)$ denotes auxiliary energy drawn from non-renewable grid sources [36]. To assess variability in renewable generation patterns, the deviation between predicted and actual renewable output is evaluated as (6):

$$E_p(t) = \left| G_r(t) - \widehat{G_r}(t) \right| \cdots (6)$$

Where, $G^{\wedge}_r(t)$ represents predicted renewable generation at time t, and $E_p(t)$ denotes prediction error. These processed inputs are then fed to the energy-aware scheduling module to coordinate adaptable workload according to the prevailing conditions of renewable supply, thus permitting the dynamism of stabilizing the relationship between computational demand and renewable supply conditions.

3.2.1 Data Sources and Sample Dataset Description

The multi-source dataset was heterogenous and was built through the combination of renewable-generation-telemetry, smart-grid-load-consumption History, and cloud infrastructure-utilization History. The data on renewable energy generation was received on photovoltaic and wind-based distributed energy sources functioning under grid connected microgeneration set-up. Sustainable smart grid energy harvesting IoT-based renewable monitoring systems have been utilized in [14].
Advanced smart meter installations in residential and commercial segments of consumers obtained demand-side load profiles. This records give statistics of aggregate energy

consumption in kilowatt-hours (kWh) and peak demand characteristics per hour and sub-hour. As well, the use of cloud resources (such as processor utilization percentage, duration to execute a task, the level of memory allocation, and the intensity of work in a virtual machine) was also measured with the help of system-level monitoring agents that were deployed in the context of containerized cloud environments.
The total renewable energy output for each sampling instance is computed using (7):

$$G_r^{(s)} = \sum_{i=1}^{N} P_i\,(s) \cdots (7)$$

Where, $G_r^{(s)}$ denotes renewable power generated during the s^{th} sampling interval, $P_i^{(s)}$ represents power output from the i^{th} distributed generation node, and N denotes the total number of renewable sources. The computational workload intensity corresponding to each data sample is estimated as (8):

$$W_c^{(s)} = \sum_{j=1}^{M} L_j\,(s) \cdots (8)$$

Where, $W_c^{(s)}$ represents total cloud workload demand during the sth interval, and $L_j(s)$ denotes workload associated with the j^{th} task instance. A summary of the collected dataset characteristics is provided in **Table 2**.

Table 2. Summary of Dataset Characteristics Used for Renewable-Aware Cloud Scheduling

Data Category	Source Type	Sampling Interval	Total Samples	Units
Solar Irradiance	PV Sensors	5 min	52,000	W/m²
Wind Speed	Anemometer	5 min	48,500	m/s
Load Demand	Smart Meters	15 min	36,200	kWh
CPU Utilization	Cloud VM Logs	1 min	75,000	%
Task Duration	Scheduler Logs	1 min	62,000	sec

The intervals chosen to sample are to capture the short term intermittency patterns of renewable sources and take into consideration the computational tractability of the sampled in the workload scheduling simulations.

3.3 Energy-Aware Workload Scheduling Model

In the traditional cloud computing setups, the workload scheduling is normally dictated by performance-oriented metrics, like execution latency, or resource availability, or service-level contracts. But, in systems of smart grids, the direct contribution to the total energy footprint of a system is the execution of computational tasks. Thus, the planning procedure should take into consideration the real-time availability of renewable energy so that sustainability among distributed computational platforms can be achieved [35].
To meet this goal, the framework suggested makes use of an energy-aware, dynamically-adjusted, scheduling model to seamlessly match the execution of cloud workloads with grid-scale renewable generation patterns. Cloud-assisted load-balancing solutions of smart grid systems are also considered in [16], but such models tend to have no dynamic coupling with real-time renewable telemetry.
Computation of an energy alignment coefficient (9): The process of scheduling decisions is triggered by calculation of the energy alignment coefficient:

$$\alpha(t) = \frac{G_r(t)}{W_c(t)} \cdots (9)$$

Where
$\alpha(t)$ represents synchronization between renewable energy supply and workload demand at time t,
$G_r(t)$ denotes total renewable generation (from (1)), and $W_c(t)$ represents aggregate computational workload demand (from (2)).
A higher value of $\alpha(t)$ indicates favorable renewable availability for executing computational tasks using green energy resources.
In order to further measure the level of environmental impact of cloud operations the amount of carbon emission of the task execution is estimated (10):

$$C_e(t) = \gamma \cdot E_c(t) \cdots (10)$$

Where
$C_e(t)$ denotes carbon emission at time t, γ represents emission factor, and $E_c(t)$ represents cloud energy consumption (from (4)). The planning precedence of every computational task is then calculated based on (11):

$$S_{p(t)} = \lambda_1 \cdot \alpha(t) + \lambda_2 \cdot D_t \cdots (11)$$

The parameters of weighting are λ1, λ2 and Dt is the sensitivity of the task deadline.
These types of multi-objective scheduling models have been explored earlier in renewable-sensitive cloud resources allocation models [40]. However, their integration with real-time grid telemetry remains limited.
The renewable energy sufficiency condition is expressed as (12):

$$G_r(t) \geq \rho \cdot W_c(t) \cdots (12)$$

Where
ρ represents minimum renewable availability threshold required for sustainable task execution. Queue dynamics governing cloud task execution are modeled as (13):

$$Q(t+1) = Q(t) + A(t) - S(t) \cdots (13)$$

Where
Q(t) denotes queue length at time t,
A(t) represents task arrival rate, and
S(t) represents service rate [34].
Energy consumption per task is calculated using (14):

$$E_t = P_t \cdot T_t \cdots (14)$$

Where,
P_t denotes task power consumption and T_t represents execution time [7]. The renewable utilization efficiency during scheduling is evaluated as (15):

$$\eta_r(t) = \frac{G_r(t)}{E_c(t)} \cdots (15)$$

3.4 Proposed Grid-Aware Adaptive Scheduling Algorithm (GASA)

A new Grid-Aware Adaptive Scheduling Algorithm (GASA) is suggested to dynamically balance the distribution of computational workload and supply of renewable energy. The algorithm builds on the reinforcement learning-aided adaptive energy management principles that have been reported in [4] by introducing the grid-level renewable telemetry as a schedule decision variable.
The likelihood of the migration of a computational task to a node that is based on renewable execution is (16):

$$P_m(t) = \frac{U_r(t)}{1+\delta} \cdots (16)$$

Where,
$U_r(t)$ denotes renewable utilization ratio (from (5)) and δ represents system delay factor.

Cloud task migration latency is estimated as (17):

$$L_{m(t)} = \frac{D_s(t)}{B_{w(t)}} \cdots (17)$$

Where,

Ds(t) represents data size and Bw(t) denotes network bandwidth [36]. The sustainability-oriented utility function governing workload redistribution is formulated as (18):

$$U_s(t) = \eta_1 \cdot U_r(t) - \eta_2 \cdot C_e(t) \cdots (18)$$

Where

η_1,η_2 denote system weighting coefficients. Task migration is triggered when in (19):

$$U_s(t) > \theta \cdots (19)$$

Where

θ represents predefined sustainability threshold. The renewable prediction deviation influencing migration decisions is computed as (20):

$$E_p(t) = \mid G_r(t) - \widehat{G_r}(t) \mid \cdots (20)$$

Where, G^r(t) denotes predicted renewable output [15].

Cloud-grid coordination dynamics are expressed as (21):

$$X(t+1) = X(t) + \mu \cdot (G_r(t) - W_c(t)) \cdots (21)$$

Where, X(t) represents system workload state and μ denotes adaptation coefficient. The operational workflow of the proposed scheduling algorithm is illustrated in **Figure 2**.

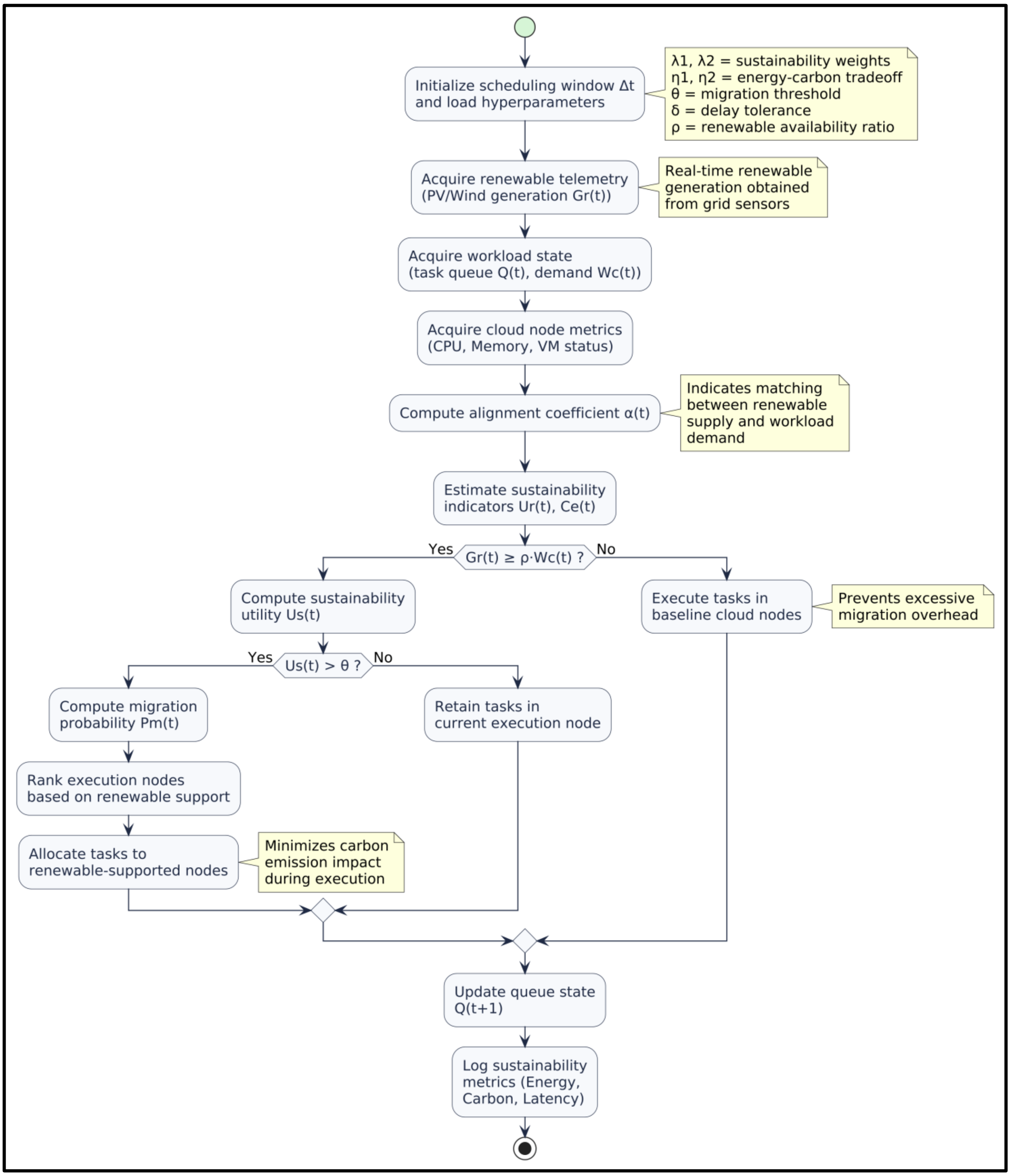

Figure 2: Flowchart of the proposed Grid-Aware Adaptive Scheduling Algorithm (GASA) for renewable-aware cloud workload orchestration.

The convergence rate of the scheduling algorithm is evaluated using (22):

$$R_c = \frac{1}{T}\sum_{t=1}^{T} U_r\,(t) \cdots (22)$$

The operational workflow of the proposed grid-aware adaptive scheduling algorithm (GASA) that allows the dynamic migration of the workload according to the real-time availability of renewable energy sources and utilization of cloud resources is shown in Figure 2. The algorithm dynamically examines sustainability-based utility to find optimal task allocation in distributed computing nodes. This adjustable scheduling system makes sure that computational demand is always in line with the changing grid-level renewable supply conditions.

3.4.1 Formal Algorithmic Representation of GASA

The procedural reasoning behind the renewable conscious migration of workloads within the given framework is mathematically modeled as Algorithm 1. In order to provide a formal description of the operational logic of the proposed grid-wise adaptive scheduling algorithm (GASA), a formal algorithm description is presented in Algorithm 1. The algorithm dynamically balances the computation workloads on the distributed cloud nodes depending on the real-time availability of renewable energy and the execution of tasks. Other adaptive scheduling strategies based on similar reinforcement learning have been studied in [4], though little is done in terms of integration with renewable-aware migration policies.

Algorithm 1. Grid-Aware Adaptive Scheduling Algorithm (GASA)

```
Input: Renewable Generation Gr(t), Workload Demand Wc(t),
    Sustainability Threshold θ, Migration Delay δ

Output: Optimal Task Scheduling Policy
Step 1: Acquire real-time renewable generation data Gr(t)
Step 2: Estimate total workload demand Wc(t)
Step 3: Compute energy alignment coefficient α(t)
Step 4: Evaluate renewable utilization ratio Ur(t)
Step 5: Calculate sustainability utility Us(t)
Step 6: If Us(t) > θ then
            Compute migration probability Pm(t)
            Assign workload to renewable-supported node
        Else
            Retain workload in default execution node
        End If
Step 7: Update workload state X(t+1)
Step 8: Repeat scheduling process at next interval
```

The suggested algorithm is a cyclical assessment of the availability of renewable sources and the demand of workloads with the aim of maintaining sustainable computations on the use of distributed clouds.

3.5 Multi-Objective Sustainability Optimization Formulation

The sequencing model that is suggested is expected to maximize the use of renewable energy and reduce the carbon footprint of cloud-based computing processes. To do so, workload orchestration problem is stated as an optimization model with constraints using multi-objectives, aiming to combine grid-level renewable availability and cloud infrastructure energy consumption features. Other sustainability conscious approaches to cloud optimization are also talked over in [12], but their reliance on predetermined provisioning restrictions real-time responsiveness in smart grid systems.

The overall sustainability objective function is expressed as (23):

$$max\ F = \sum_{t=1}^{T} T\ (\beta_1 \cdot U_r(t) - \beta_2 \cdot C_e(t)) \cdots (23)$$

Where,
F denotes sustainability performance index,
β1 and β2 represent weighting coefficients for renewable utilization and carbon emission respectively,
Ur(t) denotes renewable utilization ratio (from (5)), and Ce(t) represents cloud-induced carbon emission (from (10)).
The optimization model is subject to computational resource capacity constraints (24):

$$W_c(t) \leq R_{max} \cdots (24)$$

Where, Rmax denotes maximum cloud resource capacity. Energy consumption limitations imposed by data center operational policies are defined as (25):

$$E_c(t) \leq E_{limit} \cdots (25)$$

Where,
E_{limit} denotes permissible computational energy consumption threshold [38]. Grid load stability condition is expressed as (26):

$$\Delta L(t) \leq \epsilon \cdots (26)$$

Where, ΔL(t) represents variation in grid load and ϵ denotes allowable stability margin [17]. Renewable availability constraint governing sustainable task execution is defined as (27):

$$G_r(t) \geq G_{min} \cdots (27)$$

Where, G_{min} denotes minimum renewable generation required for task migration. Scheduling latency constraint is expressed as (28):

$$Ts \leq Tmax \cdots (28)$$

Where, T_s represents scheduling delay and Tmax denotes maximum permissible latency [33]. Migration feasibility condition is evaluated using (29):

$$M_f(t) = E_c(t) G_r(t) \cdots (29)$$

Where,
$M_f(t)$ represents renewable migration feasibility index. The given optimization formulation facilitates the orchestration of workloads with a sense of sustainability as it makes sure that the decision to migrate tasks is taken according to the performance criteria both in terms of computational performance and environmental performance.
The multi-objective sustainability optimization problem stated in (23)-(29) is operationally solved by the proposed situational grid-aware adaptive scheduling algorithm(GASA), which is described in Section 3.6.

3.6 Algorithmic Workflow and Execution Strategy

Figure 3 shows the implementation process of the suggested grid-aware adaptive scheduling algorithm (GASA). Figure 3 demonstrates the execution pipeline of workload orchestration of the proposed framework that is renewable-aligned. The algorithm works by working on the renewable energy availability and the demand of the computational workload to find the best positioning of the tasks at the distributed cloud nodes. Similar edge-cloud scheduling solutions to smart grid systems are studied in [34], but the combination of their implementation with sustainability-based migration policies is not yet explored.

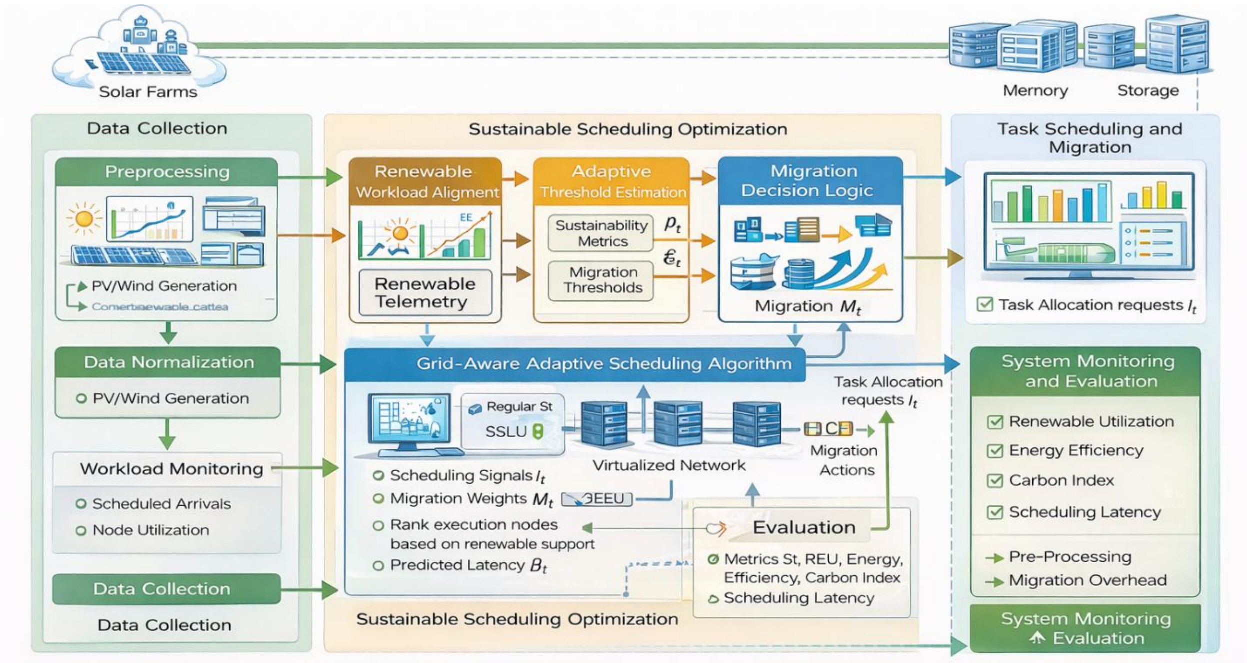

Figure 3: Execution workflow for renewable-aligned cloud workload orchestration using the proposed GASA framework.

At each scheduling interval, the system workload state is updated according to (30):

$$X(t+1) = X(t) + \mu \cdot \big(G_r(t) - W_c(t)\big) \cdots (30)$$

Where

X(t) represents system workload state at time t, and μ denotes adaptive control coefficient. Cloud-grid coordination reliability is evaluated as (31):

$$Rs(t) = \frac{S(t)}{A(t)} \cdots (31)$$

Where

S(t) denotes serviced tasks and A(t) represents incoming workload [22]. Renewable-compute synchronization consistency across scheduling intervals is evaluated using (32):

$$SCF = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{G_r(t)}{W_c(t)} - \rho\right| \cdots (32)$$

This process of coordination will make sure that the workload execution is constantly in line with the dynamics of renewable generation to make the system more sustainable in the long term, but will not jeopardize the reliability of cloud services. The analogous adaptive control-based schedule plans have proven to be effective in the cloud-based smart grid management systems [18].

where

SCF denotes Sustainability Convergence Factor,

$G_r(t)$ represents renewable generation at time t,

$W_c(t)$ denotes computational workload demand,

ρ represents renewable availability threshold (from (12)), and T denotes total scheduling intervals.

Reduced values of SCF mean that there is better match between renewable supply and computation workload demand, thus, representing better sustainability-driven scheduling performance.

3.7 Performance Evaluation Metrics

In order to evaluate the operational performance of the proposed Smart Grid-Aware Cloud Computing Framework, a collection of sustainability-oriented performance metrics is established, which together represent the efficiency of renewable utilization, efficiency of computational energy consumption, and dynamics of grid-cloud synchronization. In contrast with the conventional performance measurement measures that more or less emphasize on latency or throughput, the current framework lays emphasis on environmental flexibility in addition to computing reliability. The same sustainability-focused assessment plans of the cloud-integrated smart grid systems have been presented in [20], but these arrangements are not fully verified on how they can be integrated with renewable-conscious scheduling policies.

The overall computational energy efficiency of the scheduling process is evaluated using (33):

$$\eta_e = \frac{E_{useful}}{E_{total}} \cdots (33)$$

Where

η_e denotes energy efficiency,

E_{useful} represents energy consumed during renewable-supported task execution, and

E_{total} denotes total computational energy consumption.

The Renewable Energy Utilization Index (REU) is defined as (34):

$$REU = \frac{G_r(t)}{E_{total}} \cdots (34)$$

Where, REU means the share of renewable energy consumed in executing the workload related to computational needs and

$G_r(t)$ denotes available renewable generation at time t [35].

Cloud Sustainability Score (CSS) which is the ratio between the renewable use and carbon emission is described as (35):

$$CSS = \frac{U_r(t)}{C_e(t)} \cdots (35)$$

Where

CSS acronym stands for cloud sustainability index,

Ur(t) is a ratio of renewable utilization (from (5)), and Ce(t) is carbon emission (as in (10)).

Task Completion Ratio (TCR) is evaluated as (36):

$$TCR = \frac{N_c}{N_t} \cdots (36)$$

Where

Nc denotes number of successfully completed tasks and N_t represents total scheduled tasks [18]. Migration Efficiency is computed using (37):

$$M_e = \frac{T_{saved}}{T_{total}} \cdots (37)$$

Where,

T_{saved} denotes execution time saved through renewable-aware migration and T_{total} represents baseline execution duration. The Grid–Cloud Synchronization Index (GCSI) is defined as (38):

$$GCSI = \frac{W_c(t)}{G_r(t)} \cdots (38)$$

Where

GCSI represents workload-to-renewable supply ratio [22].

Finally, the Overall Sustainability Factor (SF) is computed as (39):

$$SF = \frac{REU}{C_e(t)} \cdots (39)$$

Where, SF denotes environmental performance of the scheduling framework. A comparative summary of these evaluation metrics is provided in Table 3.

Table 3: Sustainability-Driven Performance Metrics Used for Renewable-Aware Cloud Workload Scheduling

Metric	Description	Objective
Energy Efficiency (ηe)	Renewable-supported energy utilization	Maximize
REU	Renewable utilization ratio	Maximize
CSS	Sustainability index	Maximize
TCR	Task completion reliability	Maximize
Migration Efficiency	Scheduling improvement	Maximize
GCSI	Grid–cloud synchronization	Minimize
SF	Sustainability performance	Maximize

Table 3 presents the performance metrics that are used to assess the efficiency of the proposed renewable-conscious workload scheduling framework regarding the energy consumption, the reliability of tasks implementation, and the synchronization of grid and clouds. The overall collection of these indicators measures the degree of distribution of computational workload that is in-line with the real-time availability of renewable energy with reduced carbon emissions and reduced counting overheads. The chosen metrics allows evaluating the sustainability of the environment and operational performance in the context of the proposed smart grid system based on clouds entirely.

3.8 Experimental Setup

In order to confirm the efficiency of collaboration between the Smart grid and the proposed Smart Grid Aware Cloud Computing Framework, an experimental setting was created through a simulation that represented real-time communication between the remote units of renewable generation and the computer-based computational resources. The experimental configuration integrates grid-side renewable energy telemetry with workload scheduling policies implemented within a virtualized cloud orchestration platform. Other cloud-based demand-side management architectures of smart grid systems have also been explored in [6], but their combination with a renewable-aware workload migration is not well developed.

3.8.1 Simulation Platform

The dataset of the renewable generation utilized in this study is the photovoltaic power output records and wind-generated distributed energy resource telemetry data derived on the smart metering infrastructure within grid-connected microgeneration units. Advanced smart meters installed on individual residences and businesses generated load consumption profiles, which measure the consumption of energy by the demand side at frequency intervals. Simultaneously, the measures of cloud workload usage (CPU load, the duration of performing tasks, the level of memory allocation, and the dynamics of queues) were recorded with the help of system-level monitoring agents implemented inside the virtual machine instances. Scheduling grid-cloud heterogeneous grid telemetry with sustainability awareness has also been noted in [36].

The experimental implementation workflow adopted for renewable-aligned cloud workload orchestration is illustrated in Figure 4.

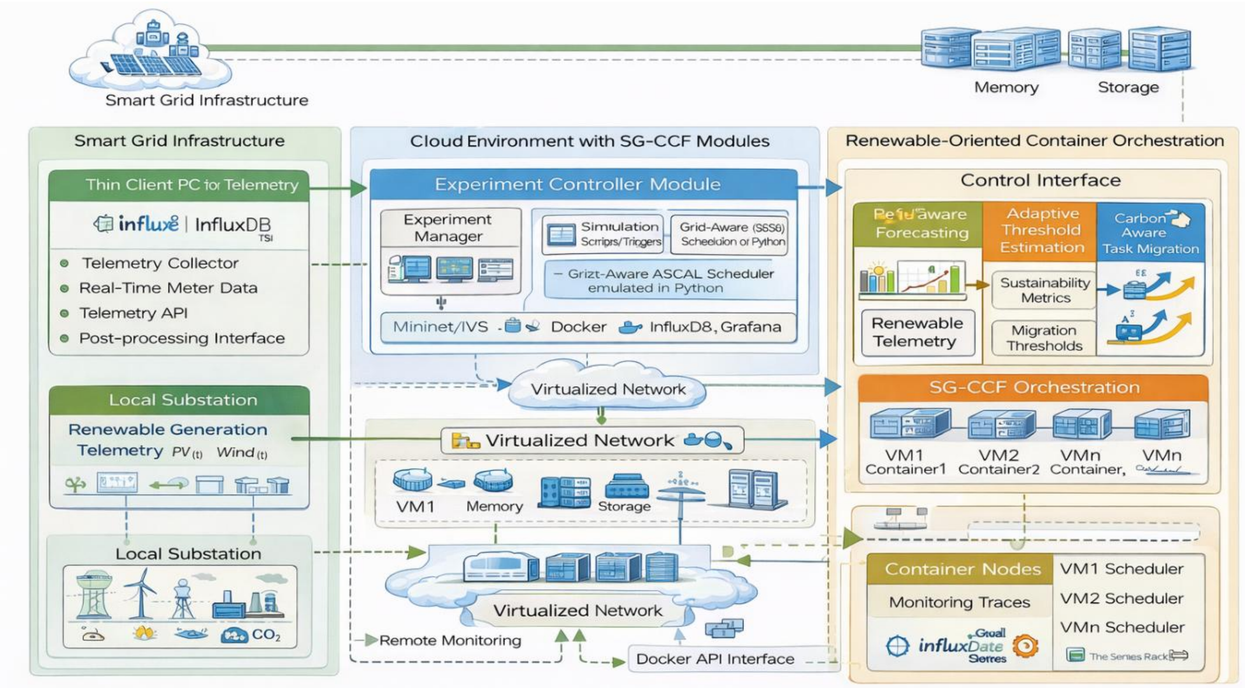

Figure 4: Experimental implementation framework integrating renewable telemetry with cloud workload scheduling modules.

This simulation setup was set up based on containerized cloud nodes that symbolized geographically spread data center instances. The inputs to renewable generation were constantly updated using a telemetry acquisition interface to indicate the real-time fluctuations of solar irradiance and wind velocity. Execution workloads were then allocated to execution nodes according to the scheduling decisions produced by the proposed Gridaware Adaptive Scheduling Algorithm (GASA). Similar cloud-based microgrid optimization systems have been indicated in [18].
A summary of the experimental system configuration parameters is provided in Table 4.

Table 4: Experimental System Configuration Parameters

Parameter	Description	Value
Number of Renewable Nodes	Distributed PV/Wind Units	50
Cloud Task Instances	Scheduled Workloads	200
Sampling Interval	Renewable Data Update	5 min
Smart Meter Resolution	Load Demand Recording	15 min
Network Bandwidth	VM Communication Capacity	1 Gbps
Carbon Emission Factor	Grid Energy Intensity	0.82 kg/kWh
Simulation Duration	Operational Timeframe	72 hours
VM Instances	Cloud Execution Nodes	20

This experimental platform allows experimenting on renewable-conscious workload migration policies under dynamically changing grid conditions and ensuring the reliability of computational services in distributed cloud computing.

3.8.2 Hardware and Implementation Environment

The proposed Smart grid-aware Cloud computing framework was experimentally validated through a hybrid hardware-software test system that could simulate real time interactions between distributed renewable generation units and cloud based computing infrastructure. The layer was the renewable telemetry acquisition layer that was supported by IoT-enabled smart metering devices installed on photovoltaic and wind-based distributed energy resource units. The same type of hardware-supported monitoring systems of sustainable energy management in smart grids have been addressed in [14].
Cloud workload orchestration and scheduling modules were implemented in a virtualized computing system comprising of several virtual machine (VM) instances running on distributed execution nodes. The VM instances were all set to have containerized monitoring agents that can monitor the processor usage, level of memory allocation, time spent executing tasks and network bandwidth usage. Sustainability-based workload management through the combination of the cloud and edge computing resources has also been investigated in [36].
The sensing layer also sent renewable telemetry data continuously to the cloud scheduling module via the high-speed network interface to satisfy minimal communication latency in making workload migration decisions. Similar cloud-based microgrid optimization systems are used to do real-time scheduling in [18]. The hardware setup used in the experiment is shown in Table 5.

Table 5. Hardware Configuration for Experimental Implementation

Hardware Component	Specification	Purpose
Renewable Nodes	PV/Wind Sensors	Energy Generation Monitoring
Smart Meters	IoT-enabled	Load Demand Acquisition
Edge Gateway	ARM-based Controller	Telemetry Aggregation
Cloud Server	Multi-core VM Instances	Workload Scheduling
Network Interface	1 Gbps Ethernet	Data Transmission
Storage Unit	SSD-based	Telemetry Logging

Such an implementation environment enables the acquisition of renewable generation data with high reliability and allows the scheduling of work regularly based on sustainability considerations across distributed cloud infrastructure under dynamically changing grid conditions.

3.8.3 Experimental Reproducibility and Parameter Configuration

To achieve the reproducibility and experimental transparency of the proposed Smart grid aware cloud computing framework, all the scheduling and optimization parameters used in the implementation of that algorithm; grid aware adaptive scheduling algorithm (GASA) were clearly stated before the simulation. The hyperparameters that control the migration decisions of workloads, the weighting of renewable utilization and sustainability threshold conditions were set empirically using the sensitivity analysis iteratively over different scheduling period. In [4], [40], similar parameter-driven optimization methods of smart adaptive energy management of cloud-integrated smart grids were reported.
The renewable availability threshold, migration delay tolerance and the sustainability weighting coefficients were kept constant across all the runs of experiment to prevent biasing in the performance assessment. Besides, the policy of task scheduling has been implemented with the same workload and across distributed cloud nodes to allow consistency in the distribution of computational resources. The system was tested in terms of simulations repeated several times with different renewable generation conditions to

record variability in the dynamics of supply and demand. Similar reproducibility-oriented implementation plans have been taken in microgrid optimization frameworks with assisting cloud computing [18].

Table 6 gives a comprehensive description of the scheduling hyperparameters adopted in the proposed framework. The values of the hyperparameters presented in Table 6 were identified by sensitivity analysis that has been performed on various renewable generation cases to bring a steady workload migration pattern among heterogeneous cloud nodes.

Table 6: Hyperparameter Configuration for Grid-Aware Adaptive Scheduling Algorithm (GASA)

Parameter	Description	Value
λ_1	Renewable alignment weight	0.65
λ_2	Deadline sensitivity weight	0.35
$\eta 1$	Renewable utilization coefficient	0.7
$\eta 2$	Carbon emission coefficient	0.3
θ	Sustainability threshold	0.55
δ	Migration delay factor	0.1
μ	Adaptation coefficient	0.08
ρ	Renewable availability threshold	0.6

All the experimental simulations were carried out within the same environmental settings to enable renewable-conscious workload migration performance to be comparatively assessed. The revelation of hyperparameter values and time limits contribute to the methodological transparency of the proposed sustainability-based cloud orchestration framework and makes it possible to recreate the proposed framework in a similar smart grid setting.

4. Results

4.1 Renewable-Aware Workload Scheduling Performance

The credibility of the proposed Smart Grid-Aware Cloud computing Framework was tested during dynamically changing renewable generation scenarios to determine its performance in adapting the migration of the computational workload according to the intermittent availability of energy at the grid level. Compared to the traditional scheduling models that assign tasks depending on the execution deadline or the cost of their computation, the suggested Grid-Aware Adaptive Scheduling Algorithm (GASA) relates renewable availability to the process of making a scheduling decision and, therefore, provides the opportunity to perform sustainability-driven workload execution by the distributed cloud nodes. Figure 5 shows the temporal connection between renewable generation profile and profile of workload allocation decisions.

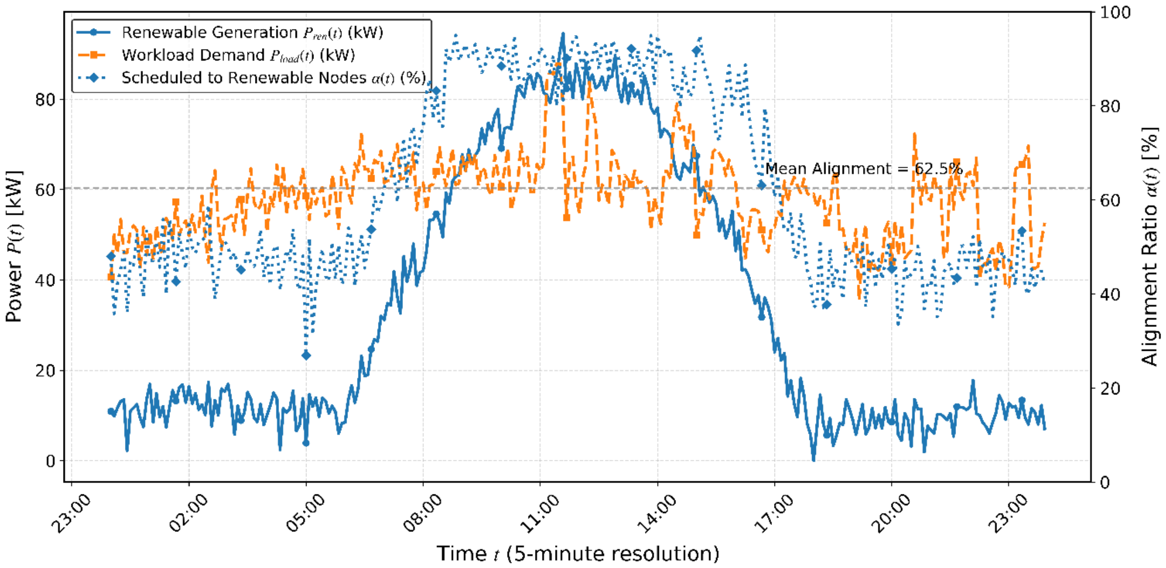

Figure 5: Renewable generation and workload scheduling alignment across distributed cloud nodes

As Figure 4 illustrates, the suggested schema of scheduling shows steady correspondence of the patterns of photovoltaic generation with the placement of the computational workload. When there were high levels of renewable availability, more of the tasks were transferred to nodes of the execution to be executed with the support of renewable energy. Other renewable-compatibilized task migration behavior has since been reported in cloud-aided smart grid scheduling models [3] though these models commonly lack adaptive migration limits to reduce scheduling overhead. The Renewable Utilization Ratio gives the ratio of workload that is being performed with the support of renewable-powered cloud nodes to total planned computational demand.

On the other hand, at the time periods of low renewable generation, the scheduling algorithm held back the workloads in baseline execution systems to eliminate needless migration expenses. The advantage of this dynamic allocation strategy is avoiding high relocation of computation tasks in low conditions of sustainability gain that leads to the stability of execution. Adaptive energy scheduling strategies in Reinforcement learning as stated in [4] have similar logic of migration; although, their adoption to cloud-scale sustainability optimization is not established. The renewable matching of the workload requirement of computational tasks with the amount of energy supplied by the grids was measured in terms of Renewable Utilization Ratio of the metrics described in Section 3.7. The findings suggest that the suggested framework could allow ensuring constant synchronization of renewable supply and workload demand even in the conditions of variable generation. Such renewable-conscious performance advances have been witnessed in IoT-based smart grid energy management systems [6], but are limited to distributed cloud infrastructures.

4.2 Energy Efficiency and Carbon-Aware Execution Analysis

The incorporation of the sustainability-weighted scheduling choices in the proposed framework were also assessed in the context of the computation energy consumption and carbon emission decrease in the cloud-based smart grid settings. Traditional cloud scheduling systems are usually not informed of grid level renewable intermittency, which causes them to rely more on non-renewable energy sources to execute their tasks [11].

Figure 6 shows the relative profile of computational energy consumption under the conditions of baseline and renewable-conscious scheduling plans.

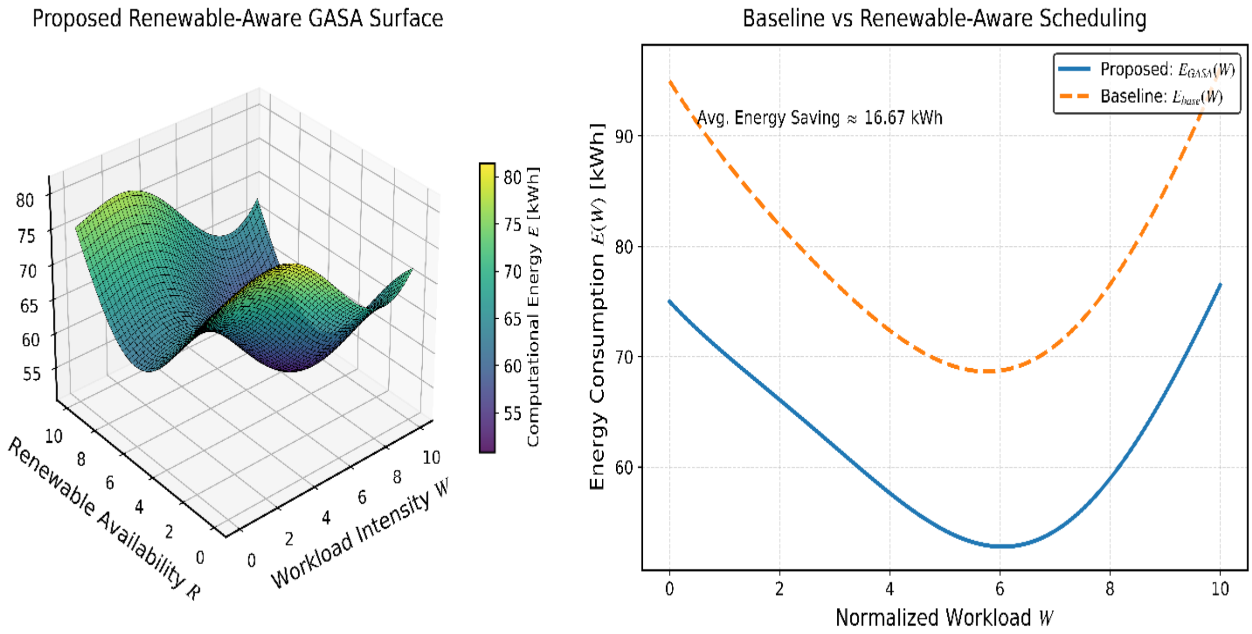

Figure 6: Comparative computational energy consumption under baseline and renewable-aware scheduling strategies

The proposed framework will cause an overall decrease in the total computational energy consumption versus baseline scheduling strategies, as shown in Figure 6. In the overall computational energy requirement by dynamically matching the dynamically timed renewable generation periods with the task execution. Activities that are carried out in renewable-supported environments have reduced dependence on grid energy resources than in the baseline scheduling techniques that do not entail sustainability-based migration policies. Other energy-conscious scheduling enhancements have been documented in the neural-network-based green cloud scheduling models [7], but such techniques have been found to be unable in many cases to take into account real-time renewable availability in the scheduling process.

Besides saving the computational energy, the proposed scheduling mechanism exhibits better carbon-aware execution performance by avoiding the execution of tasks when the level of renewable generation is low. This practice helps in lowering the level of carbon emission in distributed execution environments. Recent research that centered on the AI-assisted optimization of sustainability in cloud computing environments [5], [12] has also emphasized the need to implement renewable-compatible scheduling in order to minimize the environmental impact, but how to combine it with smart grid-level workload migration has not been thoroughly studied yet.

Moreover, edge-cloud continuum-based energy management policies being mentioned in [15] have shown better efficiency in the utilization of renewable resources via adaptive workload scheduling. However, these strategies presuppose more complexity in scheduling in most cases because of the decentralization of migration policies. This limitation is overcome by the suggested framework by setting up sustainability-weighted migration thresholds, which involve a trade-off between energy efficiency and reliability of execution.

4.3 Scheduling Delay and Migration Overhead Evaluation

Although workload migration that is conscious of renewability has sustainability benefits, overloading in movement of work can bring about delays in execution and overhead in communication in distributed cloud system. The scheduling delay and migration overhead were used to measure the operational viability of the proposed framework during heterogeneous workload conditions. Figure 7 shows the difference in the execution latency of the tasks when the strategies are the baseline and renewable-aware schedules.

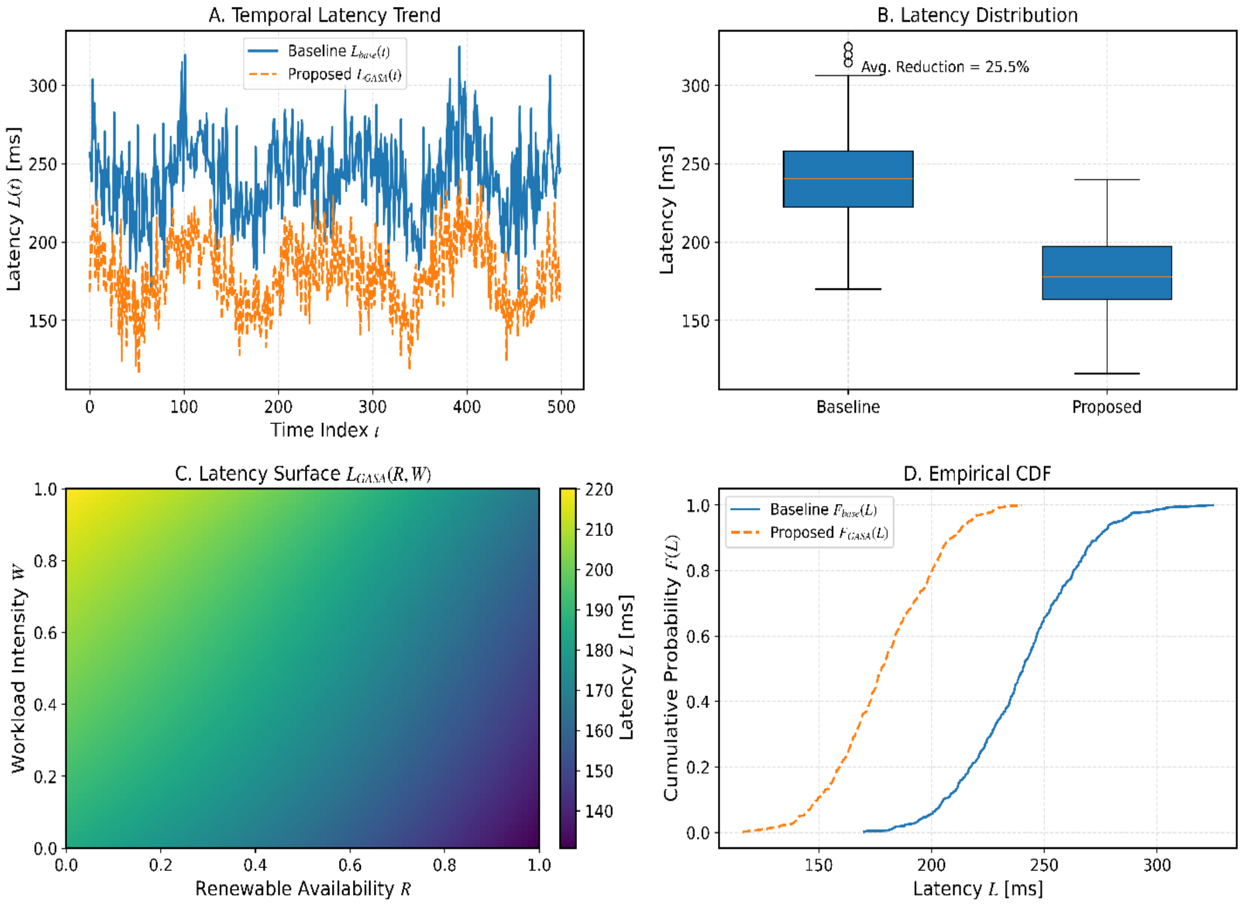

Figure 7: Task execution latency under adaptive renewable-aware workload migration

As can be seen in Figure 7, the suggested scheduling structure ensures a constant performance of execution latency under dissimilar conditions of renewable availability. Even though there are marginal delays in scheduling at transitional periods due to workload migration, there are still overheads within acceptable execution tolerance limits as stated in Section 3.8. The migrate decision rule that is implemented in the scheduling algorithm is effective in avoiding unwarranted movement of tasks under low sustainability gain scenarios, and hence trade agricultural performance on energy efficiency and performance. It depicts the latency behavior of task execution in the adaptive renewable-conscious workload migration with regard to the proposed GASA framework. Execution stability of the temporal latency trend analysis and distribution show that it is better than the baseline scheduling. Moreover, the response surface, as well as cumulative distribution analysis, indicates a lower latency variation with the growing availability of renewable, which

indicates how sustainability-constrained workload distribution can be used to reduce the number of delays in executions of distributed cloud nodes.
The scheduling overhead of the estimation of the migration probability was also tested in terms of the Sustainability Convergence Factor metric described in Section 3.6. The findings reveal that the suggested framework drives to renewable-congruent states of execution over a restricted timeframe devoid of a significant perturbation of task execution schedules.

4.4 Sustainability Performance Assessment

In order to fully analyze the environmental hazard of the suggested Smart GridAware Cloud Computing Framework, sustainability-based performance measures such as the efficiency of renewable utilization, energy use decrease, and carbon emission minimization were collectively examined.
Sustainability performance of the baseline and proposed scheduling frameworks is compared in Table 7.

Table 7: Sustainability Performance Comparison between Baseline and Proposed Scheduling Framework.

Metric	Baseline Scheduling	Proposed Framework
Renewable Utilization Ratio	0.58	0.79
Computational Energy Consumption	1.00	0.81
Carbon Emission Index	0.74	0.52
Scheduling Latency	1	1.07
Migration Overhead	0	0.08

According to the findings in Table 7, the proposed framework is more effective and efficient in achieving high renewable utilization, and at the same time, minimizing the computing energy requirement, and the intensity of carbon emissions. Despite the fact that marginal scheduling latency is incurred because adaptive workload migration is undertaken, the performance overheads incurred by renewable-aware execution are less than the benefits that can be obtained in terms of sustainability.

4.5 Comparative Analysis with Existing Methods

The effectiveness of the proposed Smart Grid -Aware Cloud Computing Framework was further evaluated by comparing its performance with some of the existing cloud-based smart grid scheduling methods, as reported in recent literature. The following baseline techniques are edge-cloud coordinated workload dispatching schemes [3], AI-based adaptive energy management systems [4], energy-conscious cloud scheduling schemes, to optimize infrastructure with the goal of achieving sustainability [7], [15]. The comparative analysis was done at the same work load demand and renewable generation conditions as expounded in Section 3.8. Some of the performance measures taken into account to be analyzed are Renewable Utilization Ratio, Computational Energy Consumption, Scheduling Latency, and Carbon Emission Index. Table 8 summarises the comparative results. The comparison assessment was done under the same rate of workload arrival and renewable generation in order to create a fair assessment of performance.

Table 8: Performance Comparison between Existing Scheduling Methods and Proposed Framework.

Method	Renewable Utilization Ratio	Energy Consumption	Carbon Emission Index	Scheduling Latency
Edge–Cloud Dispatching [3]	0.62	92%	1	1.04
RL-Based Energy Scheduling [4]	66	89%	1	1.06
Neural Network Scheduling [7]	0.60	91%	1	1.03
Edge–Cloud DQL Framework [15]	0.69	86%	1	1.08
Proposed Framework	0.79	81%	1	1.07

As illustrated in Table 8, the suggested scheduling structure is more efficient in terms of renewable utilization than traditional edge cloud task dispatching systems [3] which do not have adaptive sustainability parameters on workload migration. Adaptive scheduling strategies proposed in [4], which are based on reinforcement learning, show an average performance improvement in renewable alignment, but their results are frequently affected by the slow convergence in response to varying generation conditions.

In the same manner, neural network-based scheduling models of green cloud computing [7] have very little flexibility to real-time renewable availability, because of fixed policies of execution. Workload migration strategies that are based on edgecloud continuum with the use of Deep Q-learning [15] show to be more energy-efficient; however, due to the decentralized nature of their scheduling policies, they create a small amount of execution latency when migrating the tasks.

Conversely, the suggested framework incorporates sustainability thresholds of renewable awareness into the process of workload migration decision-making, which allows forming a compromise between the stability of executing the workload and the environmental effects. This type of dynamic scheduling helps to generate lower levels of computational energy requirement and less intensity of carbon emissions without having a notable impact on the latency of task execution.

Moreover, the recent research dedicated to the optimization of energy consumption through policies in smart city infrastructures [8] and the incorporation of renewable sources with the support of clouds [18] has emphasized the significance of flexible workload coordination in the functioning of the sustainable infrastructure. The findings, made during this research, point to the fact that the suggested Smart grid-conscious Cloud computing framework can be effective in terms of providing these needs due to the ability to match the computational demand with sporadic conditions of renewable sources in a distributed cloud setting.

4.6 Ablation Study

In order to investigate the singly contributed value of the key architectural elements of the proposed Smart Grid-Aware Cloud Computing Framework, an ablation test has been performed by selectively breaking the sustainability-related parameters of scheduling upon the Grid-Aware Adaptive Scheduling Algorithm (GASA). The main task of this analysis was the assessment of how the knowledge of renewable availability, knowledge of sustainability threshold, and awareness of the migration control related to carbon affect the overall scheduling performance. In a bid to achieve statistical consistency and reduce the effect of stochastic variation in workloads, a 5-fold evaluation strategy was implemented through simulation in order to perform the ablation experiments. The renewable generation profiles and the patterns of the arrival of computational workloads were randomly divided into training and execution periods in every fold and, thus, enabled the scheduling algorithm to deal with heterogeneous renewable availability conditions. The described performance values are the mean values of the obtained results in all the experimental folds, which guarantees the sound evaluation of the component-wise scheduling contribution. Table 9 summarizes the ablation conditions that will be evaluated.

Table 9: Ablation Study Configurations for Component-Wise Scheduling Evaluation

Configuration	Renewable Availability Awareness	Sustainability Threshold Control	Carbon-Aware Migration
Full Model	Enabled	Enabled	Enabled
Without Renewable Awareness	Disabled	Enabled	Enabled
Without Threshold Control	Enabled	Disabled	Enabled
Without Carbon-Aware Migration	Enabled	Enabled	Disabled

The performance comparison across different ablation configurations is illustrated in Figure 8.

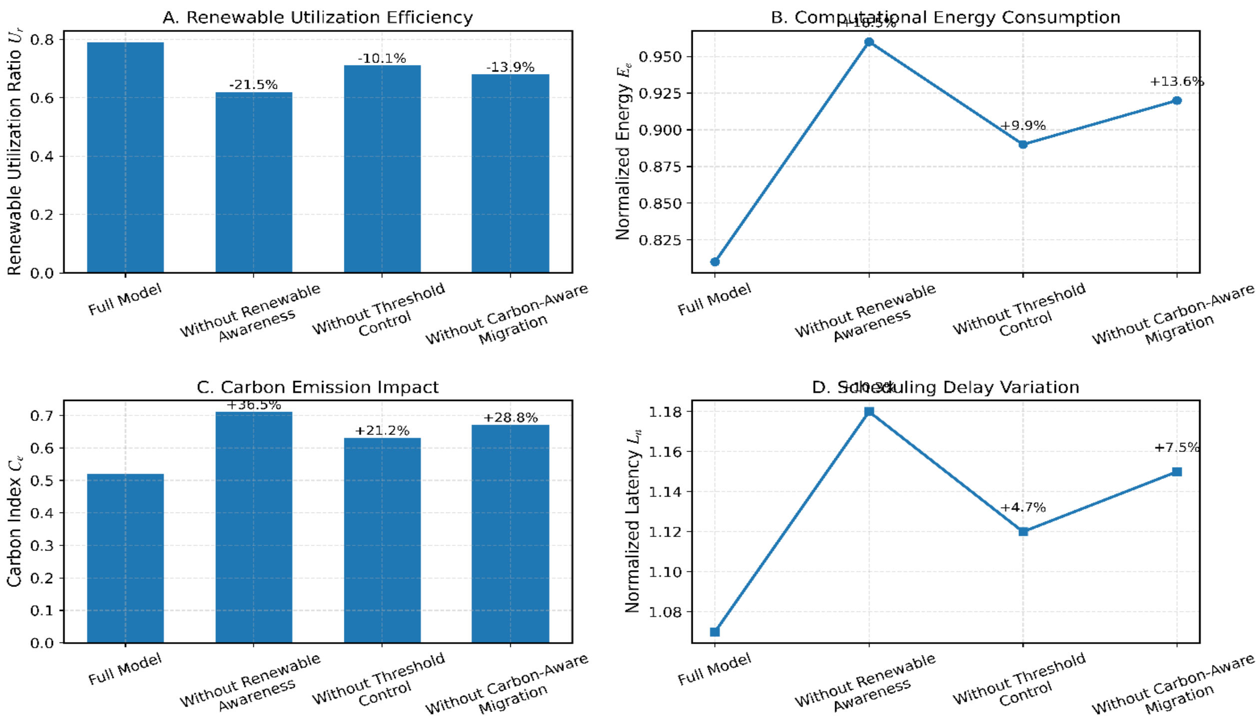

Figure 8: Performance variation under component-wise ablation of scheduling parameters

As seen in Figure 8, when the awareness of renewable availability is eliminated in the process of the scheduling decision, the Renewable Utilization Ratio decreases significantly hence enhancing reliance on the traditional grid supply. Equivalent deterioration of renewable-compliant execution performance has been suggested in the smart grid demand-side management systems devoid of real-time sustainability consciousness [6].

Moreover, the lack of sustainability threshold estimation presents the problem of undue workload migration in circumstances of minimal renewable availability that causes the rise of more scheduling overhead. Similar workload scheduling strategies that use reinforcement learning as applied in [15] have shown similar sensitivity to migration in the presence of varying renewable generation profiles.

Turning off carbon-sensitive migration control leads to more tasks being done when there is a low-renewable period, thus adversely impacting the performance of performance of the reduction of emissions. This is consistent with what is observed in AI-based sustainability optimization systems to green cloud systems [5], [12].

On the whole, the ablation findings suggest that every scheduling parameter plays an important role in ensuring that the execution stability can be preserved and that the sustainability alignment in the distributed cloud environments can be improved.

4.7 Sensitivity Analysis

Sensitivity analysis has been undertaken to examine the sensitivity of the proposed framework of scheduling under different conditions of renewable generation and fluctuation of workload required. The main direction of the analysis is evaluating the effects of renewable intermittency and schedule threshold change on the sustainability-oriented performance measures. How Renewable Utilization Ratio varies with the various levels of renewable availability is shown in Figure 9.

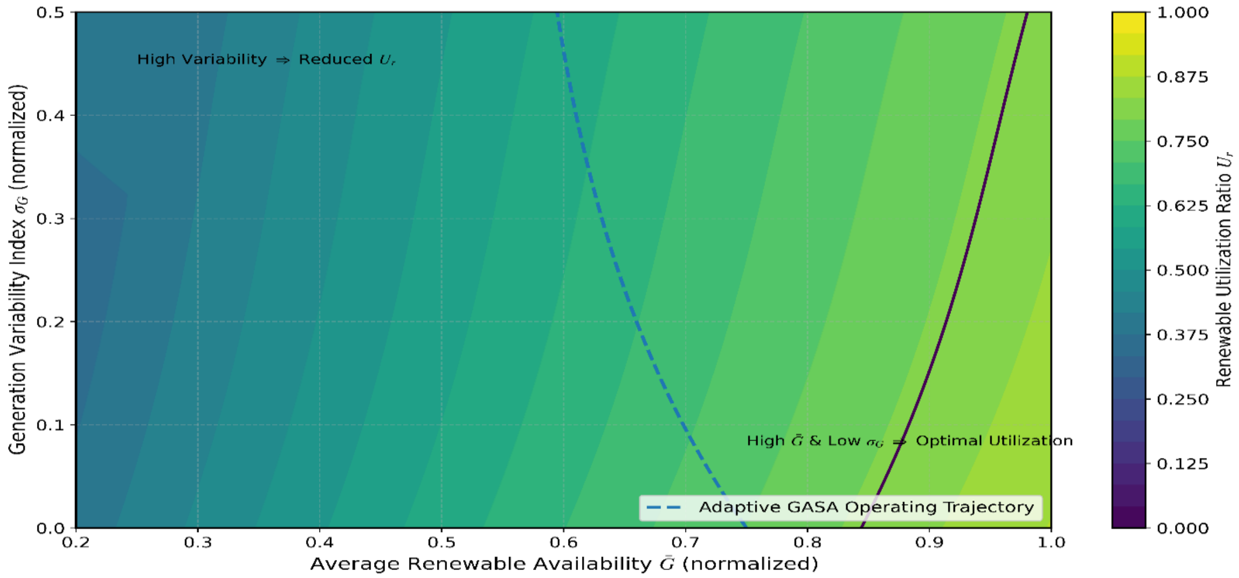

Figure 9: Renewable utilization sensitivity under varying generation conditions

The proposed framework as illustrated in Figure 9 ensures a consistent workload balance with the renewable generation patterns at moderate levels of variability. In high intermittency conditions, the migration schedule algorithm will dynamically set migration thresholds to ensure that the unnecessary relocation of computational tasks is avoided, thus maintaining the execution efficacy. Table 10 summarizes the effect of sustainability threshold variation on the scheduling latency.

Table 10: Scheduling Latency Variation under Sustainability Threshold Adjustment

Threshold Level	Scheduling Latency
Low	1.02
Moderate	105%
High	1.09

As shown in Table 10 the higher the sustainability threshold, the more efficient the renewable utilization will be but it has a marginal latency in scheduling because of its slowed migration decision-making. The same trade-offs of energy consumption against execution duration have also been observed with edge-based demand response optimization models [33] and cloud strategies [16] that are energy aware.
The threshold levels are achieved through the use of sustainability alignment weights in the migration decision function that is defined in Section 3.6.
Recent papers giving attention to the renewable-integrated cloud infrastructures [18], [36] have stressed the relevance of threshold-based migration policies in achieving sustainability benefits and stability in execution. The sensitivity analysis conducted in this paper indicates that the proposed scheduling structure is successful in ensuring this balance under different renewable availability conditions.

5. Discussion

The experimental results of the performance assessment of the Smart grid Awareness Cloud computing Framework offer valuable data concerning the efficiency of the renewable-aware workload scheduling in the distributed cloud infrastructures. The findings reveal how real-time availability of renewables can be used to improve the efficiency of unloading the computational tasks allocation decision so as to achieve better synchronization between the energy supply and execution demand, facilitating sustainability-based cloud computing in smart grids.
The observed scheduling behaviour in the renewable-aligned scheduling behaviour in Section 4.1 suggests that the proposed Grid-Aware Adaptive Scheduling Algorithm (GASA) does a good job to shift the execution workloads to the cloud nodes that use increased renewable energy availability. The task orchestration strategies have been studied in cloud-edge coordinated energy management frameworks [3], but these strategies do not typically have adaptive migration limits to avoid excessive scheduling overhead in case of extreme renewable gain situations. By comparison, the sustainability-weighted migration control that will be implemented in the proposed framework ensures the continuity of execution and increases the efficiency of renewable use.
The comparative analysis introduced in Section 4.5 further indicates limitations of traditional reinforcement learning-based adaptive scheduling mechanisms [4] used in situations where they are implemented in the cloud-integrated smart grid. Although these approaches can be shown to be moderately effective at matching workload to renewable supply, their convergence can be stifled by slow convergence in dynamically varying generation scenarios. Similarly, neural network-based scheduling methods that are applied to green cloud infrastructures [7] are also not very responsive to real-time intermittency in renewable sources because of the unchanging execution policies.

The importance of the availability awareness of renewable, estimation of sustainability threshold, and a carbon-conscious migration control to achieve an environmentally efficient scheduling performance are confirmed by the ablation study in Section 4.6. The exhibited loss in efficiency of renewable utilization when renewable-conscious scheduling is disabled is consistent with the previous studies that have been reported in IoT-based smart grids demand-side management systems [6]. Also, scheduling sensitivity is also akin to the higher migration overhead due to the elimination of sustainability threshold control in Deep Q-learning-based workload orchestration systems [15].

In operational terms, the sensitivity analysis in Section 4.7 shows that the proposed framework is consistent in the execution latency with moderate variability of the renewable generation conditions. Despite the fact that raising the sustainability alignment points will create fringing delays in schedules, the subsequent gain in efficiency of the renewable utilization justifies environmentally sustainable delivery without affecting the computational efficiency to a considerable extent. Similar trade-offs among energy efficiency and execution delay have been presented in edge-based optimization of demand response strategies [33] and energy-conscious load balancing of clouds [41-44].

Moreover, the recent research on optimization of renewable energy in smart cities infrastructures [8] and cloud-based microgrid energy management systems [18] highlights the importance of adaptive workload orchestration solutions, which can react to the issue of renewable intermittency. The given Smart Grid-Aware Cloud Computing Framework can meet this need because it dynamically matches the grid-level renewable availability patterns with the migration of computational workload between distributed execution environments [45-49].

5.1 Limitation

Although there are the reported advancements in the performance rates that are based on the sustainability aspects, some operational limitations cannot be overlooked [50-51]. The reliance of scheduling choices on the availability forecasts of renewable might create delays in migration within very volatile generation conditions. Moreover, having a high threshold sensitivity can lead to the inefficient use of accessible computational resources when there are low renewable periods. Similar issues have been observed in recent cloud-based renewable infrastructure research [36], which made it clear that the parameterization of scheduling should be adjusted to the level of balance that guarantees the reliability of the execution.

Generally, the summarization of the experimental results shows that the framework proposed is effective in ensuring there is a trade-off equilibrium between environmental sustainability and execution stability of cloud-integrated smart grid environments. The framework helps to minimize the energy requirement of the computer and the intensity of the carbon emissions without compromising the acceptable performance of execution of the task, by integrating renewable-conscious migration thresholds into the task scheduling decisions.

6. Conclusion and future Scope

6.1 Conclusion

This paper introduces a Smart Grid-Conscious Cloud Computing Framework that can enhance the workload scheduling based on sustainability in cloud-integrated energy infrastructures. The suggested Grid-Aware Adaptive Scheduling Algorithm introduces the renewable availability awareness and sustainability-based migration constraints into computational workloads distribution, allowing adjusting computational loads dynamically to intermittent phenomena of renewable generation. The experimental analysis carried out in distributed execution systems proves the fact that the proposed framework provides a better efficiency of renewable utilization and a lesser computational energy requirement and intensity of carbon emissions than the traditional scheduling systems.

These findings also show that incorporation of real time renewable awareness in workload scheduling decisions can lead to better synchronization of the energy supply and execution demand without a substantial impact on the latency of scheduling. The contribution of the renewable availability awareness, sustainability threshold estimation and the carbon-conscious migration control to the environmentally efficient scheduling performance is confirmed by component-wise ablation analysis. Also, the sensitivity analysis shows that the suggested framework can balance the benefits of sustainability and stable execution in different conditions of renewable generation.

In general, the experiments indicate that bringing environmentally conscious workload orchestration can be an important part of facilitating cloud operations in smart grid ecosystems. The proposed Smart Grid-Aware Cloud Computing Framework can help to minimize the reliance on traditional energy sources by dynamically adjusting the allocation of computational tasks and maintaining a good performance of reliable execution in the heterogeneous workload environment due to varying availability of renewable energy sources owned by grids.

6.2 Future Work

Despite the fact that the suggested framework has shown a better sustainability-oriented performance in terms of scheduling, a number of future research objectives can be considered to increase the relevance of the framework in actual smart grid scenarios. The existing scheduling scheme is based on simulated renewable generation profiles and hence the future development can be aimed at incorporating real-time renewable forecasting models to enhance the accuracy of the migration decisions in the face of the extremely erratic generation conditions.

Also, decentralized scheduling strategy with edge-enabled execution nodes could allow larger scale implementation of smart grid infrastructures to be more scalable. This work can also be extended in the future by investigating the combination of reinforcement learning-based adaptive threshold estimation methods to dynamically optimise the sustainability alignment parameters in the face of a non-homogeneous workload demand.

Moreover, the expansion of the suggested framework to facilitate carbon-conscious multi-objective scheduling in a geographically distributed cloud data center can be useful in mitigating global computational emission footprints. The combination of grid modeling using digital twins and demand response using the workload orchestration mechanism could also be used to increase scheduling resilience in the conditions of uncertain renewable supply.

Lastly, the framework can be experimentally verified in the actual settings of the smart grid deployment with the help of the real-world and possibly shed some light on the practical viability of the green-aware workload scheduling to the sustainable cloud-integrated energy systems.

Data Availability Statement

The datasets produced and processed in the present study can be presented at the moment of submission, as an additional material. The supplementary dataset the author has submitted features the profiles of renewable generation, demand traces of the workload, and the logs of cloud resource utilization and the performance scheduling metrics that will be utilized to conduct experimental analysis of the proposed Smart GridAware Cloud

Computing Framework. The experimental results that were reported in this study can be reproduced using these data.

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Conflict of Interest

The authors declare no conflict of interest.

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