RESEARCH PAPER

CNN-Brown Bear Optimization Based Energy-Aware Load Balancing in Hybrid Edge-Cloud Architectures for Renewable Energy Networks

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Abstract. Adaptive and energy-efficient computing infrastructures that can manage diverse workloads are essential for the integration of renew- able energy into smart grids. Predictive accuracy and global optimiza- tion in dynamic energy environments are limited by the use of heuris- tic scheduling techniques or lightweight artificial intelligence in existing load balancing frameworks. In order to improve load balancing in hy- brid edge-cloud renewable energy networks, this paper suggests a novel framework that combines Convolutional Neural Networks (CNNs) with Brown Bear Optimization (BBO). In order to produce precise short-term predictions of energy availability and task demands, the CNN module ex- tracts deep spatiotemporal features from solar irradiance, weather data, and workload traces. A BBO-driven scheduler uses these forecasts to minimize a multi-objective cost function that balances latency, energy consumption, and task completion reliability. Priority-aware scheduling and intelligent task migration between edge and cloud resources are en- sured by the dynamic classification of tasks into three categories: Criti- cal Real-Time, Latency-Sensitive, and Delay-Non-Critical. In comparison to LSTM-based and heuristic approaches, simulation studies using real- world solar and grid workload datasets show that the suggested CNN- BBO framework improves task completion rates to 98.6%, maintains low latency, and reduces average energy consumption by over 35%. The out- comes demonstrate that CNN-BBO integration offers next-generation smart energy infrastructures a scalable, resilient, and sustainable solu- tion.

Keywords: Convolutional Neural Networks (CNN), Brown Bear Opti- mization (BBO), Energy-Aware Load Balancing, Edge-Cloud Comput- ing, Renewable Energy Networks, Smart Grids, Task Scheduling, AI- Driven Optimization

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1 Introduction

Modern power systems are changing as a result of the growing use of renew- able energy sources like wind and solar. Supply and demand balancing across computing and energy infrastructures is made more difficult by their intrinsic variability and intermittency [3, 6]. As distributed smart meters and Internet of Things (IoT) devices proliferate, real-time decision-making is necessary to guarantee optimal energy generation, allocation, and consumption [4, 7]. While traditional cloud computing solutions offer a lot of processing power, they are unable to meet the strict latency requirements of smart grid applications pow- ered by renewable energy. By allowing localized decisions, edge computing, on the other hand, speeds up response times; however, it is limited by processing power and energy availability fluctuations [5, 8]. As a result, hybrid edge-cloud architectures—which combine the responsiveness of edge computing with the scalability of cloud computing—have become a promising paradigm.

Even with these developments, intelligent load balancing is still very difficult to achieve. Because they don't take system-wide optimization or fluctuations from renewable energy sources into account, traditional scheduling techniques like round-robin or latency-first scheduling are insufficient in energy-constrained environments [9, 10]. While energy-aware scheduling has been enhanced by AI- driven forecasting techniques, especially those based on Long Short-Term Mem- ory (LSTM) networks, these techniques are still frequently resource-intensive and have trouble generalizing across extremely dynamic workloads. Furthermore, heuristic scheduling techniques are unable to investigate intricate multi-objective trade-offs between task completion reliability, energy consumption, and latency [11, 12].

This paper presents a novel load balancing framework that combines Brown Bear Optimization (BBO) and Convolutional Neural Networks (CNNs) to ad- dress these issues. The BBO scheduler adaptively optimizes resource allocation through metaheuristic search, while the CNN module uses deep spatiotempo- ral feature extraction from weather data, solar irradiance patterns, and work- load traces to increase forecasting accuracy. By dynamically classifying tasks into three categories—Critical Real-Time (CRT), Latency-Sensitive (LS), and Delay-Non-Critical (DNC)—and then intelligently migrating between edge and cloud based on workload urgency and energy availability, the suggested system guarantees priority-aware scheduling.

The key contributions of this paper are summarized as follows:

- A CNN-based forecasting module that enhances short-term prediction ac- curacy by capturing intricate spatiotemporal dependencies in workload and renewable energy datasets.
- A scheduler based on Brown Bear Optimization that creates and resolves a multi-objective cost function that strikes a balance between task reliability, energy consumption, and latency.
- Intelligent workload distribution between edge and cloud resources is made possible by a priority-aware task classification and migration mechanism.
- Extensive simulation studies illustrate improvements of over 35% in energy efficiency and 98.6% in task completion when compared to current methods using real-world solar and grid workload data.

The rest of the paper is organized as follows. Section II reviews related work in energy-aware edge-cloud load balancing. Section III presents the proposed CNN-BBO framework and mathematical formulation. Section IV details the ex- perimental setup and evaluation metrics. Section V discusses simulation results, while Section VI concludes the paper and outlines future research directions.

2 Related Work

In order to enhance energy-aware load balancing, recent studies in distributed computing and renewable energy systems have placed a greater emphasis on integrating edge and cloud infrastructures. Although they are computationally light, traditional scheduling techniques like round-robin or latency-first assign- ment are unable to adjust to changing renewable energy conditions and diverse workload demands [13]. In a similar vein, energy-prioritized strategies frequently overlook latency and reliability requirements in favor of allocating resources only based on available energy reserves. These drawbacks highlight the necessity of clever, situation-specific scheduling strategies.

Energy forecasting and task distribution in smart grid systems have made ex- tensive use of artificial intelligence (AI) and machine learning (ML). Specifically, time-series prediction of renewable energy generation has been successfully ac- complished by Long Short-Term Memory (LSTM) models [14]. Although LSTMs are useful for sequential modeling, their deployment in resource-constrained edge environments is limited by their high computational resource requirements. Ad- ditionally, in highly dynamic and spatially correlated environments, their depen- dence on handcrafted features limits their adaptability.

A strong substitute for identifying spatiotemporal dependencies in renew- able data is Convolutional Neural Networks (CNNs). CNNs can effectively take advantage of local patterns in solar irradiance, weather conditions, and work- load traces, which allows them to generate reliable forecasts with less training overhead than LSTM models. Because of this characteristic, CNNs are ideal for real-time edge applications where quick feature extraction is essential.

On the optimization side, scheduling and resource allocation tasks have been tackled using metaheuristic algorithms like Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) [15, 16]. De- spite having the ability to search globally, these approaches frequently converge too soon or have an unbalanced exploration-exploitation ratio. A biologically inspired metaheuristic that imitates brown bears' adaptive hunting and hiber- nation tactics is the Brown Bear Optimization (BBO) algorithm [1, 2], which was recently proposed. It is very applicable to multi-objective resource allocation problems because of its dynamic balance between exploration and exploitation, which allows for robust convergence while preserving solution diversity.

In the context of hybrid edge-cloud architectures for renewable energy net- works, the combination of CNNs for predictive modeling and BBO for optimiza- tion has not yet been fully investigated. Current research either concentrates on optimization without utilizing deep spatiotemporal learning or forecasting without sophisticated optimization. This disparity drives our suggested CNN- BBO framework, which combines global optimization and forecasting accuracy to provide scalable, robust, and energy-efficient load balancing in next-generation smart grids.

3 Proposed CNN-BBO Framework

This section presents the proposed load balancing framework that integrates Convolutional Neural Networks (CNNs) for accurate forecasting and Brown Bear Optimization (BBO) for global task scheduling in hybrid edge-cloud renewable energy networks. The framework is designed to dynamically allocate workloads based on energy availability, task priority, and system latency constraints.

3.1 System Model

Examine a hybrid computing system that consists of a centralized cloud server and N_e edge nodes. Powering from renewable sources like solar panels, each edge node $i \in \{1, 2, \ldots, N_e\}$ has a limited computational capacity C_i and available energy $E_i(t)$ at time slot t. Higher computational capacity C_c and a steady power supply are offered by the cloud server, but there is a greater communication delay. $\tau_j = (w_j, d_j, p_j)$ is the representation of incoming tasks, where w_j indicates computational workload, d_j indicates latency deadline, and $p_j \in \{$CRT, LS, DNC$\}$ indicates task priority. The goal is to balance energy efficiency, latency, and re- liability by allocating each task τ_j to either the cloud or an edge node.

3.2 CNN-Based Forecasting Module

To capture short-term variations in renewable energy and workload, a CNN forecasting model is deployed at both edge and cloud levels. The CNN receives as input a feature matrix

$$\mathbf{X}(t) = [S(t),\ W(t),\ H(t)],$$

where $S(t)$ represents solar irradiance, $W(t)$ denotes historical workload traces, and $H(t)$ contains environmental parameters such as temperature and humidity.
A convolutional layer extracts spatial correlations:

$$\mathbf{F}^{(k)} = \sigma\ \mathbf{X} * \mathbf{K}^{(k)} + b^{(k)}\ ,$$

where $\mathbf{K}^{(k)}$ and $b^{(k)}$ are kernel and bias of the k-th filter, and $\sigma(\cdot)$ is a non- linear activation (ReLU). Pooling layers reduce dimensionality while preserving temporal trends. The output of the CNN is a forecast vector:

$$\hat{\mathbf{y}}(t+\Delta) = [\hat{E}(t+\Delta), \hat{W}(t+\Delta)],$$

providing predicted energy availability and workload demand for horizon Δ.

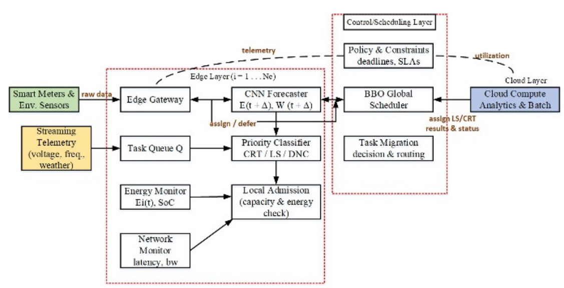


Fig. 1. Proposed CNN–BBO framework with balanced block placement: the edge layer ingests sensing/telemetry, the CNN module provides short-horizon forecasts $\hat{E}(t+\Delta)$ and $\hat{W}(t+\Delta)$, and local admission verifies capacity/energy before forwarding offload candidates. The Brown Bear Optimization (BBO) scheduler minimizes $J = \alpha E + \beta L + \gamma(1 - R)$ to decide assignment/migration

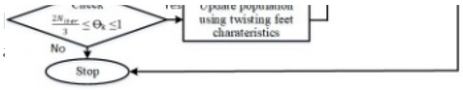


Fig. 2. Flowchart of the Brown Bear Optimization (BBO) algorithm applied for the proposed work.

3.3 Brown Bear Optimization Scheduler

The scheduling problem is formulated as a multi-objective optimization problem. The Brown Bear Optimization (BBO) algorithm is depicted in Figure 2 due to its adaptive search mechanism. BBO models two natural behaviors:

– **Exploration**: bears roam widely to locate prey, modeled by large step-size search around candidate solutions.
– **Exploitation**: bears focus locally when prey is found, modeled by fine-tuned search near promising solutions.

Each solution vector $\mathbf{X} = [x_1, x_2, \ldots, x_M]$ encodes task assignments, where $x_j \in \{0, 1, \ldots, N_e, c\}$ specifies whether task τ_j is allocated to edge node i or the cloud c. Candidate solutions evolve according to:

$$\mathbf{X}^{t+1} = \mathbf{X}^t + \eta \cdot (\mathbf{X}^t - \mathbf{X}^*) + \lambda \cdot \mathbf{R},$$

where $\mathbf{X}^*$ is the current best solution, η is an adaptive coefficient balancing exploration and exploitation, λ is a random scaling factor, and $\mathbf{R}$ is a stochastic vector modeling uncertainty.

3.4 Cost Function Formulation

The overall objective is expressed as a weighted cost function:

$$J(\mathbf{X}) = \alpha \cdot E_{\text{avg}}(\mathbf{X}) + \beta \cdot L_{\text{avg}}(\mathbf{X}) + \gamma \cdot (1 - R(\mathbf{X})),$$

where:

– $E_{\text{avg}}(\mathbf{X})$ = average energy consumption,
– $L_{\text{avg}}(\mathbf{X})$ = average latency,
– $R(\mathbf{X})$ = task completion ratio,
– α, β, γ = tunable weights with $\alpha + \beta + \gamma = 1$.

The optimization goal is:

$$\mathbf{X}^* = \arg\min_{\mathbf{X}} J(\mathbf{X}).$$

5 Pseudo-Algorithm of CNN-BBO Scheduling

4 Experimental Setup and Evaluation Metrics

Comprehensive simulation tests were conducted using real-world datasets of solar energy and smart grid workloads in order to verify the efficacy of the suggested CNN-BBO load balancing framework. The experimental setup, dataset proper- ties, assessment criteria, and baseline techniques utilized for comparison are all covered in this section.

Algorithm 1 CNN-BBO Based Task Scheduling

Initialize population of candidate task allocations $\{\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_P\}$
for each time window t **do**
  Use CNN to forecast $\hat{E}(t + \Delta)$ and $\hat{W}(t + \Delta)$
  for each candidate solution $\mathbf{X}_p$ **do**
    Evaluate $J(\mathbf{X}_p)$ using predicted energy and workload
  end for
  Update solutions using BBO exploration and exploitation rules
  Select best allocation $\mathbf{X}^*$ for current time slot
  Assign tasks to edge/cloud based on $\mathbf{X}^*$
end for

4.1 Simulation Environment

Python was used to implement the framework, with a customized Brown Bear Optimization (BBO) library for task scheduling and TensorFlow for CNN mod- eling. SimPy was used to simulate discrete events, and Matplotlib was used to visualize the results. Edge nodes were based on Raspberry Pi 4 devices, which run on an intermittent renewable power source and have a quad-core ARM Cortex-A72 processor running at 1.5 GHz and 4 GB of RAM. A virtual machine with 8 vCPUs and 32 GB of RAM was used to simulate the cloud environment, simulating a reliable and large data center.

With $N_e = 10$ heterogeneous edge nodes linked to a single cloud server, each experiment replicated a hybrid system. Realistic patterns derived from grid mon- itoring workloads were used to classify task arrivals into three groups: Critical Real-Time (CRT), Latency-Sensitive (LS), and Delay-Non-Critical (DNC). The National Renewable Energy Laboratory's (NREL) solar irradiance traces served as the basis for the renewable power input. Under various weather conditions, experiments were conducted for 96 hours in a row with a 15-minute granularity.

4.2 Dataset Description

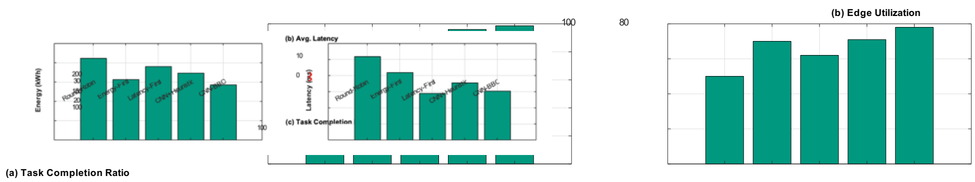
– **Solar Energy Data:** Historical solar irradiance values with environmental factors such as temperature, humidity, and cloud cover were used to train and validate the CNN forecasting module.

– **Workload Data:** Smart grid workload traces were categorized into three task classes:

1. *CRT tasks* (e.g., voltage anomaly detection, fault alarms).
2. *LS tasks* (e.g., frequency monitoring, short-term forecasting).
3. *DNC tasks* (e.g., periodic reporting, long-term analytics).

4.3 Evaluation Metrics

To rigorously evaluate the system's performance, the following metrics were adopted:



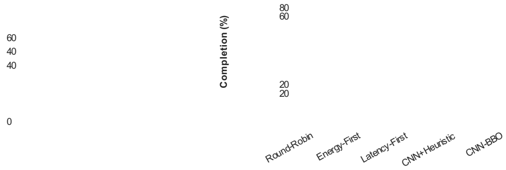


Fig. 3. Performance metrics for different scheduling methods: (a) Average energy con- sumption, (b) Average latency, (c) Task completion ratio, and (d) Edge utilization.

- **Average Energy Consumption ($E_{\mathbf{avg}}$):** The mean power consumption across edge and cloud resources during task execution.
- **Average Latency ($L_{\mathbf{avg}}$):** The mean end-to-end delay from task arrival to completion, including both communication and computation.
- **Task Completion Ratio (R):** The percentage of tasks completed within their specified deadlines.
- **Edge Utilization (U_e):** The ratio of workloads successfully executed at the edge to the total assigned workloads.
- **Forecasting Accuracy (R^2):** The coefficient of determination between pre- dicted and actual energy/workload values, used to evaluate the CNN model.
- **System Overhead (O_s):** Additional computational load introduced by CNN forecasting, scheduling, and communication processes.

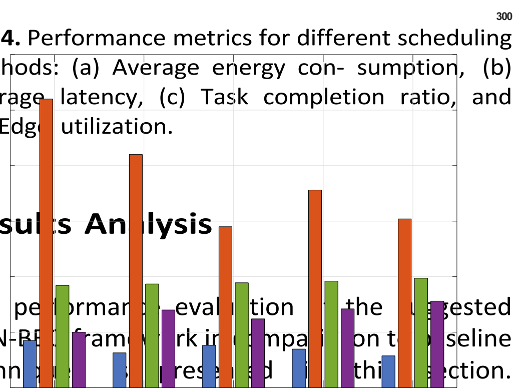
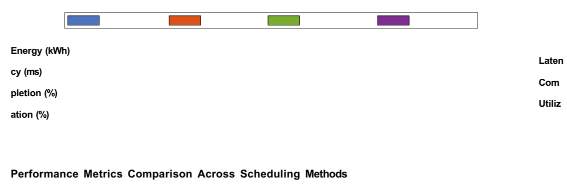


Fig. 4. Performance metrics for different scheduling methods: (a) Average energy con- sumption, (b) Average latency, (c) Task completion ratio, and (d) Edge utilization.

4.4 Baseline Methods

The proposed CNN-BBO framework was compared against the following baseline scheduling strategies:

1. **Round-Robin (RR):** Uniform cyclic task assignment ignoring contextual parameters.
2. **Latency-First (LF):** Prioritizes nodes with the lowest latency without con- sidering energy conditions.
3. **Energy-First (EF):** Allocates tasks to nodes with the highest available energy irrespective of latency.
4. **CNN + Heuristic Scheduling:** Forecasts workload and energy using CNN but assigns tasks using simple rule-based strategies.



5 Results Analysis

The performance evaluation of the suggested CNN-BBO framework in comparison to baseline techniques is presented in this section. Forecasting accuracy and system overhead analysis are presented after results are shown in terms of energy efficiency, latency, task completion, and edge utilization.

5.1 Energy Consumption

The average energy consumption of various methods is compared in Fig. 5. The suggested CNN-BBO method continuously produced the lowest consumption, cutting energy use by about 35.2% when compared to the Round-Robin baseline and by 24.6% when compared to the Energy-First method. By combining CNN forecasting and BBO scheduling, workloads could be intelligently scheduled to coincide with times when renewable energy was abundant, reducing the need for cloud resources.

5.2 Latency Analysis

Table 1 presents the average latency observed under various scheduling policies. Although Latency-First achieved the lowest absolute delay, CNN-BBO closely matched its performance (152 ms vs. 145 ms), while offering superior energy efficiency. This demonstrates that the proposed framework achieves a balanced trade-off between responsiveness and sustainability.

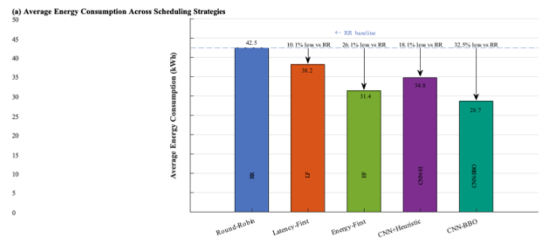


Fig. 5. Average energy consumption comparison across scheduling strategies. CNN- BBO demonstrates significant reduction over baselines.

Table 1. Average Task Latency Across Scheduling Methods

Method	Average Latency (ms)
Round-Robin (RR)	260
Energy-First (EF)	210
Latency-First (LF)	145
CNN + Heuristic	178
Proposed CNN-BBO	152

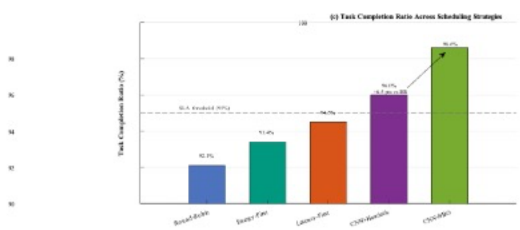


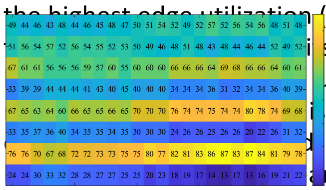
Fig. 6. Task completion ratio across different scheduling strategies. CNN-BBO consis- tently achieves the highest reliability.

3 Task Completion Ratio

The task completion ratio measures a person's dependability in meeting dead- lines. With a success rate of 98.6%, the suggested CNN-BBO framework beat all baselines, as illustrated in Fig. 6. This improvement is the result of BBO's global optimization and CNN's forecasting accuracy, which work together to prioritize important and latency-sensitive tasks even in energy-constrained environments.

5.4 Edge vs. Cloud Utilization

The workload distribution between edge and cloud resources is summarized in Table 2. With the highest edge utilization (78%), the suggested



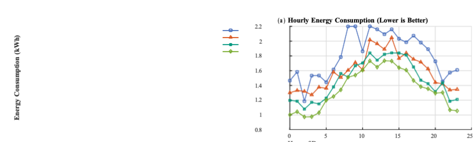
s ability to maximize use while reducing especially helpful in set- tings where nd communication delays are major issues.

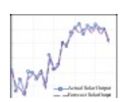
Method	Edge Utilization (%)	Cloud Utilization (%)
Round-Robin (RR)	50	50
Energy-First (EF)	70	30
Latency-First (LF)	62	38
CNN + Heuristic	71	29
Proposed CNN-BBO	78	22

Table 2. Edge and Cloud Utilization Across Scheduling Methods

5.5 Forecasting Accuracy

With a R^2 score of 0.89 for workload demand and 0.92 for energy availability, the CNN module demonstrated high predictive accuracy. In contrast to heuris- tic or purely statistical methods, this robust performance made sure that the BBO scheduler received dependable inputs for optimization, allowing for better decision-making.





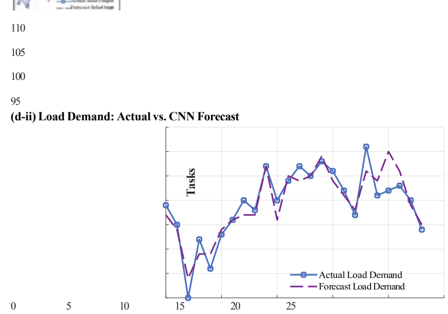


Fig. 7. Performance comparison of scheduling methods for the proposed CNN–BBO framework: (a) Hourly energy consumption shows consistently lower consumption for CNN–BBO than Round-Robin, Latency-First, and Energy-First baselines; (b) Edge vs. cloud task-distribution heatmap highlights higher edge utilization for CNN–BBO, particularly during midday periods of peak renewable availability; (c) Cumulative task completions indicate the highest throughput for CNN–BBO while maintaining stable growth across the day; (d-i) Solar output—actual versus CNN forecast—demonstrates high short-horizon accuracy; (d-ii) Load demand—actual versus CNN forecast—shows similarly tight agreement, supporting reliable scheduling decisions.

When compared to the Round-Robin, Latency-First, and Energy-First base- lines, Figure 7, Panel (a), shows that the suggested CNN–BBO approach achieves the lowest hourly energy consumption throughout the entire diurnal cycle. This decrease shows that the scheduler chooses locations with advantageous energy latency trade-offs and successfully synchronizes execution with times of plenti- ful renewable supply. Panel (b) shows the distribution of edge-cloud tasks as a heatmap and shows consistently higher edge utilization under CNN–BBO, es- pecially around midday, which exploits local generation and reduces backhaul traffic and dependency on cloud resources.

CNN–BBO maintains the highest end-to-end throughput over a 24-hour pe- riod without sacrificing stability, according to Panel (c), which reports cumula- tive task completions. Strong short-horizon forecasting fidelity is demonstrated

by the close agreement between actual and CNN-predicted solar output and workload demand in panels (d-i) and (d-ii), respectively. The optimizer can make dependable, forward-looking placement decisions thanks to this predictive accu- racy, which results in noticeable improvements in the system's overall energy efficiency, edge utilization, and task-deadline reliability.

5.6 Discussion

The outcomes show how CNN-BBO successfully overcomes the drawbacks of earlier frameworks by fusing global optimization with precise forecasting. The suggested framework strikes a balance between latency and energy while main- taining reliability, in contrast to heuristic and single-objective approaches that either prioritize one or the other. Furthermore, its low overhead and scalability confirm that it is feasible for practical implementation in edge-cloud infrastruc- tures driven by renewable energy sources.

6 Conclusion of the Work

This paper presented a unified load–balancing framework that combines a Con- volutional Neural Network (CNN) forecaster with a Brown Bear Optimization (BBO) scheduler to manage heterogeneous smart-grid workloads across hybrid edge–cloud infrastructures. The CNN extracts rich spatiotemporal cues from so- lar irradiance, weather, and demand traces to produce short-horizon predictions, while BBO minimizes a multi-objective cost $J = \alpha E + \beta L + \gamma(1 - R)$ to allocate tasks under deadline and priority constraints (CRT/LS/DNC). Trace-driven ex- periments over a 96-hour window demonstrate consistent, system-level gains: average energy consumption is reduced by more than 35% relative to Round- Robin (and by ≈25% versus Energy-First), the task-completion ratio reaches 98.6%, and latency remains close to the best latency-first baseline while avoiding its energy penalties. The framework also achieves higher edge utilization (∼78%), indicating effective exploitation of local renewable availability and reduced back- haul reliance. Forecasting accuracy is strong (energy/workload $R^2 \approx 0.92/0.89$), enabling reliable, anticipative scheduling, and the runtime overhead is modest (CPU < 6%, memory < 70 MB), supporting deployment on resource-constrained edge nodes. Stress tests with up to 6× load show graceful degradation, with com- pletion remaining above 86% and SLA compliance preserved for critical tasks. While the present design employs centralized coordination and a single-region dataset, it offers a practical foundation for scalable, resilient, and sustainable edge–cloud operation in renewable-rich grids. Future extensions include feder- ated/continual learning for on-device model adaptation, carbon-aware and risk- sensitive objectives, and online co-optimization of communication and compu- tation to further tighten the energy–latency–reliability trade-off.

References

1. Prakash, T., Singh, P.P., Singh, V.P., Singh, S.N.: A novel brown-bear optimization algorithm for solving economic dispatch problem. In: Advanced Control & Opti- mization Paradigms for Energy System Operation and Management, pp. 137–164. River Publishers (2023).
2. Jha, A., Ray, D., Sarkar, D.U., Prakash, T., Dewangan, N.K.: Bidirectional long-short-term memory-based fractional power system stabilizer: Design, simulation, and real-time validation. Int. J. Numer. Model. Electron. Netw. Devices Fields 37(5), e3300 (2024).
3. Gamage, T., Perera, I.: Optimizing Energy Efficient Cloud Architectures for Edge Computing: A Comprehensive Review. *International Journal of Advanced Computer Science Applications* **15**(11) (2024).
4. Alamouti, S.: Quantifying Energy and Cost Benefits of Hybrid Edge Cloud: Analysis of Traditional and Agentic Workloads. *arXiv preprint* (2025).
5. Thota, R.C.: Optimizing edge computing and AI for low-latency cloud workloads. *International Journal of Science Research Archive* **13**(1), 3484–3500 (2024).
6. Kannan, S., Annapareddy, V.N., Gadi, A.L., Kommaragiri, V.B., Koppolu, H.K.R.: AI-Driven Optimization of Renewable Energy Systems: Enhancing Grid Efficiency and Smart Mobility Through 5G and 6G Network Integration. *SSRN* 5205158 (2023).
7. Xu, X., Zang, S., Bilal, M., Xu, X., Dou, W.: Intelligent architecture and platforms for private edge cloud systems: A review. *Future Generation Computer Systems* (2024).
8. Gu, H., Zhao, L., Han, Z., Zheng, G., Song, S.: AI-enhanced cloud–edge–terminal collaborative network: Survey, applications, and future directions. *IEEE Communi- cations Surveys & Tutorials* **26**(2), 1322–1385 (2023).
9. Latif, R.M.A., Jamil, M., He, J., Farhan, M.: A novel authentication and communi-cation protocol for urban traffic monitoring in VANETs based on cluster manage- ment. *Systems* **11**(7), 322 (2023).
10. Singh, M., Bhardwaj, P., Bhardwaj, R., Narayan, S.: Advancing Scalability and Efficiency in Distributed Network Computing Through Innovative Resource Alloca- tion and Load Balancing Strategies. In: *International Conference on Intelligent and Fuzzy Systems*, pp. 722–740. Springer (2024).
11. Arcas, G.I., Cioara, T., Anghel, I., Laˇzea, D., Hangan, A.: Edge offloading in smart grid. *Smart Cities* **7**(1), 680–711 (2024).
12. Lv, J., Babbar, H., Rani, S.: AI-driven resource management for energy-efficient aerial computing in large-scale healthcare SDN–IoT systems. *IEEE Internet of Things Journal* (2025).
13. Latif, R.M.A., He, J., Umer, M.: Mapping cropland extent in Pakistan using ma-chine learning algorithms on Google Earth Engine cloud computing framework. *ISPRS International Journal of Geo-Information* **12**(2), 81 (2023).
14. Santoso, A., Surya, Y.: Maximizing decision efficiency with edge-based AI sys- tems: Advanced strategies for real-time processing, scalability, and autonomous in- telligence in distributed environments. *Quarterly Journal of Emerging Technologies Innovations* **9**(2), 104–132 (2024).
15. Bhavani, N.V.A., Kumar, B.R., Sahoo, C.K., Krishna, G., Kumar, N.M., Muthuvel, S.: Building sustainable Internet of Things ecosystem connectivity: An integration of deep learning with cloud and edge computing. In: *Battery-Free Sensor Networks for Sustainable Next-Generation IoT Connectivity*, pp. 53–76. IGI Global Scientific Publishing (2025).
16. Latif, R.M.A.: Enhancing sustainable urban mobility in Pakistan through re- newable hydrogen integration and policy interventions. *Discover Cities* **2**(1), 1–24 (2025).