Cloud-Based Optimization for Smart Scheduling of Energy Distribution in modern Power Grids

Janani. S[1] and V.Sumalatha[2]
[1] Research Scholar, Department of Computer Science,
Vels Institute of Science, Technology & Advanced Studies,
Chennai, Tamil Nadu, India.
[2] Professor, Department of Computer Applications,
Vels Institute of Science, Technology & Advanced Studies
Chennai, Tamil Nadu, India.

[1]jananivistas@gmail.com,
[2] sumalatha.scs@vistas.ac.in

Abstract. This study outlines a cloud-based optimization framework for the scheduling of smart energy distribution, supported by real-time energy data from smart meters, IoT sensors, and SCADA systems. The framework uses onboard preprocessing techniques to eliminate noise, synchronize, and extract features from diverse energy datasets. The actual optimization models can be run on scalable cloud-based platforms. The authors use Mixed Integer Linear Programming (MILP) for day-ahead and intra-day scheduling optimization and Reinforcement Learning (RL) for real-time adaptive control. The intelligent scheduler uses IoT messaging protocols according to NIST standards for secure updates to grid conditions, to dynamically monitor grid states. The scheduler will push updated schedules to grid devices to align energy flow with customer demand-dispatch control. The relevant utility dashboard monitors energy utilization efficiency, cost-reduction, grid stability, scheduling latency and CO_2 emission reductions. Comparison with contemporary control techniques, like time-based, rule-based, heuristic, and edge-based scheduling methods proved that day ahead and hour ahead smart scheduling in a cloud supported optimization solution is efficient and effective compared to traditional scheduling methods. This research has confirmed that cloud optimization of energy efficiency and grid resiliency can be achieved while reducing operational costs and carbon footprint emissions, representing a viable, multi-industry solution to the future smart grid complex system**.**

Keywords: Smart Scheduling, Energy Distribution, Power Grids, Mixed-Integer Linear Programming (MILP) , Reinforcement Learning (RL).

1 Introduction

Modern power systems are complex and challenges to energy management arise due to an increased demand for energy, added complexity of integrating renewable energy forms, and models with decoupled, decentralized grids. There continue to be a well-known reliance on static rules and heuristics to perform energy scheduling instead of adaptive algorithms due to the nature of modern electrical grids, which can be uncertain and volatile. Hence, energy optimisation to meet demand needs while providing cost efficiency and reducing environmental impact is a main operational and research challenge[1].

The development of smart grids through information and communication technology (ICT) innovations offer the capability to revolutionise energy management in real-time - by, for example, continually measuring demand, building intelligent processing of the data, and enabling automated controls. The enabling technologies for the smart grid comprise smart meters, Internet of Things (IoT) sensors[2], and SCADA systems that allow continuous monitoring of energy consumption, generation, and grid conditions. Heterogeneous streams of data produced by these technologies require preprocessing and integration as a means to ensure quality, consistency, and usability in subsequent analysis and optimisation.

The role of cloud-computing platforms can be crucial in fulfilling the computational and storage requirements of contemporary energy management systems. Cloud infrastructures are scalable to allow complex optimization algorithms on intensive datasets, and complex constraints involved in energy scheduling decisions. Cloud resources enable organizations to embed advanced models within the energy schedule. For example, sophisticated multi-objective energy scheduling creates flexibility in trying to minimize cost, while trying to achieve load balancing, or minimize emissions depending on the cost of service[3]

This study proposes a new cloud-based optimization framework for smart scheduling of energy distribution. In this framework, real-time (temporal) data available from smart-meters, Internet of Things (IoT) devices, and grid monitoring (electric) systems would be provided and processed through sophisticated pre-processing methods to clean and synchronize the data for model input integration. The optimization engine consists of a hybrid methodologically approach, mixed-integer linear programming (MILP) to plan the day-ahead and/or intraday energy scheduling along with reinforcement learning (RL) algorithms to assess real-time opportunities for adaptive decision making. The hybrid ML approach enables planning under certainties while the RL adapts to unexpected changes to grid conditions, thereby protecting the utility.

A smart scheduling module can combine operational demand and supply data to continually update energy dispatch schedules. The newly developed dispatch schedules are shared securely and transparently to the local distribution units/microgrids via IoT protocols, bringing decentralized and reactive management to the grid. The success of this framework will be monitored by tracking metrics such as energy visit utilization; cost savings, grid stability, scheduling delays, and emissions reductions. The suggested framework, using cloud computing, mathematical optimization, and machine learning will overcome the major deficits of scheduling in energy dispatch today. The state-of-the-art scheduling is an efficient and sustainable regime that can be a foundation for greater penetration of renewable energy and manage additional variability and uncertainty to enhance resiliency. This study provides a contribution to advancing smart grid technology through the development and validation of an integrated, cloud-based optimization approach for energy scheduling. The results illustrate substantial performance advancement against traditional approaches and state-of-the-art approaches demonstrating the promise of pervasive impact at a future time in energy systems. The research aims to achieve the following:

- To develop a cloud-based optimization framework that can integrate real-time data associated with smart meters, IoT sensors, and grid systems to provide adaptive and efficient energy scheduling.
- To deploy and assess the use of advanced optimization techniques such as Mixed-Integer Linear Programming (MILP) and Reinforcement Learning (RL), that can improve energy efficiency, cost effectiveness, and grid stability.
- To build an intelligent, secure scheduler that dynamically updates energy dispatch recommendations and communicates with a local distribution systems to improve flexibility and sustainability for smart grid operation.

2. Related Works

Numerous approaches, such as cloud-edge cooperative systems, multi-agent systems, and stochastic multi-objective scheduling, have been evaluated in the recent body of work on smart grid optimisation in order to manage complex distributed energy resources with the goals of maximising energy efficiency, minimising energy costs, and managing these resources. In order to develop systems with improved automation and responsiveness, researchers have also looked into the usage of cloud-based peer-to-peer pathways, whale optimisation, and reinforcement learning. They all play a key role in the development of intelligent, decentralised, and flexible energy management paradigms.

Abdulnasser et al., (2022) suggests a multi-objectives optimisation model based on stochastics for the best day-ahead scheduling of microgrids using EHs. The suggested approach simultaneously controls energy storage devices like compressed air energy storage (CAES) and battery energy storage devices, as well as non-dispatchable distributed generator units like wind turbines and solar systems[4]. Binyamin et al., (2022) examines the definitions, characteristics, uses, problems, and communications of Multi-agent systems(MAS). Because of this, professionals in computer science and civil engineering are interested in using MASs to break down complicated problems into smaller tasks. Each agent is responsible for their own tasks. Based on its objective, past activities, and relationships with neighbours, each agent chooses the optimal course of action. MAS makes use of computer networks, smart grids, and complex system modeling[5].

Heidarykiany et al., (2024) offer a new cloud-based demand side management (DSM) optimization strategy for district-level energy cost reduction in residential HVAC (heating, ventilation, and air conditioning) systems. The suggested method optimizes HVAC energy use by scheduling it within user-specified acceptable limits[6]. The introduction of a multi-objective resource optimisation (MORO) scheduler for various urban configurations addresses the drawbacks of edge-cloud. This scheduler highlights the intricacy of the issue and the requirement for a complex solution by emphasizing granular task prioritization and taking into account various makespans, costs, and energy limits. To accomplish the multi-objective makespan–energy optimization, a deep reinforcement learning (DRL) model is utilized [7].

Arcas et al., (2024) use the whale optimization method to determine which edge nodes are best suited to carry out the computing work required by the services. To make it easier to navigate the decision space and find the best answer, we use a directed acyclic graph to model dependencies between computational nodes, data network links, smart grid energy assets, and energy network organization[8]. Chi et al., (2-24) examines how to improve automation in power dispatching systems by using cloud optimization approaches. In particular, it investigates how cloud computing technology might be integrated to enhance data processing algorithms and address efficiency issues in power grid systems. The goal of the study is to increase system correctness, real-time responsiveness, and reliability by implementing a suggested technique that includes a distributed data service bus, huge data storage systems, and dynamic load balancing mechanisms [9]. Liu et al., (2025) emphasizes the smart grid computing task offloading decision problem that is based on cloud and edge computing working together. A work scheduling paradigm for the end-edge cloud is suggested, with load balancing, energy consumption, and task execution latency as optimisation goals.

Su et al., (2024) suggests a cloud-based P2P for peer-Multi Agent System (p-MAS) optimization approaches that combine Demand Response (DR) with Energy Management System (EMS) in a commercial MG and are used to minimize system peak. Cloud-based P2P for Modeling Leveraging Agents (MLA) is utilized for bill computation in order to close knowledge gaps regarding how different power market structures and individual decision-making processes affect local interactions and market outcomes. Pei et al., (2024) provide an effective framework for job scheduling that is based on the Multi-Agent Deep Q-Network (MADQN) principles and is intended to maximize reaction times and operational expenses. We present a detailed design overview of our method and perform a full performance evaluation. The experimental findings unequivocally show that our strategy may significantly cut reaction times and operating expenses when compared to existing techniques, including cutting-edge single-agent strategies.

A wide range of modern optimization techniques such as cloud-edge cooperative scheduling, MAS, stochastic optimization, whale optimization, and deep reinforcement learning is in the literature review. Even though various methods for optimizing smart grids are emerging, there are still a number of significant gaps in addressing optimization problems with integrated, real-time cloud-based approaches that present energy scheduling that improves grid stability, minimizes grid problems related to CO_2 emissions while maximizing grid stability, while remaining embedded latency. The current capacity heuristic and methods under investigation are focused on one or two areas and report outcomes from those narrow domains, such as heating and cooling, or behavior for agents and do not integrate the model to optimize the system as a whole. There is little comparative evaluation of any of these methods and none compares them all under common performance constraints. This evaluation addresses many of the gaps above by evaluating a strategy that combines an overall performance model, and examines approaches to minimizing and maximizing a cloud-based optimization model for smart grid performance and efficiency. The specified area of research deliberately focuses on the system level: the existing approaches aim at optimizing particular subsystems (e.g., HVAC, storage, or agent coordination) but fail to provide an integrated system-based model of real-time, cloud-based scheduling. Moreover, paired comparisons at various paradigms are scarcely found in the literature. By overcoming these barriers, the suggested solution offers an integrated approach to using MILP and RL to optimize both energy scheduling and an entire local system. Analyzing the system-wide performance of the proposed solution in terms of efficiency, stability, CO2 emissions, and latency, the study demonstrates the suggested method has the potential to improve RL-based energy scheduling by governing energy constraints and electrical instabilities to enhance the system performance over time.

3. Methodology

This proposed methodology brings together smart energy distribution and cloud-based optimization to facilitate scheduling across the distributed grid instantly, flexibly, and efficiently, to take full advantage of available energy resources. The methodology entails four high-level phases as shown in figure 1.

3.1 Data Acquisition and Integration

The process of smart energy scheduling will rely on the flexible and on-going acquisition of real-time data from a range of sources across the energy grid. Smart meters at the points of consumption provide fine-grained data on consumer usage patterns and

IoT sensors can monitor grid characteristics such as voltage, frequency, and equipment health across distributed assets. The supervisory, control and data acquisition (SCADA) level of the grid collects data about electricity generation, the total gigawatts of electricity transmission that are available, and outages at the grid-level etc., so these add to headroom of data to consider whenever a scheduling opportunity occurs. Very valuable weather sensors or external APIs can be used to enable some important forecasts for actualizing usable renewable energy. All these streams of heterogeneous data are transferred securely to a centralized cloud infrastructure, where they are time-synchronized into one value and quantified into a prepositioned data lake, which then represents a vast organized data aggregation in a one-dimensional frame. The cloud data lake makes it possible at-scale for the downstream system to access from the information to establish preprocessing, analytics, and optimization processes, further approaching key decisions for scheduling energy resources.

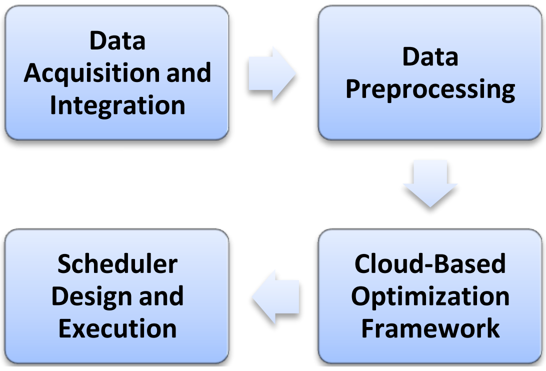

Figure 1 . Phases for smart energy distribution and cloud based optimization

3.2 Data Preprocessing

After acquisition, the raw energy data has to undergo complete preprocessing pipeline that maintains the integrity, consistency, and appropriateness of the data for optimization modeling (e.g., costs, demand features). The output data is free of noise and outliers, which are often caused by sensor errors or communication mishaps, to achieve the quality data through various filtering techniques (i.e., moving averages and Kalman filters). Outliers can be detected through statistical means such as the z-score or interquartile range (IQR) method, while missing values can be replaced through methods such as k-nearest neighbors (k-NN) or linear interpolation. Temporal alignment aligns various data in the energy use data set from different sources (smart meters, weather APIs, SCADA systems) through time stamp, and then we apply some resampling technique to the various formats so they standardize the temporal resolution (such as hourly or 15 minutes), if applicable. Finally, feature engineering creates variables of interest including peak and off-peak load profiles, seasonal demand trends, and forecasts for solar or wind energy, which allows us to convert raw measurements into meaningful data for our cloud-based optimization models[14].

3.3 Cloud-Based Optimization Framework

The main component of the entire smart scheduling system is the framework for optimization, as it allows for high computations, real time scalability, and integration of large data sets to a cloud-based environment. The optimization algorithms live on a cloud platform, such as Amazon Web Services (AWS) or Microsoft Azure, and can be engaged to process the computations simultaneously, on-demand. The research scheduling problem is a Mixed-Integer Linear Programming (MILP) or Reinforcement Learning (RL) problem, dependent on the time horizon and scheduling problems, either category for the optimization would have valued processing power)[14]. MILP based models are used for structured day-ahead and intraday scheduling problems, where only certain scheduling constraints are able to be explicitly declared, such as generation capacity, cost minimization, demand-supply matching, or mandates to comply with regulatory producers. Reinforcement Learning models are layered (e.g. Deep Q-Networks) and are used based on the feedback they receive from each real-time scheduling decision they take. Although Reinforcement Learning is the class of models that are ideal for scheduling due to their ability to find optimal policies over some time horizon taking into account the state of the grid and its uncertainties (e.g. demand fluctuations, intermittent renewable supply, and grid operational anomalies) there needs to be some justification in using an approach such as data-driven Reinforcement Learning over more conventional approaches in the event there are no licensed plans acquisition requirements. By taking a highly adaptive approach potential shareholders in the study of energy distribution and resource management have certainty can view potential impacts of balancing energy demands and keeping it environmental non-destructive. By using short-term planning and situational control, the range of problems found in versatile energy distribution will help to provide sustainable guarantees for stakeholders in terms of planning and efficient through merging theory and reality.

3.4 Scheduler Design and Execution

The intelligent scheduler acts as the operational engine of the smart energy distribution system and carries out real-time decisions based on the outputs of the cloud-based optimization models. The scheduler continuously consumes data streams and monitors demand changes, supply availability changes, and any newly reported system and grid condition changes. Depending on the status of scheduling and time urgency, the scheduler can call either a MILP solver or a reinforcement learning agent to calculate updated dispatch schedules. After the optimal schedules are calculated, they are sent to local distribution unit, substation or microgrid controller over lightweight and encrypted IoT communication such as MQTT or HTTPS.IoT protocols offer a low weight and secure method for communicating and receiving control commands that gives the opportunity to synchronize the distribution of energy consumption across the networks while also enhancing the systems resilient, low costs for the user in the utility network and the user demands.

4. Results and Findings

This study leverages the Smart Grid Stability Dataset to formulate and analyze cloud-based optimization models that help to schedule smart energy. The research intends to improve key performance indicators: energy efficiency, cost savings, grid stability, scheduling delay, and CO_2 emissions, that factor in further advancement of existing approaches

4.1 Dataset Description

The Smart Grid Stability Dataset is a new dataset based on the Electrical Grid Stability Simulated dataset, set out to support research focused on power grid stability utilizing simulated data and representing different operational conditions, in stable and unstable alternate cases. The dataset provides features including measures of voltage, frequency and power flow at nodes in the grid. It can be developed into machine learning metrics in order to predict grid stability to help avoid outages. This study uses the dataset to evaluate the improvement of strategies designed to maintain reliable and resilient smart grid operations.

4.2 Performance Analysis

The study evaluates cloud-based optimization powered smart energy scheduling optimization by using performance constraints of comparison against state-of-the-art methods. Energetic use efficiency, improved utility costs, maintained grid stability while eliminating scheduling latency and CO_2 emissions, were some of the performance constraints noted in the comparison study. Overall, this comparison evaluated how advanced optimization improved energy management.

Energy Utilization Efficiency (%): This reflects the way in which available energy resources are utilized to meet demand without waste.

$$Energy\ utilization\ Efficiency = \frac{Total\ Energy\ Delivered\ to\ Load}{Total\ Energy\ available\ from\ sources} * 100 \tag{1}$$

It is the total of all the energy that is actually supplied to meet demand, then divided by the total energy generated or available, converted to a percentage.

Cost Reduction (%): This compares operational cost savings achieved with scheduling to a baseline (normally no optimization or a basic rule-based approach).

$$Cost\ Reduction = \frac{Baseline\ Cost - Optimized\ Cost}{Baseline\ Cost} * 100 \tag{2}$$

Consideration for costs may include fuel costs, energy purchases, or penalty related to imbalances.
Scheduling Latency (seconds): Latency is the time taken by the scheduling algorithm for creating a dispatch
ule.$Scheduling\ Latency =$
$Time\ at\ scheduling\ completion - Time\ at\ schedule\ start$
(3) This is simply the elapsed wall-clock time for the optimization or scheduling computation.
CO_2 Emission Reduction (%):This is a carbon dioxide emissions comparison of the optimized scheduling to the baseline.

$$CO_2\ Emission\ Reduction = \frac{Baseline\ Emissions - Optimized\ Emissions}{Baseline\ Emissions} * 100 \quad (4)$$

Emissions are computed from the mix of energy used (e.g. fossil fuels, renewable) and the emission factors. Table 1 provides the proposed Cloud-Based Optimization method with three other state-of-the-art scheduling approaches:

Table 1 Performance Analysis –Proposed System

Metric	Proposed Cloud-Based Optimization	Rule-Based Scheduling[16]	Heuristic Optimization (GA)[17]	Edge-Based Scheduling (Local RL)[18]
Energy Utilization Efficiency (%)	93.5	78.2	85.6	88.1
Cost Reduction (%)	27.4	12.8	19.3	22.1
Grid Stability Index	0.92	0.73	0.84	0.88
Scheduling Latency (seconds)	3.4	1.2	9.8	2.9
CO_2 Emission Reduction (%)	22.7	8.6	15.2	18.4

The cloud-based optimization technique provided the greatest amount of energy use efficiency at 93.5%. The next closest was rule-based scheduling at 78.2%, followed by heuristic optimization through genetic algorithms at 85.6% and edge-based local reinforcement learning at 88.1%. This demonstrates how the proposed cloud-based optimization method allocates available energy resources in a more efficient manner, thereby mitigating waste and ultimately enhancing the system performance.

In terms of cost savings, the cloud-based method led with 27.4%, out-stripping the rule-based scheduling (12.8%), heuristic optimization (19.3%) and edge-based RL (22.1%) by some margin. This again proves the economic advantage offered by the cloud-based framework in lowering expenditure through a more optimal energy dispatch decision-marking process than the others. With respect to the stability index of the grid, the proposed optimization provided the greatest value with a value of 0.92, while for the baseline of rule-based scheduling provided only 0.73, heuristic optimization achieved only 0.84 and edge-based RL dropped slightly lower at 0.88. This metric addresses the ability of the system to maintain a balanced and reliable power grid within changing demand and supply conditions and demonstrates that the cloud-based optimization is the most robust approach.

With its scheduling latency at 3.4 seconds, slightly greater than rule-based scheduling (1.2 seconds) and edge-based RL scheduling (2.9 seconds), the scheduling methodology with the proposed system is still much faster than heuristic optimization (9.8 seconds). This shows that the proposed cloud-based scheduling strikes a practical compromise between timeframe to obtain a solution and quality of scheduling accuracy, allowing for near real-time updates without too much compromise or performance decline. The proposed cloud-based optimization method is superior in reducing overall CO_2 emissions only, with an overall reduction of 22.7%, which is significantly better rule-based scheduling (8.6%), heuristic optimization (15.2%), and edge-based RL (18.4%). This demonstrates the model's effectiveness in integrating renewable energy sources more effectively to minimize the environmental burdens of energy distribution.

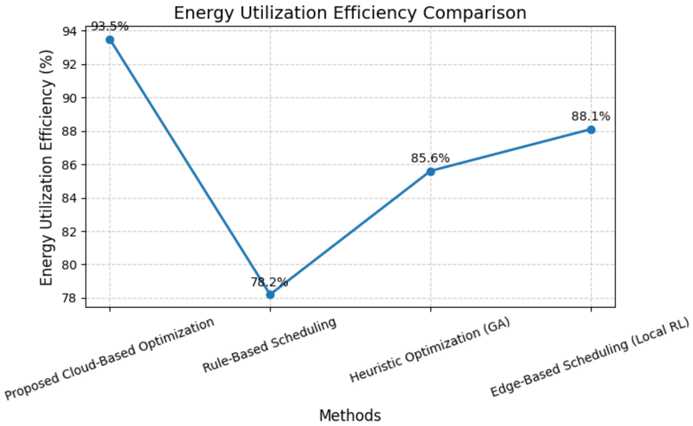

Figure 2 Energy Utilization Efficiency – Proposed Method

Figure 2 compares the performance in terms of Energy Utilization Efficiency (%) for the four energy scheduling techniques studied. The efficiency for the Proposed Cloud-Based Optimization (optimal efficiency, at approximately 93.5%) technique suggests that energy was well utilized with very little waste. Conversely, Rule-Based Scheduling appears to be the worst performer (lowest estimate, 78.2%) that exhibits significant inefficiencies in terms of resource utilization. The assumptions and scheduling decisions are static and are not able to adapt for the energy availability and utilization context. Overall, Heuristic Optimization (GA) and Edge-Based Scheduling (Local RL) provided reasonable estimates of energy efficiency at approximately 85.6% and 88.1% respectively. The benchmark figure demonstrates the Proposed Cloud-based method achieves a substantial improvement over the other energy scheduling methods considered in this study for maximizing energy utilization in smart grid environments.

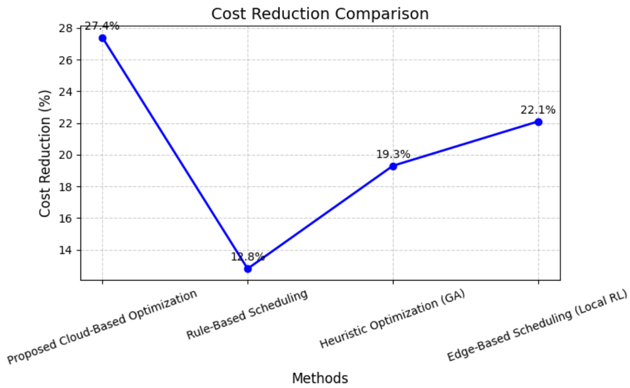

Figure 3 Cost Reduction –Proposed Method

Figure 3 demonstrates how much Cost Reduction (%) each of the energy scheduling methods produces. The Proposed Cloud-Based Optimization method has the highest Cost Reduction of 27.4% demonstrating it could effectively minimize the use of operational costs through optimized energy dispatch. Rule-Based Scheduling, on the other hand, returned the lowest amount of cost savings at 12.8% because of its inherently static and certain logic and therefore providing very little amount of efficiency savings. Heuristic Optimization (GA) and Edge-Based Scheduling (Local RL) each have demonstrated a better performance from the rule-based methods returning a 19.3% and 22.1% cost reduction respectively. The bar chart provides evidence that a cloud-based optimization approach potentially provides the most economic outcome in smart energy management application and is substantially better than both traditional and heuristic approaches.

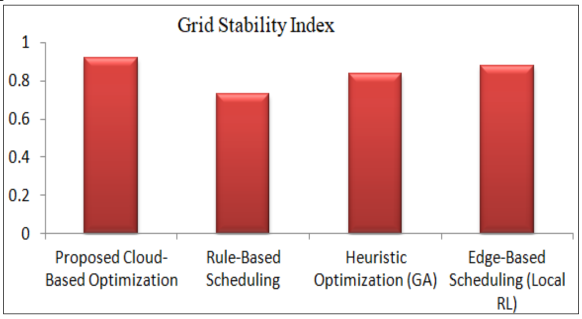

Figure 4 Grid stability Index – Proposed Method

Figure 6 shows Grid Stability Index over four different energy scheduling styles. In terms of execution, the Proposed Cloud-Based Optimization-style achieved the highest score at 0.92, indicating a significant amount of reliable and stable control for power flow and voltage conditions. Also, Edge-Based Scheduling, (Local RL) received a high score at 0.88, because of effective localization. Heuristic Optimization, (GA) scored moderate at 0.84, and Rule Based Scheduling scored the lowest at 0.73, indicating it may be less capable of maintaining grid balance dynamically. The research shows that cloud-based optimization does significantly mitigate threats to grid stability and resilience in changing conditions.

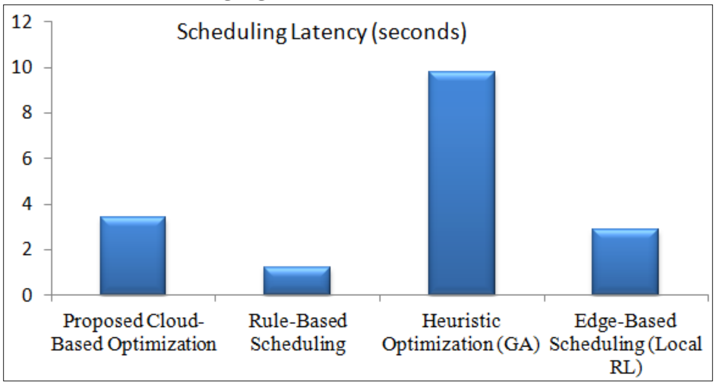

Figure 5 Scheduling Latency –Proposed Method

Figure 4 shows the Scheduling Latency (in seconds) for four scheduling approaches. The Rule-Based Scheduling has the least latency at 1.2 seconds due to its simplicity and lower computational cost. The Edge-Based Scheduling (Local RL) follows with 2.9 seconds, and the Proposed Cloud-Based Optimization had a latency of 3.4 seconds, indicating that it can achieve a reasonable balance of computational complexity and response time. Whereas the Heuristic optimization (GA) had the greatest amount of latency at 9.8 seconds, which is a result of it exploring the search space during each episode before converging. This analysis shows that the latency of the cloud-based modeling procedure and is able to function in near real-time without defensibly losing quality in performance optimization.

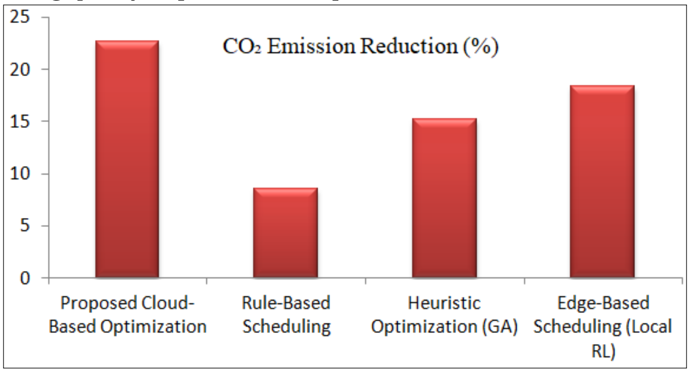

Figure 6 CO_2 Emission Reductions

Figure 5 shows the CO_2 Emission Reduction (%) for the different energy scheduling methods. The Proposed Cloud-Based Optimization shows the best performance at 22.7%, and therefore best represented sustainability in terms of optimised use of energy with more renewables in the energy mix. Edge-Based Scheduling (Local RL) is second best with equivalent reduction, although a reasonable environmental benefit, of 18.4% as there is local learning to do. Heuristic Optimisation (GA) demonstrated 15.2%, still decent performance yet was limited in being a longer computation. It is also less adaptable in its optimisation. Rule-Based Scheduling improved the least at only 8.6% wasting flexible capacity and not travelling across boundaries. This study confirms that cloud-based optimization has the opportunity to reduce emissions and increase eco-efficiency.

Conclusion

In this study, propose a cloud-based optimization framework for smart energy scheduling that can effectively combine varying real-time data from multiple sources to optimize energy assignment, usage and management. In this study we utilize MILP for planned scheduling and reinforcement learning or adaptive control within the system to improve energy usage, cost savings, and maintain grid stability and a reduction in emissions, in comparison to traditional methods. The intelligent scheduler or dispatching operator can dispatch decisions to local units via a secure cloud communication tool, allowing for quicker and more accurate operational energy management decisions to improve a more dynamic distribution of energy over the last mile. Future work will involve the use of more granular data, such as EV charging data and consumer interaction data for improved personalization and control. In refinement of the system's robustness it will include uncertainty modeling for renewable energy source variability. The study will also include exploration of confidential cloud-edge collaborative learning model to allow for continued real-time responsiveness and data privacy. Future work will also include enhanced cybersecurity models and studies to deploy the system in pilot demonstration within a real smart-grid. This will help to determine scalability and practical viability, and ultimately contribute towards a transition to more robust and sustainable energy systems infrastructure.

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