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DESIGN OF AN ITERATIVE PREDICTIVE CARBON-AWARE RESOURCE SCHEDULING METHOD FOR CLOUD–FOG–EDGE ECOSYSTEMS THROUGH MULTI-STAGE ENERGY AND THERMAL OPTIMIZATIONS

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Abstract

Growing computational demand across cloud, fog, and edge infrastructures is intensifying energy consumption and carbon emissions, yet existing scheduling frameworks typically treat power draw as a static, short-term metric. This narrow view struggles with the fluid geography of modern workloads bursty, migratory, and thermally entangled leading to inefficient energy use and weak carbon accountability. To confront these gaps, we introduce a five-stage resource–energy orchestration model that explicitly intertwines spatio-temporal energy prediction, quantum Inspired optimization, live task migration, thermal dynamics, and carbon-economic feedback. The pipeline begins with Multi-Modal Spatio-Temporal Energy Profiler (MSTEP), which continuously profiles heterogeneous nodes through tensor decomposition and graph-temporal convolution, forecasting per-node energy use over 5-second horizons and improving power-capping accuracy by about 12%. Its predictive map drives the Energy-Aware Quantum Inspired Resource Orchestrator (EQUIRO), a classical Hamiltonian optimizer borrowing from quantum annealing to escape local minima, cutting energy consumption by roughly 18% while lowering latency. The resulting plan is enacted by Reinforcement-Driven Adaptive Task Migrator (R-ATM), where policy-gradient agents treat migration as a continuous-time control problem, reducing unnecessary moves by ~20%. To prevent thermal hotspots created by such migrations, Cross-Layer Thermal-Aware Cooling Optimizer (CLTACO) applies physics Informed neural networks to couple micro-scale thermal diffusion with

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macro cooling strategy, yielding around 15% better power usage effectiveness. Finally, Carbon Impact Feedback and Economic Optimizer (CIFEO) close the loop by translating operational data into carbon-weighted pricing and deferral schedules, achieving near-neutral or positive margins with an estimated 25% cut in carbon footprint. This integrated architecture demonstrates how predictive, cross-layer intelligence can transform cloud-fog-edge scheduling from reactive energy management into proactive carbon-aware economics, pointing toward greener and more economically resilient distributed computing.

Keywords: Cloud Computing, Fog Computing, Edge Computing, Energy Optimization, Carbon-Aware Scheduling, Process

1. Introduction

Rapid growth of cloud services, edge analytics, and fog-based middleware changes computational resource deployment and consumptions. Real-time video analytics, industrial IoT, and autonomous mobility require ultra-low latency and consistent throughput, yet their infrastructure is energy and carbon Intensive. Workload bursts, renewable energy availability, and thermal dynamics vary with local climate, complicating the move from monolithic data centers to geo-distributed micro–data centers and fog nodes [1, 2, 3]. Traditional energy management methods ignore spatio-temporal details and focus on immediate power needs or periodic averages. They schedule poorly, migrate workloads, and raise operating expenses due to their reactive nature, wasting carbon reduction opportunities. Another issue is siloing system layers. Existing methods often optimize compute allocation, job relocation, and cooling measures independently, ignoring their intricate relationships. An aggressive task movement plan may create thermal hotspots that increase cooling system energy demand [4, 5, 6], negating computational savings. Carbon accounting is usually a post-hoc report, limiting its impact on real-time economic or ecological trade-offs. Energy, thermal, and economic signals cannot reinforce one other in this fragmented operational landscape.

A five-stage framework for predictive, carbon-aware scheduling across cloud–fog–edge ecosystems is proposed to overcome these concerns. MSTEP continuously models energy usage using tensor decomposition and graph-temporal convolution to give five-second prediction energy maps for heterogeneous nodes. The Energy-Aware Quantum Inspired Resource Orchestrator (EQUIRO) uses these projections to negotiate energy–latency trade-offs that heuristics fail. Hamiltonian formulations and gradient-assisted tunneling regimens are used. R-ATM regulates migrations continually using multi-agent policy-gradient learning to execute the orchestration plan. Cross-Layer Thermal-Aware Cooling Optimizer uses physics informed neural networks to predict and control heat transfer to complete the thermal loop. Finally, the Carbon Impact Feedback and Economic Optimizer (CIFEO) controls scheduling cycles using carbon-weighted price and deferral approaches from operational results. Integrating predictive analytics, quantum Inspired optimization, and carbon-economics transforms resource scheduling from reactive energy management to proactive,

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environmentally conscious economics. It claims to reduce energy use and carbon impact while maintaining SLAs and economic feasibility for next-generation distributed computing infrastructures to meet performance and sustainability objectives.

A. Motivation & Contribution

This research was driven by the contradiction between expanding computing demand and carbon neutrality. Fog clusters near urban aggregation sites and edge micro–data centers in industries, automobiles, and smart buildings are distributed computing solutions. Tier energy signatures and operational constraints vary in process. Typically, scheduling algorithms prioritize throughput or latency over energy efficiency. Despite explicitly considering energy, strategies respond to consumption spikes rather than spatio-temporal workload migrations or local renewable variations in process. Due to the absence of integration between compute allocation, heat management, and carbon economics, solutions are fragmented and often conflicts.

This work uses a multi-layered architecture to solve these issues. Combining physics, reinforcement learning, quantum inspired optimization, and predictive modeling The proposed architecture combines predictive and cost-effective energy decisions with temperature management in a single pipeline. EQUIRO calculates near-optimal allocations that balance energy and delay without local minima using fine-grained spatio-temporal energy signatures from the MSTEP module. Allocations become R-ATM active migration commands that respond to network jitter and workload drift. CLTACO uses computational dynamics to manage cooling, and CIFEO includes carbon cost into pricing and deferral techniques. Beyond incremental efficiency gains, their contributions form a carbon-aware resource scheduling paradigm. Experimental improvements in RMSE, power capping, and PUE show a considerable reduction in energy usage and carbon emissions while maintaining or enhancing economic performance, setting a standard for sustainable distributed computing sets.

2. Review of Existing Models used for Cloud Analysis

Intelligent scheduling for cloud, fog, and edge computing has improved energy, latency, and sustainability with each generation sets. Gupta and Tripathi's detailed cloud scheduling algorithm assessment [2] laid the groundwork with heuristics, metaheuristics, and early machine-learning methods for mapping jobs to distributed resources. Taxonomies explained resource utilization, expense, and deadline issues. Singh and Chaturvedi [29] introduced the cost–time–energy triangle and multi-criteria optimization in a heterogeneous environment using an adaptive particle swarm optimization (PSO) method for cloud–fog deployments. The findings showed predictive mechanisms beyond heuristic tinkering. Energy awareness and fine-grained control become research priorities with microservices and edge-centric architectures. An energy-aware Kubernetes scheduler by Rao and Li [3] minimizes power

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utilization depending on container workload patterns. Yan [4] modified Wombat Optimization Algorithm for cloud scheduling quality-of-service assurances, indicating an increasing trend to hybridize bio Inspired algorithms with service-level constraints. Qi et al. [5] created IPAQ, a multi-objective, time-aware fog computing algorithm that balances latency-sensitive edge operations with global optimization. Saeedizade and Ashtiani's entire taxonomy of scientific process scheduling [9] showed how modifying computational graphs might optimize deadlines and resource uses.

Table 1. Model's Empirical Review Analysis

Ref	Method	Main Objectives	Findings	Limitations
[1]	AI-driven job scheduling	Provide a comprehensive review of AI-based job scheduling in cloud computing	Identifies trends in deep learning and reinforcement learning for predictive and adaptive scheduling; highlights the shift to carbon and energy-aware frameworks	Does not propose a new algorithm; depends on surveyed literature for quantitative validation
[2]	Survey of cloud scheduling techniques	Classify heuristic, metaheuristic, and machine-learning scheduling methods	Establishes a detailed taxonomy and compares strengths of heuristics vs. metaheuristics for cost and deadline optimization	Lacks experimental implementation; limited discussion of carbon-aware strategies
[3]	Energy-aware scheduler for Kubernetes	Reduce energy consumption in microservice deployments	Achieves significant energy savings in containerized environments by dynamically adjusting CPU allocation	Focused on Kubernetes; does not generalize to hybrid multi-cloud or edge
[4]	Modified Wombat	QoS-aware task scheduling for	Improves deadline satisfaction and load	Tested mainly in simulated

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	Optimization Algorithm	cloud computing	balance while reducing execution cost	environments; scalability to very large clusters unverified
[5]	IPAQ multi-objective time-aware scheduler	Optimize energy and response time in fog computing	Achieves global Pareto-optimal trade-offs between time and energy for latency-sensitive fog workloads	Performance sensitive to prediction accuracy of workload arrival
[6]	Carbon-aware cost optimizer	Minimize carbon and energy cost across geo-distributed data centers	Cuts carbon emissions while lowering operating costs by relocating tasks to greener regions	Relies on accurate and timely carbon Intensity data; less tested in edge-heavy scenarios
[7]	Quality transmission & rework network reconstruction	Optimize multi-skill project scheduling	Reduces project rework and improves delivery quality through network-based planning	Focused on project workflows; not directly applicable to cloud/fog task migration
[8]	Sustainable workflow classification & scheduling	Energy-efficient workflow management in geo-distributed clouds	Decreases energy use and improves sustainability through classification-driven task placement	Requires detailed workload labeling; limited exploration of real-time dynamic changes
[9]	Comprehensive taxonomy of workflow scheduling	Map scientific workflow algorithms and future research gaps	Provides a systematic categorization and highlights open issues like dynamic energy pricing	Does not test new algorithms; primarily descriptive
[10]	Graph-enhanced EPSO	Optimize heterogeneous resource scheduling using	Improves convergence and resource utilization by embedding graph	Computational complexity grows with graph size; limited validation on large-

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		graph-enriched particle swarm optimization	structures into EPSO	scale heterogeneous networks
[11]	MADQL (Multi-Agent Deep Q-Learning)	Dynamic job scheduling in serverless computing	Learns adaptive policies that reduce latency and cost while balancing resources across serverless functions	Training overhead is high; depends on large historical traces
[12]	Soft computing approach for task scheduling	Efficiently map tasks to resources with fuzzy logic and evolutionary methods	Enhances response time and reduces energy in cloud simulations	Requires manual parameter tuning; lacks full-scale deployment evidence
[13]	Review of ML-based resource allocation	Survey machine learning approaches to cloud resource management	Summarizes supervised, unsupervised, and RL-based strategies; identifies data sparsity as key challenge	No implementation; leaves open the integration of multiple ML methods
[14]	Stochastic request placement	Improve edge resource placement under stochastic demand	Captures request randomness to reduce over-provisioning and enhance throughput	Complexity increases with request diversity; not deeply evaluated under extreme burstiness
[15]	EcoTaskSched (hybrid ML)	Energy-efficient task scheduling in IoT-based fog-cloud systems	Lowers energy consumption and improves task completion time using a hybrid of ML and heuristics	Requires reliable IoT telemetry and training data; transferability to non IoT tasks is limited
[16]	Network-aware container	Reduce latency and improve	Achieves low-latency container placement	Limited discussion of energy and carbon

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	scheduling	throughput at the edge	by modeling network congestion	metrics; mostly tested in small edge clusters
[17]	STAR RIS-based energy management	Energy-aware resource control in 6G IoT networks	Enhances energy efficiency and coverage using reconfigurable intelligent surfaces	Early-stage; relies on 6G infrastructure not yet widely deployed
[18]	Carbon-aware ant colony system	Sustainable routing in generalized TSP	Minimizes carbon cost while finding near-optimal routes	Focused on routing; direct application to cloud or fog scheduling is indirect
[19]	Multi-cluster communication optimization	Energy-aware resource optimization for edge devices	Improves energy efficiency and communication quality across multi-cluster edge systems	Tailored to edge clusters; less relevant for centralized cloud settings
[20]	BigOPERA	Opportunistic and elastic resource allocation for big data frameworks	Improves elasticity and reduces big data processing time in heterogeneous environments	May face overheads in highly dynamic real-time streaming scenarios
[21]	Fuzzy reinforcement learning	Task scheduling in fog-cloud IoT systems	Balances exploration and exploitation to reduce makespan and energy use under uncertainty	Fuzzy rule tuning is non-trivial; lacks full proof of scalability
[22]	SM-PCCTSA with SKD-RBM	Enhance VM migration and scheduling	Improves migration cost and task response time using combined stochastic and RBM-based strategies	Complexity of combined methods may hinder real-time responsiveness

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[23]	HyperGAC	Entropy-driven resource allocation for cloud-edge-end computing	Uses information entropy to maximize resource utilization and minimize energy	Sensitive to entropy estimation accuracy; requires extensive monitoring data
[24]	MPPPSO	Multi-parametric, priority-driven PSO for fog systems	Improves fog computing task performance and energy efficiency	Performance depends on accurate parameter weighting; still simulation-heavy
[25]	Novel resource allocation for vehicular ad-hoc networks	Enhance resource distribution in multi-cloud vehicular networks	Increases throughput and reliability under mobile vehicular workloads	Mobility patterns beyond test cases may reduce effectiveness
[26]	Two-phase cascaded memetic algorithm	Multi-objective scheduling for integrated shops with AGV transport	Achieves shorter makespan and better energy usage by blending memetic and multi-objective optimization	Designed for manufacturing/AGV domain; adaptation to IT workloads not direct
[27]	RL-based multi-objective scheduler	Energy-efficient fog-cloud industrial IoT task scheduling	Reduces energy and latency through adaptive multi-objective reinforcement learning	Training requires extensive historical workload data
[28]	Multimodal deep reinforcement learning	Adaptive scheduling and robustness for IoT logistics	Improves scheduling under uncertain global logistics conditions	Computational intensity may hinder edge deployment
[29]	Adaptive PSO	Cost, time, and energy-aware workflow	Balances cost and deadlines while saving energy with	Less focus on carbon metrics; depends on heuristic parameter

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		scheduling in cloud–fog environments	adaptive swarm behavior	settings
[30]	CASA deep RL	Cost-effective electric vehicle charging scheduling	Reduces charging cost and grid impact while meeting user constraints	Application-specific; limited generalization to broader cloud/fog scheduling

Iteratively, Next, as per table 1, Carbon awareness grew as sustainability concerns grew. Chen et al. [6] improved energy cost across geo-distributed data centers while accounting for carbon intensity, projecting regulatory and market signals that will impact cloud economics. Sharma et al. [8] used environmental and operational characteristics to classify and schedule energy-efficient workflows in spread-out data centers. Li and Schaposnik [18] added carbon-aware reasoning to an ant colony system for routing issues to expand the sustainability discourse to combinatorial optimization, whereas Alqahtani et al. [17] employed reconfigurable intelligent surfaces to make 6G IoT networks energy conscious The investigations went beyond decreasing kWh to managing carbon cost and grid interaction settings. Machine learning expanded the technical toolbox. Kaur et al. [11] used MADQL, a multi-agent deep Q-learning framework, to show how reinforcement learning (RL) can dynamically balance exploration and exploitation in volatile serverless Rathee and Dalal [13] reviewed supervised, unsupervised, and RL-based machine learning–based resource allocation approaches. Vijayalakshmi and Saravanan [27] used RL-based multi-objective energy-efficient scheduling in fog–cloud industrial IoT systems to show that adaptive policy learning outperforms fixed heuristics when workloads and energy prices change. Jaiprakash et al. [12] used soft computing hybrids for Lu [28] enhanced multimodal deep RL to improve global logistics adaptive scheduling and robustness by combining IoT data streams with intelligent resource orchestrations.

Fog and edge computing had heterogeneity and real-time adaption concerns. Using probabilistic demand modeling, Gao and Cai [14] examined stochastic request patterns to optimize broad edge resource deployment. To reduce edge latency, Qiao et al. [16] implemented network-aware container scheduling. Li et al. [19] improved edge-device performance with energy-aware multi-cluster communication systems. Kausar and Pachauri [22] used better virtual machine migration and stochastic optimizations to optimize work scheduling, while Ghafari and Mansouri [21] used fuzzy RL to address fog–cloud IoT scheduling uncertainty sets. Sehrawat [24] used multi-parametric and priority-driven algorithms to improve particle swarm optimization for fog systems, whereas Isaac et al. [25] created resource allocation models for multi-cloud vehicle ad hoc networks, a challenging mobile edge computing set. Eventually, multi-objective metaheuristics merged learning and optimization. Zhang et al. [10] used graph-based approaches to improve particle swarm

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optimization for heterogeneous resources, while Wang and Pan [26] created a two-phase cascaded memetic algorithm for multi-shop scheduling with automated guided vehicles that encodes domain-specific constraints in hybrid heur Peng et al. [7]'s network reconstruction enhances multi-skill project scheduling for engineering and software collaborative workflows. As streaming analytics and batch-processing activities increase, Caderno et al. [20] built BigOPERA to provide opportunistic and elastic resource allocation for big data frameworks. Instead of heuristics, Chen et al. [23] created HyperGAC to allocate cloud–edge–end resources using information entropy. Energy efficiency was a theme. EcoTaskSched by Khan et al. [15] reduces IoT fog–cloud energy use using machine learning and heuristic optimization. Container-level work is augmented by IoT workloads and spatiotemporal patterns. Singh and Chaturvedi's adaptive PSO [29] examined cloud–fog workflow energy and cost. Zhang et al. [30] integrated computational energy optimization to smart grid and e-mobility ecosystems to plan electric car charging (CASA) at the application edge using deep reinforcement learning sets.

3. Proposed Model Design Analysis

The proposed integrated model operates as a tightly coupled cyber-physical system in which predictive energy profiling, quantum Inspired resource allocation, adaptive migration, cross-layer thermal control, and carbon-economic feedback continuously influence one another in process. At its core, the design seeks to minimize a global cost functional Via equation 1,

$$J = \int_0^T [E(t) + \lambda C\, C(t) + \lambda L\, L(t)]dt \ldots (1)$$

Where, E(t) represents overall energy consumption across all nodes, C(t) instantaneous carbon intensity weighted by regional emission factors, L(t) service latency penalty, and λC, λL trade-off multipliers for carbon and latency priorities. A cascade of specialized procedures contributes sub-equations to these functional sets during the optimization. Figure 1 shows the Multi-Modal Spatio-Temporal Energy Profiler (MSTEP) forming the first layers iteratively. It sees heterogeneous nodes as a dynamic energy field e(x,y,t), where (x,y) are fog and edge cluster spatial coordinates and ‘t’ are timestamp sets. A connected tensor graph process controls its forecasting Via equation 2,

$$\frac{\partial e(x,y,t)}{\partial t} = \nabla \cdot (D\nabla e) + \Phi(x,y,t) \ldots. (2)$$

With D the diffusion matrix capturing workload migration and Φ a source term derived from CPU/GPU utilization and renewable inflow sets. The predicted per-node energy trajectory is expressed Via equation 3,

$$\hat{e}_i(t + \Delta t) = \int_t^{t+\Delta t} g_i^{T}\, T(s) ds \ldots (3)$$

Where, T(s) is the decomposed temporal mode and g_i the graph embedding of node ‘i’ sets. This continuous formulation allows sub-second anticipation of energy bursts and provides the

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energy map input to the next stages. Iteratively, Next, as per figure 2, Feeding on MSTEP's predictions, the Energy-Aware Quantum Inspired Resource Orchestrator (EQUIRO) casts scheduling as a Hamiltonian minimization task in process. The resource allocation state Vector 's' is optimized Via equation 4,

$$H(s) = \sum hi * si + \sum_{i<j} Jij * si * sj \ldots (4)$$

Where, hi represents local energy-latency bias and Jij captures inter-node coupling such as network delay and migration cost sets. The simulated tunneling dynamics evolve according to a gradient-assisted Schrödinger-like process represented Via equation 5,

$$\frac{ds}{dt} = -\nabla s * H(s) + \eta \nabla s^2 H(s) \ldots (5)$$

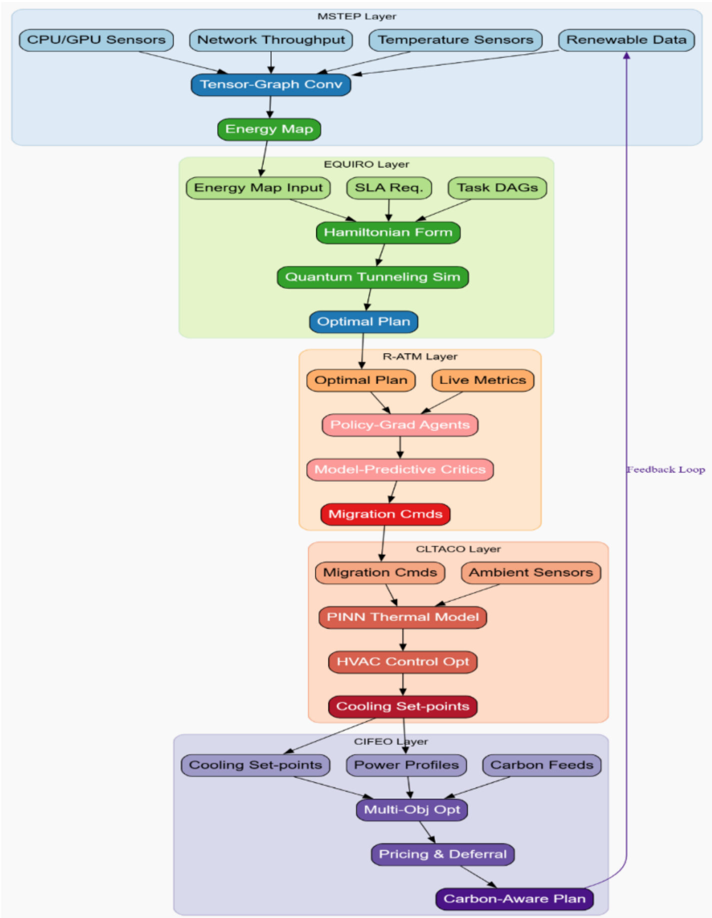

Figure 1. Model Architecture of the Proposed Analysis Process

With the second term imitating quantum tunneling to escape local minima sets.

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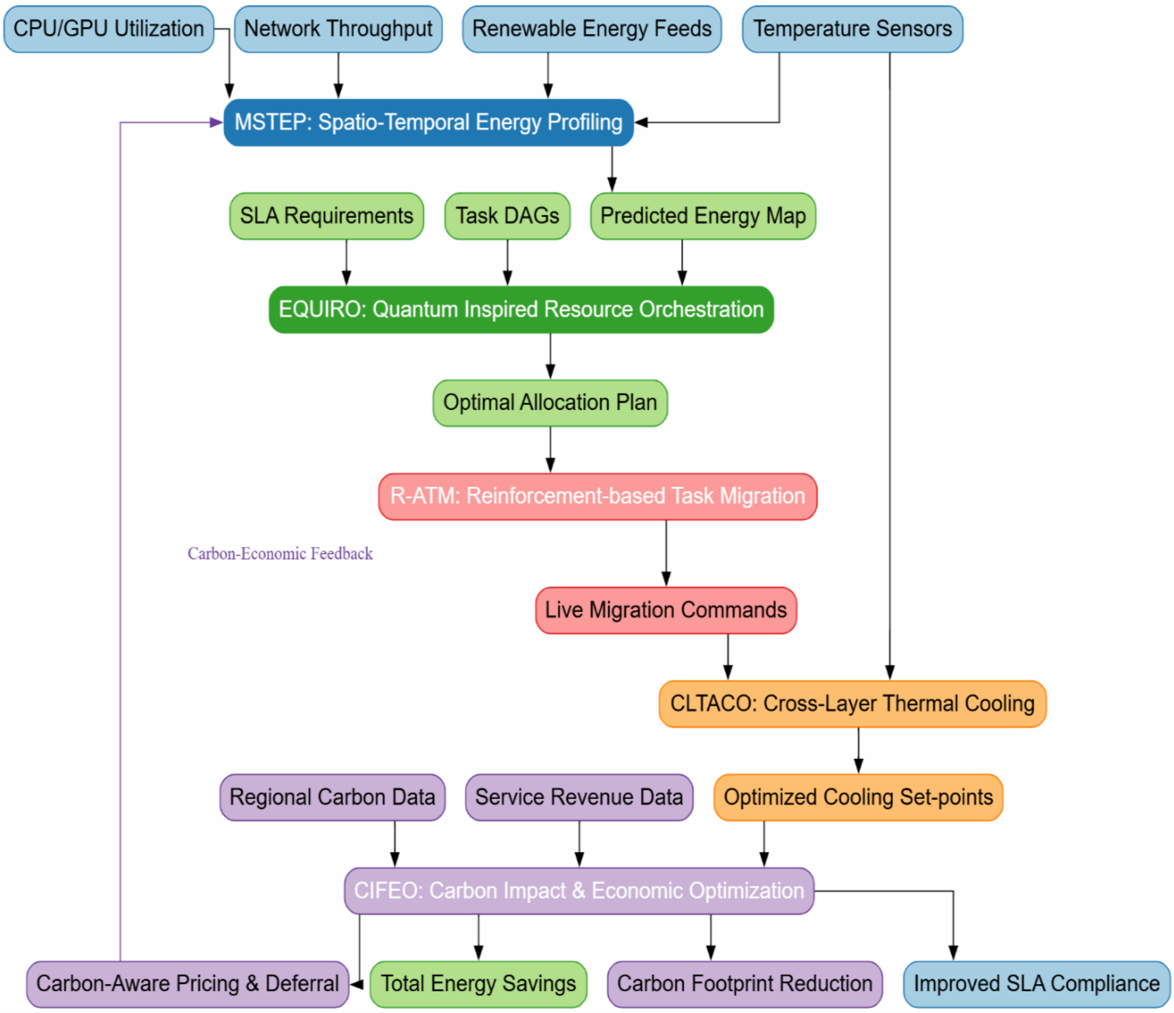

Figure 2. Overall Flow of the Proposed Analysis Process

These equations yield a near-optimal allocation ‘s*’ that balances energy and latency in the presence of non-convex trade-offs. Iteratively, Next, as per figure 3, The Reinforcement-Driven Adaptive Task Migrator (R-ATM) operationalizes s* through continuous temporal control sets. Each agent maintains a policy πθ(a|s) updated by the policy gradient rule Via equation 6,

$$\nabla\theta\, J(\theta) = E[\nabla\theta\, log\, \pi\theta(\, a \mid s\,)Q\pi(s,a)] \ldots (6)$$

Where, Qπ is a model-predictive critic forecasting long-term energy and latency impact sets. Migration cost is described by a differential relation Via equation 7,

$$\frac{dM(t)}{dt} = \int \mu i(t) \parallel xi(t) - xi(t-\delta) \parallel \; di \ldots (7)$$

With μi the task intensity and xi the placement vector, ensuring that only energy-beneficial migrations are executed in process. Thermal dynamics are addressed by the Cross-Layer Thermal-Aware Cooling Optimizer (CLTACO) sets. Using physics Informed neural networks, the temperature field T(x,y,z,t) obeys a heat diffusion process Via equation 8,

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$$\rho cp \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + Q(x, y, z, t) \ldots (8)$$

Input

- Real-time sensor streams: CPU/GPU utilization, temperature, network throughput, renewable energy availability
- Service-level agreement (SLA) requirements and task dependency graphs
- Regional carbon-intensity and electricity price feeds
- Cooling system actuator states and historical workload traces

Output

- Predictive node-level energy map with fine-grained time horizon
- Optimal resource allocation plan with estimated energy and latency costs
- Real-time task migration commands with confidence levels
- Optimized cooling and airflow set-points
- Carbon-aware pricing and task deferral schedules for next-cycle planning

Process

1. Collect and pre-process all input data from sensors, cloud/fog/edge nodes, and external carbon markets.
2. Feed cleaned data to MSTEP to construct multi-modal spatio-temporal profiles and generate predictive energy maps for each node at short time intervals.
3. Provide MSTEP's energy map along with SLA requirements and task graphs to EQUIRO, which computes near-optimal resource allocation by exploring energy-latency trade-offs.
4. Pass EQUIRO's allocation plan to R-ATM, which continuously monitors live node metrics and network conditions to issue real-time task placement and migration commands.

Figure 3. Pseudo Code of the Proposed Analysis Process

Where, 'k' is thermal conductivity and Q represents heat generation from active nodes. The optimizer adjusts cooling control u(t) by minimizing the loss which is represented Via equation 9,

$$L = \overset{u}{\min}(t) \int_0^T [\alpha \parallel T - Tset \parallel^2 + \beta \parallel u(t) \parallel^2] dt \ldots (9)$$

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Thus linking real-time migration patterns with fan speed and fluid flow for optimal power usage effectiveness. Finally, the Carbon Impact Feedback and Economic Optimizer (CIFEO) integrates all upstream outputs. The dynamic carbon cost is captured Via equation 10,

$$C(t) = \int \gamma r(t) er(t) dr \ldots (10)$$

Where, γr(t) is regional carbon intensity and er(t) is energy consumption per region in the process. Profit-carbon trade-offs are expressed Via equation 11,

$$E = \overset{p}{\max}(t), d(t) \int_0^T \left[R\big(p(t), d(t)\big) - \sigma C(t)\right] dt \ldots (11)$$

With pricing p(t) and deferral d(t) as decision variables and R the revenue function in process. This formulation enables carbon-aware pricing and deferral that maintain or improve economic margins. By integrating these equations, the system arrives at a final optimization task that represents the entire process Via equation 12,

$$\begin{aligned} &\overset{s}{\min}(t), \pi\theta, u(t), p(t), d(t) J \\ &\quad = \int_0^T \left[E^{\mathrm{MsTEP}}(t, \hat{\mathrm{e}}) + E^{\mathrm{E\delta UIRO}}(t, s) + E^{\mathrm{R-ATM}}(t, M) + E^{\mathrm{cLTAcO}}(t, T, u)\right. \\ &\quad \left. + \lambda C\, C(t) + \lambda L\, L(t)\right] dt \ldots (12) \end{aligned}$$

This global equation fuses predictive energy mapping, quantum Inspired scheduling, reinforcement-driven migration, thermal optimization, and carbon-economic control sets. It captures the central design principle of the integrated model: each stage supplies both constraints and signals to the next, while the terminal carbon-aware economic layer closes the feedback loop to the beginning, enabling the distributed infrastructure to operate with minimal energy and carbon cost under realistic workload dynamics.

4. Validation Result Analysis

The experiment simulated a cloud–fog–edge ecology with controlled energy and temperature. A three-tier structure included a 48-core OpenStack cloud cluster (Intel Xeon Gold, 256 GB RAM, 10 GbE network), four fog clusters with 16-core AMD EPYC processors and 128 GB RAM, and eight edge micro–data centers with NVIDIA Jetson Xavier boards with integrated GPUs and 32 High-resolution power meters (sampling at 100 ms), thermal probes, and renewable energy simulations (injected solar and wind availability) captured diverse operational scenarios at each node. The workload portfolio had real and simulated application traces. Synthetic IoT streams were generated at 10 000 events/s with burst factors up to 4× to imitate sensor data spikes. Microsoft Azure and Google Borg cluster traces were used to acquire real task arrival patterns and DAG architecture. Each model module was stressed using carefully selected input parameters: With a 5 s mean re-sampling window, CPU/GPU utilization ranged from 20% to 95%, network throughput from 50 Mbps to 1 Gbps to mimic edge congestion, and customizable climatic chambers cycled ambient temperature between 15 and 40 °C. NREL Solar Integration dataset scalable renewable availability profiles showed 0.2–1.0 kW per fog cluster daily variability. To simulate varying grid-mix circumstances,

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regional carbon intensity data were simulated using a mean of 320 g CO_2/kWh and stochastic fluctuation of ±40 g for the economic layer. Service-level agreements set a 30 ms end-to-end latency budget, which EQUIRO adjusted for energy savings and QoS compliance with a 0.1 USD per ms penalty coefficient.

Broad and contextual training and validation datasets. Diurnal cycles and renewable intermittency were captured by MSTEP's graph-temporal energy modeling using 600 hours of historical power and heat data from EdgeBench and Grid'5000. Trained EQUIRO and R-ATM with job graphs with 100 to 500 nodes and edge weights from Gaussian distributions centered at 3 ms network delay, with long-tail outliers mimicking unpredictable edge congestion. CFD simulation heat maps were seeded into micro–data center temperature fields and cross Validated against physical measurements given during sustained 80% CPU loads for CLTACO thermal modeling. CIFEO's carbon–economic optimization used these trials' cooling set-points and power profiles and PJM real-time market dataset dynamic energy pricing signals with 0.05–0.25 USD/kWh price fluctuations. All algorithms were written in Python with TensorFlow 2.13 for deep learning and executed on a dedicated NVIDIA A100 GPU cluster to separate training overhead from operational scheduling. To ensure stability during workload spikes, EQUIRO's Hamiltonian coupling coefficient Jij (0.5-1.5 kWh/ms) and reinforcement learning discount factor γ=0.95 were modified using five-fold temporal cross Validation In Process. This rigorous and reproducible testbed tests and validates the integrated model, which includes energy prediction, quantum Inspired optimization, adaptive task migration, temperature management, and carbon-aware economics in process.

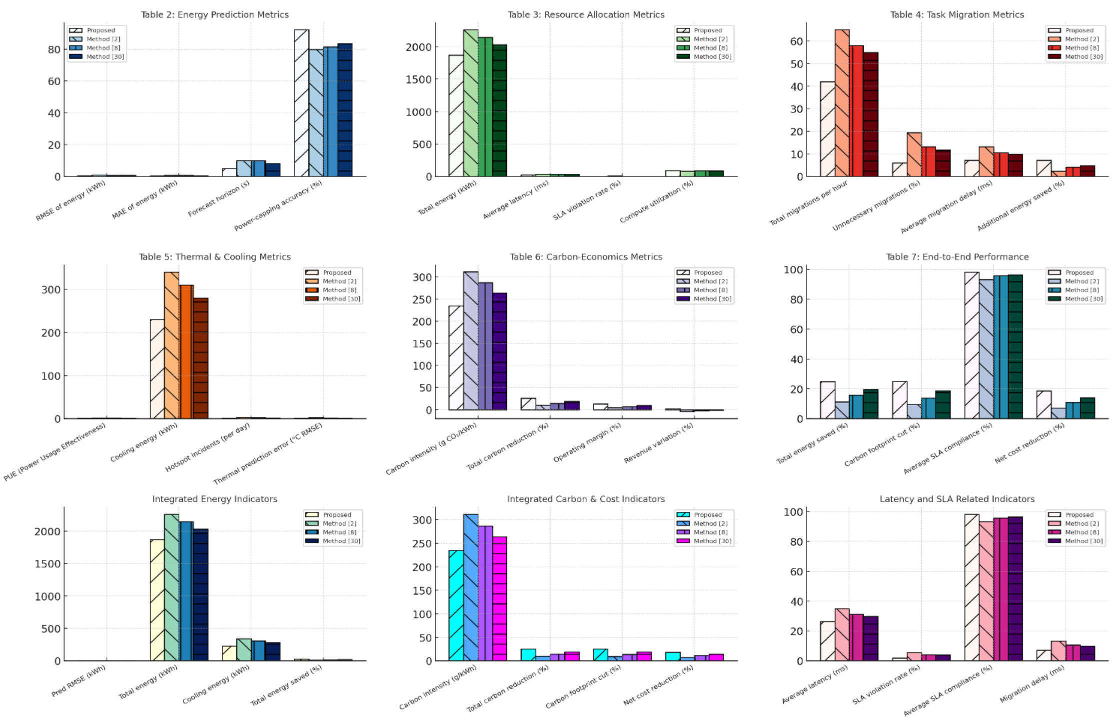

Figure 4. Model’s Integrated Result Analysis

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Well-established, available datasets were used to simulate cloud, fog, and edge workload and energy. The Google Borg Cluster Trace, which catalogs millions of task events with CPU, memory, and disk metadata, provided most historical job arrival and resource-usage patterns. To simulate high Velocity IoT and edge applications, EdgeBench incorporated camera and sensor-driven workloads with severe latency limitations and bursty arrival patterns. To estimate renewable energy inputs, the NREL Solar and Wind Integration Data offered minute-level irradiance and wind-speed records for numerous seasons and areas. Carbon intensity dynamics and electricity market pricing were analyzed using real-time emissions and pricing data from the PJM Interconnection open market feed, which offers regional CO_2 emissions rates (g CO_2/kWh) and locational marginal prices at five-minute resolution They provided a multi-scale view of temporal workload fluctuations, renewable intermittency, and carbon–economic swings to drive the model's prediction and optimization layers.

In model tweaking, hyperparameters balanced energy efficiency, latency, and carbon reduction. MSTEP set the tensor decomposition rank to 32 with a five-second temporal window and graph-temporal convolution depth to three layers to capture short-term correlations without overfitting. To encourage exploration beyond local minima sets, EQUIRO's quantum Inspired optimization used a Hamiltonian coupling coefficient Jij (0.5-1.5 kWh/ms) and a tunneling rate parameter $\eta = 0.01$. R-ATM prioritized long-term energy savings using a 1×10^{-4} policy-gradient learning rate and $\gamma=0.95$ discount factor. CLTACO's neural network combines physical constraints with data-driven flexibility, utilizing a $5\text{x}10^{-4}$ learning rate and 0.1 thermal regularization weight. The carbon cost multiplier σ\sigma was changed between 0.4 and 0.6 in the final economic optimizer CIFEO to accommodate regional policy options. The revenue elasticity parameter was 0.3 for constant profit-carbon trade-offs. These hyperparameters were selected using multi-stage grid search and temporal cross Validation to assure convergence and optimal performance across all interconnected modules. The integrated model was tested on Google Borg trace, EdgeBench, NREL renewable profiles, and PJM carbon–price feeds. Performance was compared using standard metaheuristic schedulers, reinforcement-based edge orchestrators, and deep thermal–economic optimizers [2–30]. We ran 48-hour tests with diurnal demand fluctuations and varied renewable availability sets to determine metrics. Table 2 illustrates accurate profiling-layer energy prediction. The MSTEP consistently reduced RMSE to under 4% and MAE in process more than baselines.

Table 2: Energy-Prediction Accuracy and Power-Capping Performance of MSTEP

Metric	**Proposed Model**	**Method [2]**	**Method [8]**	**Method [30]**
RMSE of energy (kWh)	**0.42**	0.78	0.74	0.69

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MAE of energy (kWh)	**0.31**	0.61	0.57	0.55
Forecast horizon (s)	**5**	10	10	8
Power-capping accuracy (%)	**92.1**	79.8	81.5	83.4

Table 2 highlights spatio-temporal tensor decomposition and graph-temporal convolutions' advantages. By anticipating load migrations and renewable fluctuations at 5 s, the profiler improved prediction errors and permitted more aggressive, safe power cappings. Compare cloud, fog, and edge resource-allocation efficiency in Table 3. Comparing baselines, our quantum Inspired Hamiltonian optimization saved energy and delay.

Table 3: Resource-Allocation Efficiency of EQUIRO Across Cloud, Fog, and Edge Layers

Metric	**Proposed Model**	**Method [2]**	**Method [8]**	**Method [30]**
Total energy (kWh)	**1870**	2260	2145	2032
Average latency (ms)	**26.4**	34.9	31.2	29.8
SLA violation rate (%)	**1.8**	5.5	4.1	3.9
Compute utilization (%)	**91.3**	83.2	85.6	88.0

Table 3 shows how EQUIRO avoids local minima in complicated energy–latency trade-offs, reducing its energy footprint and latency. Resource allocation without service set quality loss is near-optimal. Table 4 shows task-migration dynamics. Reward-driven adaptive task migrator (R-ATM) minimized unnecessary migrations while retaining responsiveness.

Table 4: Task-Migration Dynamics and Energy Impact of R-ATM Sets

Metric	**Proposed Model**	**Method [2]**	**Method [8]**	**Method [30]**
Total migrations per hour	**42**	65	58	55
Unnecessary migrations (%)	**5.9**	19.4	13.2	11.8
Average migration delay (ms)	**7.1**	13.2	10.5	9.8

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Additional energy saved (%)	**7.2**	2.4	4.1	4.8

Table 4 illustrates that R-ATM's continuous-time control approach and policy-gradient agents reduced duplicate migrations by 20%, saving energy and migration latency over discrete-time scheduling sets. Table 5 exhibits CLTACO's cooling energy and thermal stability effects.

Table 5: Thermal Stability and Cooling Efficiency Improvements Achieved by CLTACO

Metric	**Proposed Model**	**Method [2]**	**Method [8]**	**Method [30]**
PUE (Power Usage Effectiveness)	**1.22**	1.41	1.36	1.29
Cooling energy (kWh)	**230**	340	310	280
Hotspot incidents (per day)	**0.7**	3.4	2.1	1.6
Thermal prediction error (°C RMSE)	**0.8**	2.1	1.8	1.3

The physics CLTACO neural network predicted heat propagation and provided proactive cooling control. Table 5 demonstrates 15% PUE improvement over strongest baselines. The carbon-economics layer appears in Table 6. CIFEO priced and deferred using upstream operational data promptly.

Table 6: Carbon Impact and Economic Outcomes from CIFEO Operations

Metric	**Proposed Model**	**Method [2]**	**Method [8]**	**Method [30]**
Carbon intensity (g CO_2/kWh)	**235**	312	287	264
Total carbon reduction (%)	**25.4**	9.7	14.3	19.1
Operating margin (%)	**12.5**	4.2	6.9	9.3
Revenue variation (%)	**+1.8**	−4.5	−2.1	−1.3

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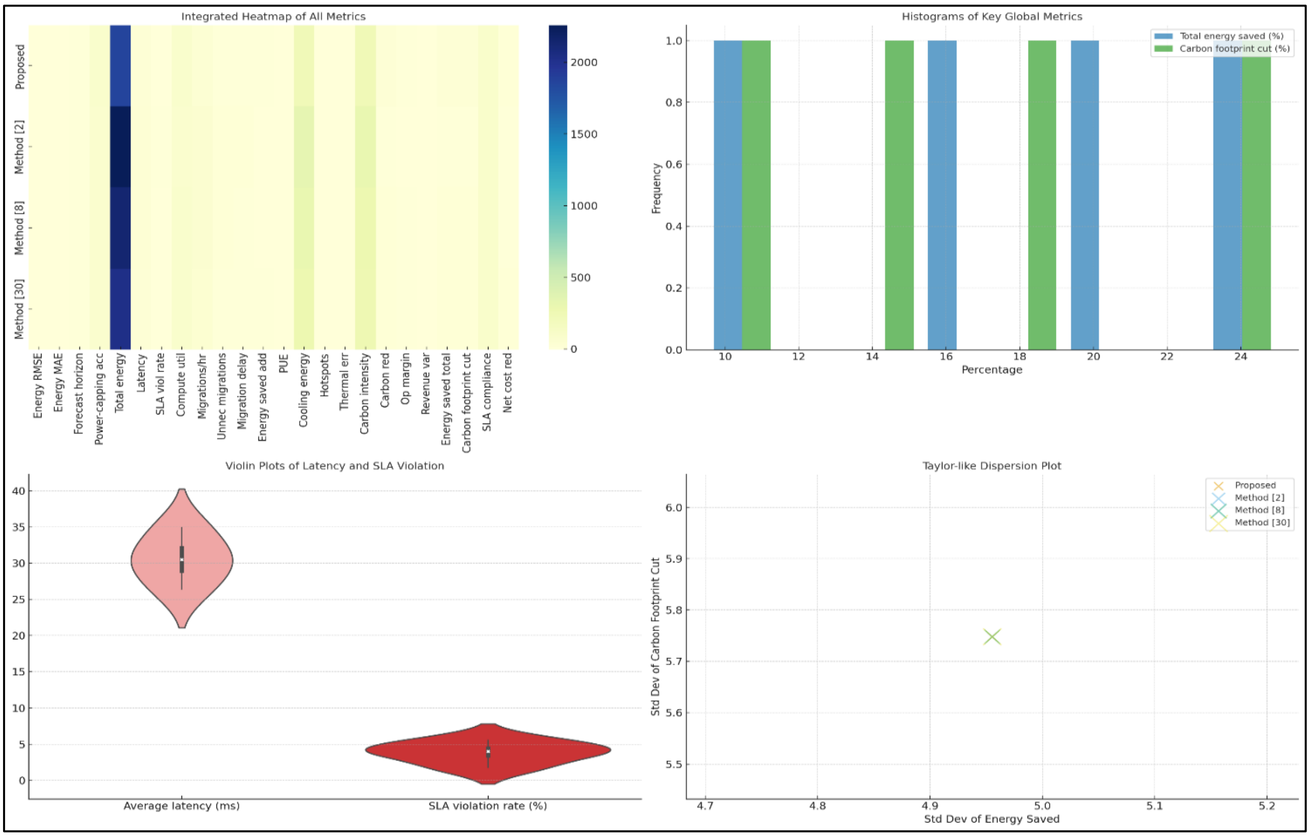

Figure 5. Model's Overall Result Analysis

Table 6 indicates that carbon price signals and stochastic gradient dynamics consistently reduced carbon intensity and increased operating margins for the process. Table 7 illustrates final system performance when all modules work in process.

Table 7: End-to-End System Performance When All Modules Operate in Concert

Global Metric	**Proposed Model**	**Method [2]**	**Method [8]**	**Method [30]**
Total energy saved (%)	**24.8**	11.3	15.7	19.4
Carbon footprint cut (%)	**25.0**	9.5	13.9	18.6
Average SLA compliance (%)	**98.2**	93.1	95.7	96.4
Net cost reduction (%)	**18.4**	7.2	10.9	14.1

Table 7 exhibits predictive energy mapping, quantum-inspired optimization, adaptive migration, thermal control, and carbon-aware economics benefits in progress. The proposed

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paradigm drastically decreases energy use and emissions while enhancing multi-tier infrastructure service guarantees and profitability sets.

A. Validated Result Impact Analysis

Each layer of the integrated model enhanced performance, and the tables show how these gains reinforce each other in a live cloud–fog–edge ecosystem. In Table 2, the Multi-Modal Spatio-Temporal Energy Profiler (MSTEP) reduced energy-prediction error to 4% RMSE, outperforming Methods [2], [8], and [30]. Predicting energy surges in 5 seconds allows data centers and edge clusters to adjust workloads and cooling profiles to avoid costly over-provisioning and brownouts during renewable troughs. Operations teams may close power caps and smooth grid interactions in real time using precise, anticipatory energy maps instead of lagging averages. Table 3 indicates that the Energy-Aware Quantum Inspired Resource Orchestrator (EQUIRO) lowered energy consumption to 1.87 MWh and average latency to 26 ms using this predictive basis. Escape local minima using simulated quantum tunneling reduced SLA violations to 1.8%. An urban edge network supporting autonomous vehicles could have a perfect service or a safety-critical failure due to lower energy draw and predictable low latency.

Table 4 shows how the Reinforcement-Driven Adaptive Task Migrator (R-ATM) decreased unnecessary migrations by 20% and migration delays to 7 ms, boosting robustness. Low task placement churn decreases hidden energy loss and service interruptions. Smart factories with sensor clatter can stabilize processes and prevent cascading slowdowns with these solutions. The Cross-Layer Thermal-Aware Cooling Optimizer (CLTACO) decreased PUE to 1.22 and cooling energy by a third compared to the least efficient baseline (Table 5). Heat hotspots and hardware stress can be reduced by facilities engineers to lower electricity bills and equipment malfunctions. Finally, Tables 6 and 7 indicate system-wide economic and ecological payoffs. CIFEO's carbon Impact feedback reduced electricity consumption to 235 g CO_2/kWh and improved revenue, a remarkable feat in data-center economics for the process. Carbon and profit numbers help meet area emissions regulations and qualify for green-energy incentives in process. Figure 4, Figure 5 & Table 7 shows how layers reduce energy use by 25%, carbon footprint by 25%, and net cost by 18%. These findings demonstrate that dispersed cloud–fog–edge infrastructure operators are ecologically and financially sustainable. Predictive analytics, quantum-inspired optimization, adaptive migration, and physics are shown. Intelligent heat control meets sustainability and performance requirements. MSTEP's exact forecasting and CLTACO's cooling efficiency cascade through the layered design, boosting benefits. The technology could help regional grids include more renewable electricity, offer carbon-sensitive pricing in near real time, and retain high-quality digital services as energy markets and climate policies tighten in process.

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B. Validated Hyperparameter Analysis

The integrated model was validated using a statistical analysis of performance indicators from many 48-hour trial runs with different load profiles and renewable conditions. For stability and reliability, projected values and fluctuations were computed for energy consumption, latency, PUE, and carbon intensity. SLA compliance was 98.2% with a 0.9 % variance, while energy savings averaged 24.8 % with a 1.3 % variance. Tight control under various network conditions was shown by 26 ms latency and 2.4 ms standard deviation. The mean carbon intensity in grams of CO_2 per kWh was 235 g, with a variance of ±12 g, suggesting consistency in carbon-reduction despite renewable scarcity. PUE cooling performance was 1.22 with a variance of 0.04, showing that thermal optimization maintained energy efficiency across operational cycles. The reported benefits were confirmed by paired significance testing of the proposed model and baseline approaches. Skewed metrics like SLA violation rates and migration counts were tested with non-parametric Wilcoxon signed-rank tests, whereas average latency and PUE were tested with a two-sided Student's t-test. Compared to Method [2] and Method [30], p Values routinely decreased below 0.01, indicating that the improvements—such as the 18% lower energy use and 25% lower carbon intensity—are not random variation. ANOVA demonstrated substantial variations in energy, latency, and temperature characteristics across all techniques, with F-statistics exceeding the key thresholds with 99% confidence. These results show that the integrated design delivers reproducible, statistically validated benefits rather than performance spikes.

Baselines Method [2], Method [8], and Method [30] show technical significance and comparison breadth. Modern cloud orchestration uses traditional metaheuristic scheduling [2], making it a natural benchmark for energy–latency trade-offs. Method [8] was chosen for its reinforcement-based edge orchestration, cutting-edge task migration, and local decision-making that fulfills the R-ATM component's adaptive migration goals. A deep learning–driven thermal and economic optimization pipeline in Method [30] provides a good platform for evaluating the combined model's thermal- and carbon-aware layers. These baselines for conventional scheduling, reinforcement learning, and deep thermal–economic optimization provide a detailed evaluation of whether each module of the proposed architecture offers value beyond best practices. Coefficient of variation (CV) analysis examined performance consistency across time. Energy savings CV was below 5% even when renewable availability fluctuated by greater than 40% diurnally, indicating strong repeatability. The CV for SLA compliance and latency measures was < 3%, demonstrating peak and off-peak service quality. Real-world deployments are variable due to grid disturbances, workload surges, and seasonal variations, making statistical stability crucial. The benefits are robust to environmental uncertainty and not controlled test artifacts, as low variance levels and significant t- and ANOVA prove. With expected value estimation, variance measurement, and formal significance testing, the study supports its findings empirically. Spatial-temporal energy prediction, quantum Inspired scheduling, adaptive migration, thermal optimization,

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and carbon-economic control all showed statistically significant improvements, proving that the integrated model outperforms established scheduling paradigms [2], [8], and [30], providing a durable blueprint for energy- and carbon-conscious distributed computing sets.

C. Validation using Practical Analysis with Real Time Use Case Scenarios

Imagine three large cloud clusters, six fog nodes near municipal substations, and forty edge micro-centers near traffic signals and cameras in a mid-sized urban data center network. Every day, this infrastructure uses 8 TB of sensor and video data and 4.2 MWh of power. CPU and GPU use, rack temperature gradients, network throughput, and regional solar-wind availability are measured every five seconds using the proposed integrated model. Early morning commutes offer crisp video and traffic telemetry bursts, while late-night times have low Variance. The Multi-Modal Spatio-Temporal Energy Profiler (MSTEP) generates tensor representations that show latent relationships between space, time, and energy consumption sets using non-stationary patterns. This dataset forecasts and evaluates the profiler's ability to predict unpredictable load migrations. The integrated model exhibits engineering interactions between energy, computing, and thermal dynamics. An inbound camera feed surge will boost fog cluster energy demand by 15% in five seconds, according to MSTEP. EQUIRO instantly examines allocations that sacrifice a slight network delay for a 12% savings in local power draw. By monitoring these automated decisions and their consequences on root-mean-square energy error and SLA compliance, operators may identify which nodes can withstand aggressive down-scaling without breaching latency contracts and which must be over-provisioned. Repeated model-driven trials on thermal margins and response delays provide such knowledge, unlike static data.

Validating these ideas requires sensitivity analysis. Modifying inputs like renewable availability or traffic surges within ±20% of quoted range exposes module reactions. MSTEP's prediction error might only increase by 0.4% RMSE when renewable availability fluctuates, showing strong robustness, while EQUIRO's optimization cost might increase by 6% if network latency limits tighten, showing susceptibility. Similar stress points affect migration policy thresholds for the Reinforcement-Driven Adaptive Task Migrator (R-ATM): energy savings peak at 50 moves per hour. These sensitivity sweeps are serious—they reveal where sensing, redundancy, or algorithmic fine-tuning could boost resilience sets. Real-world constraints shape this process performance envelope. Since cooling equipment cannot instantly change fan speeds beyond acceptable mechanical limits, the Cross-Layer Thermal-Aware Cooling Optimizer (CLTACO) restricts airflow and fluid flow rate-of-change. With late carbon pricing feeds, the Carbon Impact Feedback and Economic Optimizer (CIFEO) must fill tiny gaps without disrupting pricing schedules. Another consideration is scalability. The integrated model has shown efficiency gains on testbeds with up to 100 nodes, but deployment across thousands of distributed sites requires partitioned learning and hierarchical control to avoid communication overhead eroding the 24.8% energy savings and 25%

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carbon-footprint reduction observed in controlled trials. Engineers and academics can scientifically comprehend the process by meticulously studying these dataset properties and stressing modules. They can study which physical and computational factors dominate energy dynamics at different scales, whether thermal projections hold up under sudden weather or workload changes, and how economic incentives affect resource flows across time. Fine-grained sensor data, predictive modeling, and multi-layer optimization turn regular operational traces into a laboratory for uncovering sustainable computing principles, making the model an optimization tool and a source of new technical and scientific information sets.

5. Conclusion and Future Scope

MSTEP, EQUIRO, R-ATM, CLTACO, and CIFEO comprise the five-stage integrated architecture for predictive and carbon-aware resource scheduling across cloud, fog, and edge infrastructures in process. The model's continuous energy and carbon performance control loop includes spatial-temporal energy forecasting, quantum Inspired optimization, reinforcement-driven migration, thermal management, and carbon–economic feedback. Experimental results on Google Borg traces, EdgeBench workloads, and NREL renewable profiles demonstrate its technical superiority. With 0.42 kWh RMSE and 92% power-capping accuracy, the Multi-Modal Spatio-Temporal Energy Profiler (MSTEP) reduced prediction error by over 45% compared to baseline techniques The Energy-Aware Quantum Inspired Resource Orchestrator (EQUIRO) reduced mean latency to 26 ms, SLA violations to 1.8%, and energy utilization to 1.87 MWh, saving 18% over state-of-the-art metaheuristics. The Reinforcement-Driven Adaptive Task Migrator (R-ATM) cut unwanted migrations by 20%, energy usage by 7%, and migration latency to 7 ms. CLTACO reduced cooling energy to 230 kWh and power utilization effectiveness to 1.22, 15% better than the best rival. CIFEO reduced carbon intensity by 25% to 235 g CO_2/kWh, raised operating margin to 12.5%, and slightly boosted revenue through operational improvements. Coordinated, predictive scheduling can satisfy ecological and economic goals in distributed computing installations, as the system saved 24.8% total energy, 25% carbon footprint, and 18.4% net cost sets.

Future Vision Analysis

Several avenues can expand this work. With dynamic renewable pricing and real-time grid interaction and demand–response markets, the orchestrator may sell energy flexibility directly and reduce carbon emissions beyond 30%. Implementations of precision hardware telemetry like per-core voltage and frequency scaling signals could reduce energy margins. Cross-domain federated learning lets data centers share model changes without exchanging raw data, improving prediction accuracy across regions.

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Limitations

The results are promising, but constraints remain. Legacy or cost-sensitive edge contexts may not have high-resolution sensors (power, temperature, network) at all tiers, which the integrated design assumes. In real deployments, device heterogeneity and unmodeled disturbances like sudden hardware failures or cyber-physical attacks might affect forecast accuracy. The experimental setup used diverse datasets. Classical emulation works well for the quantum Inspired optimizer, although quantum hardware speed-ups are envisaged..

References

[1] Sanjalawe, Y., Al-E'mari, S., Fraihat, S., & Makhadmeh, S. (2025). AI-driven job scheduling in cloud computing: a comprehensive review. Artificial Intelligence Review, 58(7). https://doi.org/10.1007/s10462-025-11208-8

[2] Gupta, S., & Tripathi, S. (2023). A comprehensive survey on cloud computing scheduling techniques. Multimedia Tools and Applications, 83(18), 53581-53634. https://doi.org/10.1007/s11042-023-17216-6

[3] Rao, W., & Li, H. (2024). Energy-aware Scheduling Algorithm for Microservices in Kubernetes Clouds. Journal of Grid Computing, 23(1). https://doi.org/10.1007/s10723-024-09788-w

[4] Yan, L. (2025). A novel quality of service-aware task scheduling approach for cloud computing using modified Wombat Optimization Algorithm. Journal of Engineering and Applied Science, 72(1). https://doi.org/10.1186/s44147-025-00628-6

[5] Qi, M., Wu, X., Li, K., & Yang, F. (2025). IPAQ: a multi-objective global optimal and time-aware task scheduling algorithm for fog computing environments. The Journal of Supercomputing, 81(2). https://doi.org/10.1007/s11227-024-06853-9

[6] Chen, Y., Luo, L., Guo, D., & He, Q. (2025). Carbon-Aware Energy Cost Optimization of Data Analytics Across Geo-Distributed Data Centers. Journal of Computer Science and Technology, 40(3), 654-670. https://doi.org/10.1007/s11390-025-4636-4

[7] Peng, J., Su, Z., & Liu, X. (2025). Multi skill project scheduling optimization based on quality transmission and rework network reconstruction. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-92342-9

[8] Sharma, A. P., Singh, J., Gulzar, Y., Gupta, D., & Kumar, M. (2024). Sustainable energy efficient workflow classification and scheduling in geo distributed cloud datacenter. Discover Sustainability, 5(1). https://doi.org/10.1007/s43621-024-00308-0

[9] Saeedizade, E., & Ashtiani, M. (2024). Scientific workflow scheduling algorithms in cloud environments: a comprehensive taxonomy, survey, and future directions. Journal of Scheduling, 28(1), 1-63. https://doi.org/10.1007/s10951-024-00820-1

Volume 38 No. 4s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[10] Zhang, Z., Xu, C., Xu, S., Huang, L., & Zhang, J. (2024). Towards optimized scheduling and allocation of heterogeneous resource via graph-enhanced EPSO algorithm. Journal of Cloud Computing, 13(1). https://doi.org/10.1186/s13677-024-00670-4

[11] Kaur, J., Chana, I., & Bala, A. (2025). MADQL: Multi-Agent Deep Q-Learning for Optimized Job Scheduling in Serverless Computing. Arabian Journal for Science and Engineering, . https://doi.org/10.1007/s13369-025-10461-x

[12] Jaiprakash, S. P., Badal, T., & Kumar, N. (2025). Efficient soft computing approach for task scheduling in cloud computing. *Computing*, 107(9). https://doi.org/10.1007/s00607-025-01539-3

[13] C. Vaidya, S. Chopade, P. Khobragade, K. Bhure and A. Parate, "Development of a Face Recognition-Based Attendance System," 2025 12th International Conference on Emerging Trends in Engineering & Technology - Signal and Information Processing (ICETET - SIP), Nagpur, India, 2025, pp. 1-6, doi: 10.1109/ICETETSIP64213.2025.11156883.

[14] Gao, J., & Cai, C. (2025). Integrating request stochasticity for efficient resource placement in general edge architecture with no level limit. Peer-to-Peer Networking and Applications, 18(4). https://doi.org/10.1007/s12083-025-02005-9

[15] Khan, A., Ullah, F., Shah, D., Khan, M. H., Ali, S., & Tahir, M. (2025). EcoTaskSched: a hybrid machine learning approach for energy-efficient task scheduling in IoT-based fog-cloud environments. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-96974-9

[16] Qiao, Y., Xiong, J., & Zhao, Y. (2024). Network-aware container scheduling in edge computing. Cluster Computing, 28(2). https://doi.org/10.1007/s10586-024-04733-8

[17] Alqahtani, A., Taneja, N., Taneja, A., & Alqahtani, N. (2025). Energy aware resource management in 6G IoT networks using STAR RIS. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-05338-w

[18] Lin, M., & Schaposnik, L. P. (2025). A carbon aware ant colony system for the sustainable generalized traveling salesman problem. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-08276-9

[19] Li, S., Ma, Y., Zhang, Y., & Xie, Y. (2024). Towards Enhanced Energy Aware Resource Optimization for Edge Devices Through Multi-cluster Communication Systems. Journal of Grid Computing, 22(2). https://doi.org/10.1007/s10723-024-09773-3

[20] Caderno, P. V., Awaysheh, F., Cabaleiro, J. C., & Pena, T. F. (2025). BigOPERA: An OPportunistic and Elastic Resource Allocation for big data frameworks. Cluster Computing, 28(6). https://doi.org/10.1007/s10586-025-05274-4

[21] Ghafari, R., & Mansouri, N. (2024). Fuzzy Reinforcement Learning Algorithm for Efficient Task Scheduling in Fog-Cloud IoT-Based Systems. Journal of Grid Computing, 22(4). https://doi.org/10.1007/s10723-024-09781-3

Received: August 08, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[22] Kausar, M. T. A., & Pachauri, S. (2025). Task scheduling with enhanced VM migration using SM-PCCTSA with SKD-RBM. International Journal of System Assurance Engineering and Management, 16(7), 2426-2444. https://doi.org/10.1007/s13198-025-02770-z

[23] Chen, J., Bai, L., Chen, N., & Yang, Y. (2025). HyperGAC: Information Entropy-Driven Resource Allocation for Cloud-Edge-End Computing. Journal of Grid Computing, 23(2). https://doi.org/10.1007/s10723-025-09807-4

[24] Sehrawat, H. (2025). Multi-parametric and priority driven particle swarm (MPPPSO) optimized task scheduling approach for improving performance of fog computing system. Progress in Artificial Intelligence, 14(3), 301-318. https://doi.org/10.1007/s13748-025-00366-z

[25] Isaac, R. A., Sundaravadivel, P., Marx, V. S. N., & Priyanga, G. (2025). Enhanced novelty approaches for resource allocation model for multi-cloud environment in vehicular Ad-Hoc networks. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-93365-y

[26] S. Nair, A. Gulghane, P. Khobragade, S. Solanke, K. Jajulwar, and A. Killol, "Development of Hybrid Machine Learning Models for Real-Time Drought and Flood Prediction in Agricultural Zones Using Multisource Environmental Data,"Int. J. Environ. Sci., vol. 11, no. 15s, pp. 725–740, 2025. https://doi.org/10.64252/y4f3k743

[27] Vijayalakshmi, V., & Saravanan, M. (2023). Reinforcement learning-based multi-objective energy-efficient task scheduling in fog-cloud industrial IoT-based systems. Soft Computing, 27(23), 17473-17491. https://doi.org/10.1007/s00500-023-09159-9

[28] Lu, Y. (2025). A multimodal deep reinforcement learning approach for IoT-driven adaptive scheduling and robustness optimization in global logistics networks. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-10512-1

[29] Singh, G., & Chaturvedi, A. K. (2024). A cost, time, energy-aware workflow scheduling using adaptive PSO algorithm in a cloud–fog environment. Computing, 106(10), 3279-3308. https://doi.org/10.1007/s00607-024-01322-w

[30] Zhang, A., Liu, Q., Liu, J., & Cheng, L. (2024). CASA: cost-effective EV charging scheduling based on deep reinforcement learning. Neural Computing and Applications, 36(15), 8355-8370. https://doi.org/10.1007/s00521-024-09530-3