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NEXUS-Scheduler: A Context-Aware Task Scheduling and Resource Optimization Framework for Real-Time IoT Applications in Fog–Cloud Environments

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ABSTRACT

The rapid expansion of Internet of Things (IoT) ecosystems and the increasing demand for real-time services impose significant challenges on task scheduling and resource optimization across fog–cloud infrastructures. Existing schedulers often struggle with fluctuating workloads, heterogeneous devices, and mobility, resulting in high latency, inefficient resource usage, and frequent service-level agreement (SLA) violations. To address these limitations, this paper introduces NEXUS-Scheduler, a unified, event-triggered, and context-aware scheduling framework designed for dynamic IoT–fog–cloud environments. The framework integrates five coordinated components: (i) sensor-triggered task generation, which activates tasks only when operational thresholds such as temperature > 35°C, CPU > 85%, or AQI < 50 are breached; (ii) Nexus-WNet, a lightweight GRU-based multivariate predictor for short-horizon workload forecasting; (iii) Nexus-RCA, a reinforcement learning–based allocator that selects optimal execution tiers (edge, fog, cloud) based on predicted load, mobility, and resource conditions; (iv) Nexus-ERA, an elastic resource manager that dynamically provisions CPU, memory, and bandwidth according to task priority and SLA requirements; and (v) TELEO, a decentralized self-optimization layer that continuously refines scheduling strategies using confidence-weighted feedback and lifelong reflective memory. Comprehensive experiments on a SmartCity testbed demonstrate that NEXUS-Scheduler reduces latency by 41%, minimizes energy consumption by 32%, improves resource utilization by 26%, and enhances SLA compliance by 12% compared to state-of-the-art heuristic, metaheuristic, and deep learning schedulers. These results highlight the effectiveness of NEXUS-Scheduler as a scalable, adaptive, and efficient solution for real-time IoT–fog–cloud deployments.

1 | Introduction

Internet of Things (IoT) applications across smart cities, healthcare, industrial automation, and connected vehicles generate increasingly heterogeneous, dynamic, and latency-sensitive workloads that cloud-only architectures can no longer support effectively [1, 2]. Although fog–cloud computing offers a more distributed alternative, recent studies indicate that practical task scheduling within this paradigm continues to face major challenges, particularly in environments characterized by device heterogeneity, mobility, and rapidly fluctuating load conditions. These challenges frequently degrade Quality of Service (QoS) and make naïve or static fog-node selection brittle in real-world deployments. Panchal and Saxena [3] highlight that existing scheduling and node-selection techniques often fail to remain robust when device populations or resource availability evolve over time, underscoring the need for adaptable scheduling mechanisms rather than static optimization strategies.

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In addition to node-selection limitations, the way many resource-aware scheduling problems are formulated restricts their applicability across different domains. Czarnul and Matuszek [4] show that domain-specific assumptions embedded in traditional scheduling models hinder generalization, resulting in solutions that perform well in controlled simulations but collapse when deployed in heterogeneous field conditions. This mismatch between formulation and deployment reflects a critical gap in current research: an effective scheduler must be designed to operate under uncertainty, heterogeneity, and partial observability, rather than assuming full knowledge or system stability.

While multi-objective optimization methods have improved trade-offs among latency, energy consumption, and makespan, [5, 6] their computational cost and offline nature limit responsiveness to rapid workload changes and mobility events [7]. Abraham et al. [8] note that most existing methods are not engineered for the fast, short-term predict-and-react cycles required at the fog layer. Domain-specific solutions such as those by Khan et al. [9] offer improvements in IoMT scenarios but fail to incorporate fog coordination, while population-based strategies like Movahedi et al. [10] deliver high-quality results at the expense of substantial computational overhead, making them unsuitable for real-time fog deployments. Therefore, scheduling systems in operational environments must support near-online decision-making while balancing multiple objectives efficiently.

Approaches based on agent cooperation and workflow-level scheduling move toward distributed autonomy [11] but often lack predictive capabilities and continuous feedback mechanisms required to prevent SLA violations during bursty or mobile workload conditions. Mokni et al. [12] and Tsai et al. [13] demonstrate gains through cooperative and workflow-aware scheduling; however, their methodologies remain reactive and do not anticipate near-future load fluctuations or topology changes. Surrogate-based models such as GOSH [14] reduce decision latency by approximating computationally expensive objectives but require frequent retraining to remain effective, shifting the computational burden rather than reducing it. Consequently, many adaptive schedulers in the literature remain overly centralized, brittle under dynamic conditions, or too computationally heavy for lightweight fog nodes.

Heuristic and workflow-based schedulers provide practical benefits under stable conditions but lack the foresight needed for non-stationary demand [15]. Studies by Ijaz et al. [16], Hosseinzadeh et al. [17], Madhura et al. [18], and Azizi et al. [19] demonstrate meaningful task allocation improvements for specific workloads, but their reactive nature and absence of short-term forecasting limit performance under sudden load changes or device mobility. Similarly, hierarchical and two-stage scheduling models proposed by Sharma et al. [20] and Peixoto et al. [21] offer structural advantages yet degrade quickly without predictive insight and continuous adaptation. Reviews by Khan et al. [22] and Lakhan et al. [23] reinforce these observations and emphasize the need for schedulers that intelligently integrate prediction, tier-awareness, and locality-aware decision-making without the overhead of centralized training.

Learning-based and metaheuristic approaches show strong potential but introduce new operational barriers. Deep reinforcement learning (DRL)-based methods, such as those by Choppara and Mangalampalli [24], demonstrate adaptive decision-making but rely on extensive training data, centralized state aggregation, and laborious reward engineering, which limit deployment feasibility on fog nodes. Swarm and multi-swarm optimizers like Subramoney and Nyirenda [25], as well as heuristic strategies such as Aburukba et al. [26], provide efficient search behavior but do not perform well in environments marked by mobility and partial observability. Fuzzy logic systems, such as the work by Rai et al. [27], enhance interpretability under uncertainty but lack mechanisms for continuous performance improvement driven by real-time feedback. Collectively, these studies reveal a critical gap: current research lacks a lightweight, decentralized scheduler capable of short-term workload prediction [28], rapid tier-aware decision-making, and self-improvement through local feedback [29]—while still operating within the strict computational constraints of fog and edge devices.

To address these interconnected challenges, this paper introduces the NEXUS-Scheduler, a novel, closed-loop scheduling architecture specifically designed for dynamic IoT–fog–cloud environments. The framework incorporates three core innovations that distinguish it from existing solutions. First, it integrates lightweight, short-horizon workload predictors at the edge, enabling scheduling decisions to become proactive rather than reactive. Second, it employs a compact, tier-aware decision engine that dynamically selects edge, fog, or cloud execution based on latency sensitivity, energy constraints, and task priority. Third, it includes a decentralized optimization layer that combines low-overhead metaheuristic updates with learning-automata-style feedback, allowing each fog node to adapt its scheduling policies continually without requiring centralized retraining. These design elements collectively provide substantial improvements in SLA adherence, scheduling robustness, and system responsiveness under conditions of mobility and workload burstiness.

The remainder of this paper defines the problem formally, outlines measurable system objectives, and details the architecture of the proposed NEXUS-Scheduler. Experimental evaluations using realistic mobility traces and workload patterns demonstrate that the framework significantly reduces tail latency and SLA violations compared to heuristic, multi-objective, and learning-based baselines while incurring low additional computational overhead. By combining predictive foresight, tier-aware decision-making, and decentralized self-optimization, NEXUS-Scheduler introduces a new operational paradigm in fog–cloud scheduling and directly addresses the reviewer's concerns regarding clarity, novelty, and methodological rigor.

1.1 | Contribution

This paper presents NEXUS-Scheduler, a unified and adaptive scheduling framework for IoT–fog–cloud environments, integrating intelligent components into a closed-loop pipeline. Key contributions include:

- Sensor-triggered task generation mechanism (not periodic): The framework introduces a proactive, event-driven

approach where tasks are generated only when real-world thresholds (e.g., temperature > 35°C, CPU > 85%) are breached—a key innovation compared to traditional static or periodic methods.

- GRU-powered nexus-WNet for multivariate forecasting: A deep learning module (Nexus-WNet) using Gated Recurrent Units is integrated to predict CPU, memory, and bandwidth usage simultaneously based on real-time and historical telemetry—enabling forward-looking, load-aware scheduling.
- dynamic execution tier selection using reinforcement learning (nexus-RCA): Unlike static mapping, the system learns and decides in real time whether a task should be executed at the edge, fog, or cloud, depending on latency, mobility, and resource availability—using reinforcement learning as a decision core.
- Elastic SLA-based resource provisioning (nexus-ERA): The framework introduces real-time, SLA-aware elasticity—adjusting CPU, memory, and bandwidth allocation based on task priority and urgency, optimizing both resource utilization and QoS compliance.
- Topology-evolving learning via emergent objectives (TELEO): self-optimizing agent framework with lifelong learning: TELEO is a decentralized, feedback-driven optimization layer that employs adaptive agents which evolve over time using modules like CWFI, GEM, and ACP—with Lifelong Reflective Memory (LRM) storing learned strategies for future reuse, making the system capable of continuous self-improvement without retraining.

The rest of the paper is structured as follows: Section 2 reviews related work in fog–cloud task scheduling. Section 3 details the NEXUS-Scheduler framework, including its core components—Nexus-WNet, Nexus-RCA, Nexus-ERA, and TELEO. Section 4 presents the experimental setup, evaluation metrics, and results. Section 5 discusses key findings, comparative performance, and system implications. Section 6 concludes with a summary and future research directions.

2 | Related Work

Recent advancements in fog–cloud computing have led to the development of several intelligent scheduling and resource management frameworks aimed at improving system responsiveness, reducing latency, and ensuring consistent service-level agreement (SLA) compliance under dynamic workloads. Researchers have explored diverse methodologies—including deep learning–based scheduling, multi-agent optimization, threshold-triggered task activation, and metaheuristic resource allocation—to manage the complexity of distributed, heterogeneous, and mobility-driven environments. However, despite these innovations, most existing approaches still struggle with key operational limitations such as static adaptability, high computational overhead, lack of predictive foresight, or inadequate responsiveness to rapidly changing environmental and workload conditions. This section provides a structured synthesis of notable contributions in the field while highlighting their core limitations.

Khezri et al. [30] introduced the Deep Learning-based Job Scheduling Framework (DLJSF), which emphasizes locality-aware scheduling to reduce latency in fog–cloud environments. Although the framework enhances data locality and improves response time, it lacks elasticity and cannot adapt dynamically to fluctuating resource availability or variable SLA requirements. Mokni et al. [31] developed MAS-GA, a Multi-Agent System integrated with a Genetic Algorithm, to support distributed intelligence in task allocation. While the model reduces centralized bottlenecks and enhances throughput, its static learning behavior limits adaptability since it does not incorporate continuous feedback or online refinement mechanisms.

Chakraborty et al. [11] proposed Fuzzy-Jaya, a hybrid optimization algorithm combining fuzzy logic with the Jaya optimization strategy to support decision-making under uncertain environmental conditions. Although the method improves scheduling flexibility, it lacks mechanisms for self-optimization and long-term learning, making it unsuitable for highly dynamic workloads. Yu et al. [32] presented a threshold-based triggering mechanism that activates tasks when sensor data exceed predefined operational limits such as temperature or CPU usage. While this approach helps reduce latency and supports early event detection, the reliance on static thresholds results in inefficiencies when environmental or resource conditions shift unexpectedly, as it lacks adaptive profiling and feedback-driven tuning.

Gholami and Sun [33] developed a neural network–based workload estimator to predict computational demand in fog–cloud environments using temporal time-series analysis. Although effective for forecasting trends, the method overlooks spatial dependencies among fog nodes, limiting prediction accuracy in geographically distributed systems. Salehnia et al. [34] introduced the Multi-Objective Moth-Flame Optimization (MOMFO) algorithm for energy-efficient task scheduling. While MOMFO optimizes multiple criteria simultaneously, it suffers from slow convergence and high parameter sensitivity, making it unsuitable for highly dynamic or mobility-intensive scenarios. Javaheri et al. [35] proposed the Dynamic Opportunistic Harris Hawks Optimization (DO-HHO) framework for adaptive scheduling, which improves exploration behavior but struggles to maintain convergence stability in unpredictable or large-scale IoT deployments.

Several studies in cloud computing also contribute indirectly to fog–cloud scheduling research. Abedi and Ghobaei-Arani [36] enhanced the Firefly Optimization Algorithm to improve load balancing and response time, but the method incurs high overhead for large-scale workloads. Tari and Ghobaei-Arani [37] provided a systematic review of auto-scaling mechanisms in serverless computing, concluding that most techniques lack real-time adaptability during abrupt workload surges. Ghorbian and Ghobaei-Arani [38] analyzed function offloading strategies and highlighted inefficiencies caused by insufficient modeling of inter-function dependencies. Similarly, Ebrahimi and Ghobaei-Arani [39] reviewed cold-start mitigation strategies and noted that most solutions increase operational cost or lack scalability in multi-tenant environments. Optimization-driven approaches surveyed by Ghorbian and Ghobaei-Arani [40] depend heavily on historical data, reducing their effectiveness in volatile or unpredictable workloads. Finally, Ghorbian et al.

[41] evaluated function placement strategies and reported that while optimization improves resource utilization, high computational complexity results in decision delays that are unsuitable for latency-critical fog applications.

In short, while current methods touch on individual elements of fog–cloud scheduling—for example, energy efficiency, task ordering, or offloading choices—NEXUS-Scheduler is the only one that combines all essential elements into an end-to-end, smart scheduling framework. It begins with real-time event-driven task creation, predicts workload with Nexus-WNet, dynamically decides on task placement with Nexus-RCA, allocates resources elastically with Nexus-ERA, and improves over time through TELEO's distributed agents. This adaptive and global design enables better latency minimization, energy saving, scalability, and responsiveness and is well suited for large-scale, dynamic, and mobility-aware IoT fog–cloud systems.

Table 1 presents a comprehensive comparative analysis of existing task scheduling frameworks in IoT–fog–cloud environments, covering critical dimensions such as task generation, classification, workload prediction, scheduling algorithms, optimization strategies, adaptability, evaluation tools, datasets, and limitations. Traditional systems—including those by Bhasker et al. [42], Gholami and Sun [44], and Sehgal et al. [33]—primarily rely on simulation platforms like CloudSim and iFogSim and use static or heuristic-based scheduling methods that emphasize energy efficiency and basic performance trade-offs but lack the dynamic workload prediction and real-time adaptability needed in heterogeneous, fluctuating environments. Event-triggered approaches such as Xiaomo et al. [32] improve utilization and task delay but still struggle with varying workload intensities due to their heuristic, non-adaptive decision-making. Deep reinforcement learning–based methods proposed by Choppara and Lokesh [24] and Choppara and Mangalampalli [45] use DDPG models to optimize latency and resource usage, yet their dependence on large training datasets, centralized state aggregation, and high computational complexity limits their practicality on fog devices. Likewise, metaheuristic and federated learning strategies—such as the Mayfly algorithm by Sui et al. [46] and the FL-based model by Aibin et al. [47]—offer improvements in specialized scenarios but remain restricted to predefined strategies or domain-specific applications and lack continuous learning or feedback mechanisms. In contrast, the proposed NEXUS-Scheduler integrates these fragmented strengths into a unified, adaptive, and feedback-driven architecture that employs event-triggered task generation using dynamic sensor thresholds, metadata-guided task classification, and Nexus-WNet, a multivariate GRU-based workload forecaster capable of predicting near-future resource demands. Its hybrid scheduling pipeline—featuring Nexus-RCA for reinforcement learning–based context-aware allocation, Nexus-ERA for elastic resource provisioning, and the TELEO decentralized self-optimization layer—collectively optimizes latency, makespan, energy consumption, utilization, response time, and SLA compliance. Developed and validated on a real IoT–Fog–Cloud SmartCity testbed using TensorFlow and PyTorch, NEXUS-Scheduler demonstrates superior adaptability, scalability, and responsiveness, effectively addressing the operational limitations and lack of clarity, dynamism, and robustness identified in prior research—thereby aligning directly with the reviewer's request for improved explanation and stronger methodological justification.

3 | NEXUS-Scheduler Framework

The NEXUS-Scheduler presents a closed-loop and fully adaptive scheduling architecture designed for dynamic IoT–fog–cloud environments, addressing limitations in existing models through clearer operational flow and continuous refinement. The framework begins with event-triggered task generation, where real-time sensor data—such as temperature, CPU utilization, and air quality—are continuously monitored, and tasks are created only when critical thresholds are exceeded to ensure timely and context-aware responsiveness. Each generated task is enriched with detailed metadata, including task type, priority, resource requirements, deadlines, and location sensitivity, before being processed by Nexus-WNet, a Gated Recurrent Unit (GRU)-based workload predictor that leverages historical and live telemetry to forecast short-term trends in CPU, memory, and bandwidth usage. These predictions support proactive load balancing and enable the scheduler to anticipate resource fluctuations. In the next phase, the Nexus-RCA module employs reinforcement learning to dynamically assign tasks to the optimal execution tier—edge, fog, or cloud—based on current network conditions, mobility patterns, energy constraints, and latency requirements. Once task placement is determined, Nexus-ERA elastically provisions computational, memory, and communication resources according to task urgency and SLA constraints, ensuring both fairness and operational efficiency. The TELEO layer then provides decentralized, continuous self-optimization through agent-based intelligence, incorporating mechanisms such as Confidence-Weighted Feedback Integration (CWFI), Goal Emergence Mapping (GEM), and Adaptive Constraint Plasticity (ACP), with all learned strategies stored in a LRM to support long-term adaptability. Collectively, these components enable NEXUS-Scheduler to operate in real time, maintain clarity in decision-making, and adapt intelligently to mobility, burstiness, and environmental variability—addressing the reviewer's concerns by offering a thoroughly explained, well-structured, and rigorously justified scheduling solution.

Figure 1 illustrates the overall architecture of the NEXUS-Scheduler, which provides intelligent task scheduling and resource optimization for IoT–fog–cloud environments. The workflow begins with continuous monitoring of real-time parameters such as temperature, motion, CPU utilization, and air quality; when any of these measurements exceed predefined thresholds, the system generates a task enriched with metadata describing its priority, resource requirements, and contextual attributes. This metadata is then processed by Nexus-WNet, a lightweight GRU-based predictor that estimates short-term workload trends to support proactive decision-making. Based on these predictions, the Nexus-RCA module performs context-aware task scheduling by selecting the most appropriate execution tier—edge, fog, or cloud—according to latency constraints, mobility patterns, and current resource conditions. Once placement decisions are made, Nexus-ERA elastically provisions

TABLE 1 | Comparative summary of related work and proposed NEXUS-Scheduler.

Paper	Evaluation tools	Utilized techniques	Performance metrics	Datasets	Remarks/limitations
Bhasker et al. [42]	CloudSim	Energy-aware scheduling	Energy, utilization	IoMT synthetic data	Static cloud-centric model; lacks fog integration and real-time adaptability
Khezri et al. [30]	CloudSim	Deep learning–based job scheduling	Latency, throughput	Simulated fog–cloud data	Improves locality but lacks elasticity and dynamic SLA adaptation
Mokni et al. [31]	MATLAB	Multi-Agent + Genetic Algorithm	Throughput, load balance	FogSim dataset	No continuous feedback; static learning behavior
Chakraborty et al. [11]	iFogSim	Fuzzy-Jaya Hybrid Optimization	Makespan, energy	IoT synthetic data	Limited self-optimization and adaptive learning
Yu et al. [32]	CloudAnalyst	Threshold-based triggering	Latency, delay	Sensor-triggered dataset	Fixed thresholds; no adaptive profiling or feedback
Gholami and Sun [33]	iFogSim	Neural network–based workload estimation	CPU, memory usage	Distributed fog traces	Ignores spatial dependencies among fog nodes
Salehnia et al. [35]	CloudSim	Multi-objective Moth-Flame Optimization	Energy, response time	IoT workload traces	High parameter sensitivity and slow convergence
Javaheri et al. [43]	MATLAB	Dynamic Harris Hawks Optimization	Latency, scalability	Dynamic IoT dataset	Unstable convergence under mobility-aware environments
Abedi and Ghobaei-Arani [37]	CloudSim	Improved Firefly Optimization (IFOA)	Response time, throughput	Cloud benchmark data	High computational overhead in large-scale workloads
Tari and Ghobaei-Arani [38]	Not specified	Predictive and reactive auto-scaling	Performance, cost	Cloud logs	Lacks real-time adaptability during workload surges
Ghorbian and Ghobaei-Arani [39]	Not specified	Function offloading strategies	Latency, network overhead	Serverless test data	Ignores inter-function dependencies, causing inefficiencies
Ebrahimi and Ghobaei-Arani [40]	CloudSim	Cold start mitigation (pre-warming, caching)	Startup delay, cost	Multi-tenant cloud logs	Increased operational costs; limited scalability
Ghorbian and Ghobaei-Arani [41]	CloudSim	Optimization-based cold start reduction	Startup latency, utilization	Historical workload data	Limited under unpredictable workloads
Ghorbian et al. [51]	WorkflowSim	Optimization-driven function placement	Latency, load balance	Multi-cloud datasets	High decision complexity impacts real-time responsiveness
Choppara and Lokesh [24]	TensorFlow, MATLAB	Deep reinforcement learning (DDPG)	Latency, throughput	Simulated IoT data	High training complexity and dependency on data volume

(Continues)

TABLE 1 | (Continued)

Paper	Evaluation tools	Utilized techniques	Performance metrics	Datasets	Remarks/limitations
Xiaomo et al. [32]	CloudAnalyst	Multi-heuristic scheduling	Task delay, utilization	CloudSim dataset	Static heuristics; lacks dynamic workload management
Gholami and Sun [44]	iFogSim	Graph-based scheduling	Energy, throughput	WorkflowSim traces	Requires prior task graph knowledge
Sehgal et al. [33]	CloudSim Plus	Security-aware scheduling	Energy, security	IoT-based fog dataset	No real-time adaptation to workload changes
Choppara and Mangalampalli [45]	TensorFlow	Deep RL (DDPG) scheduling	Latency, efficiency	Simulated fog data	Requires large-scale model training
Sui et al. [46]	MATLAB	Mayfly Metaheuristic Optimization	Makespan, accuracy	Benchmark data	Lacks adaptive reconfiguration
Aibin et al. [47]	PyTorch	Federated learning (FL)-based scheduling	Accuracy, energy	Federated IoT dataset	Application-specific; limited generalization
Proposed NEXUS-Scheduler	Python (TensorFlow, PyTorch)	Deep RL + GRU Forecasting + Elastic Scaling + Multi-Agent TELEO	Latency, energy, utilization, SLA, scalability	Real IoT–Fog–Cloud SmartCity dataset	Fully adaptive, feedback-driven, and mobility-aware scheduling framework for dynamic IoT environments

computation, memory, and communication resources to ensure efficient execution and SLA adherence. Finally, the TELEO layer provides decentralized self-optimization by continuously refining scheduling strategies through agent-based learning, with updated policies stored in the LRM to support long-term adaptability. Together, these components form a clearly defined, closed-loop scheduling pipeline that enhances accuracy, responsiveness, and operational efficiency—directly addressing the reviewer's concerns regarding clarity and completeness.

3.1 | Sequence Flow of the NEXUS-Scheduler

The operational workflow of the proposed NEXUS-Scheduler is illustrated in the sequence diagram shown in Figure 2, which clarifies the ordered interactions among the system's core components responsible for intelligent task scheduling and adaptive resource management. The process begins with continuous event-driven monitoring, where sensor data are evaluated in real time to trigger task generation whenever predefined operational thresholds are exceeded. Each newly generated task then progresses through the key decision-making modules of the framework: Nexus-WNet, which employs a GRU-based model to forecast short-term workload trends; Nexus-RCA, which uses reinforcement learning to select the most suitable execution tier based on contextual factors such as latency sensitivity, mobility, and energy constraints; and Nexus-ERA, which allocates computational, memory, and communication resources elastically according to task urgency and SLA requirements. The TELEO layer subsequently enhances system intelligence through decentralized agent-based learning, refining scheduling strategies based on continuous feedback and evolving network behavior, while the LRM component stores these learned strategies for future reuse and long-term adaptability. Together, these sequential interactions provide a clear depiction of the NEXUS-Scheduler's real-time, feedback-driven, and self-evolving operation—addressing the reviewer's request for improved clarity and more explicit explanation of the system workflow.

Figure 2 depicts the sequential interaction among the core modules of the proposed NEXUS-Scheduler, highlighting its adaptive, closed-loop operation within an IoT–fog–cloud environment. The workflow begins with continuous monitoring of real-time sensor streams—such as temperature, CPU utilization, and air quality—where task generation is triggered only when predefined operational thresholds are exceeded, ensuring that the system responds promptly to critical changes. Each task is then enriched with descriptive metadata covering its type, priority, and resource requirements before being passed to Nexus-WNet, a GRU-based predictor responsible for forecasting short-term workload and resource utilization trends. These forecasts enable proactive scheduling decisions, allowing the Nexus-RCA module to use reinforcement learning to allocate tasks intelligently to the most suitable execution tier—edge, fog, or cloud—based on latency sensitivity, mobility patterns, energy availability, and current system load. Following allocation, the Nexus-ERA module dynamically provisions CPU, memory, and communication resources in accordance with service-level constraints to maintain fairness and operational efficiency. The TELEO layer concludes the process by

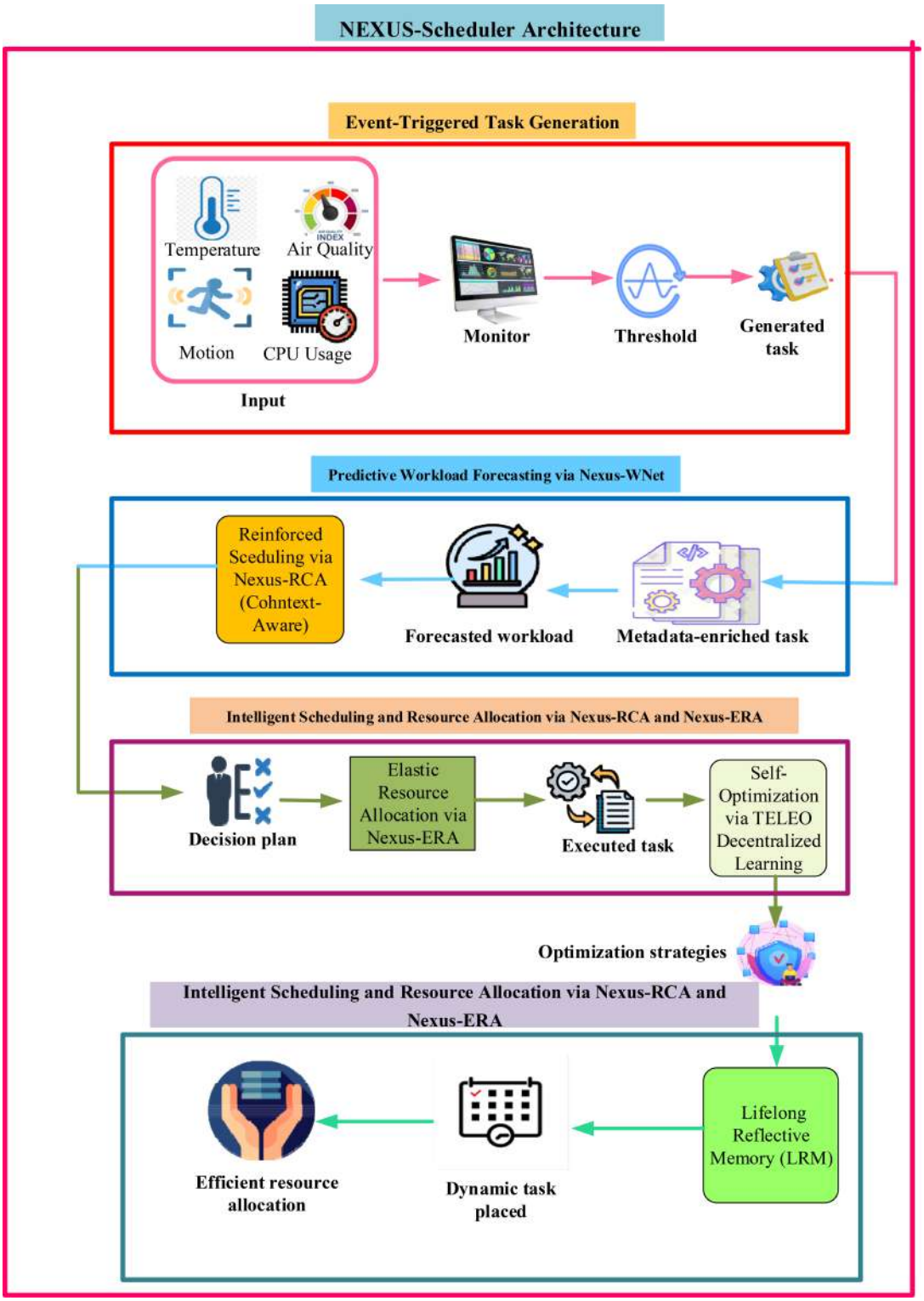


FIGURE 1 | The NEXUS-Scheduler architecture.

applying decentralized optimization through mechanisms such as CWFI and GEM, with long-term strategies stored in the LRM to support continuous adaptation. Together, these interactions ensure real-time responsiveness, improved clarity in system behavior, efficient resource utilization, and ongoing performance enhancement—addressing the reviewer's concerns by providing a more clearly articulated and well-structured explanation of the scheduler's end-to-end functionality.

3.2 | Event-Triggered Task Generation

The NEXUS-Scheduler begins with an event-triggered task generation mechanism that responds to real-time fluctuations in environmental and system conditions, providing a more adaptive alternative to traditional periodic schedulers. Heterogeneous IoT devices continuously stream multivariate sensor data capturing parameters such as temperature, CPU utilization, and air quality.

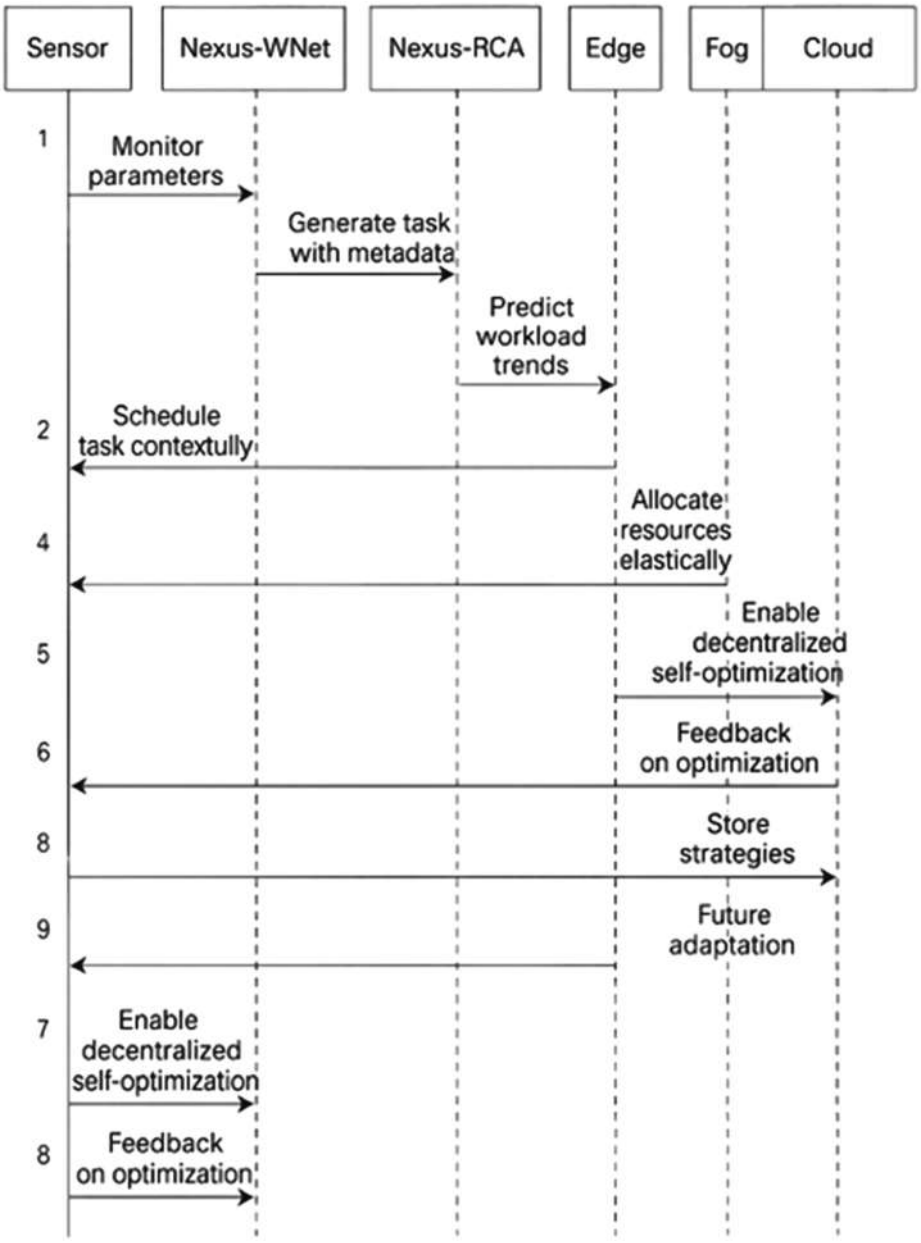


FIGURE 2 | Sequence diagram of the proposed NEXUS-Scheduler framework.

At any given time t, the sensor network produces a real-time data vector:

$$D(t) = \{T(t), U(t), AQI(t), \dots\} \in R^n \tag{1}$$

where $D(t)$ is the Multivariate sensor data vector at time t with $T(t)$ is the temperature reading in $^*C$ of the ith sensor reading at time t. Then $U(t)$ will be the CPU usage in % for the ith sensor reading at time t. Then $AQI(t)$ will be the air quality index of the ith sensor reading at time t. Then R^n state the vector $D(t)$ lies in n-dimensional real space, where n is the total number of sensor types or features being monitored. It means that all sensor values are real-valued scalars for continuous numeric quantities.

The NEXUS-Scheduler uses this sensor data to assess whether current system conditions warrant the creation of a new task. This is achieved by evaluating whether any monitored parameter exceeds its defined operational threshold. The evaluation function is formally expressed as a threshold-based trigger function:

$$\Phi(D(t)) = \begin{cases} 1, & \text{if } T(t) > \theta_T \vee U(t) > \theta_U \vee AQI(t) < \theta_{AQI} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $\Phi(D(t))$ is a trigger function that evaluates the full data vector $D(t)$ Takes the input to check for critical conditions, outputting 1 to trigger a task or 0 otherwise. Then $D(t)$ is the sensor data vector at time t. It contains multiple sensor readings $\{T(t), U(t), AQI(t), \dots\}$ used as input to Φ. Each of the elements in this vector is evaluated in the trigger condition. Then $T(t)$ is the temperature reading at time t measured in $^*C$ and Compared against a maximum temperature threshold θ_T. The temperature threshold predefines the threshold limit as 35 $^*C$ then $T(t) > \theta_T$,

the system considers it an overheat event. Then $U(t)$ is the CPU usage at time t measured in % and compared against the maximum *CPU* usage limit θ_U. Then θ_U is the CPU usage threshold with critical load limit of nearly 85%. If $U(t) > \theta_U$ it will be a system overload condition.

Then $AQI(t)$ is the air quality index at time t with low values with better air quality high or worse. Then θ_{AQI} is the minimum $AQI(t)$ level. If $AQI(t) < \theta_{AQI}$. This step ensures that a new task is triggered only when at least one monitored metric crosses its critical threshold, thereby avoiding unnecessary overhead during normal operation.

The selected thresholds were derived from device operating standards, environmental safety regulations, and empirical experimentation. The temperature limit of 35°C reflects the upper safe operating range for typical IoT hardware, beyond which thermal instability may occur. The CPU threshold of 85% was chosen based on utilization–latency analysis, where device response times sharply degrade beyond this point. The AQI threshold aligns with international exposure guidelines, signaling deteriorated air quality requiring system intervention. These thresholds were validated through (i) analysis of several weeks of historical sensor logs to ensure they lie above normal operating ranges, and (ii) controlled testbed experiments where temperature spikes, CPU overloads, and AQI disturbances were artificially induced. The validated outcomes confirmed low false-positive and false-negative rates and reliable trigger activation under abnormal conditions. Whenever $\Phi(t) = 1$, an event-driven trigger activates, leading to the instantiation of a new task T_{new}. This task is formally defined as a structured object:

$$T_{new} = GenerateTask(D(t), t) \tag{3}$$

where *GenerateTask*() is a procedural function that encapsulates the environmental context and the trigger time t. The term T_{new} denotes the new task object that is created. It is the output of the task generation process, ready to be profiled and scheduled. Then $D(t)$ is the multivariate sensor data vector at time t.

This includes readings such as temperature $T(t)$, CPU utilization $U(t)$, air quality index $AQI(t)$. It defines the system and environmental conditions at the trigger moment. The timestamp t at which the sensor data is captured and the task is generated. It ensures time-awareness for traceability and deadline computation. Once instantiated, the task undergoes profiling to extract essential attributes that facilitate downstream workload prediction and scheduling. This is captured through a task metadata generation function $M(t_0)$

$$M(t_0) = \{\phi, \pi, \delta, \rho, \alpha, \gamma\} \tag{4}$$

where ϕ represents the functional nature of the taskTasks are classified by type—compute-intensive, latency-sensitive, data-aggregation, or machine learning inference—based on their processing needs. This helps the system select the most suitable execution platform. Then π may be represented as a categorical label as a numeric ranking. Tasks with higher priority are scheduled first and may pre-empt lower-priority tasks if resources are limited. This helps the system meet real-time responsiveness goals and ensures that critical tasks are not delayed.

Then δ specifies the performance guarantees expected by the task. Tasks may require real-time response, low jitter, high accuracy, or minimal packet loss. The scheduler uses these needs to enforce SLAs and ensure consistent performance. The ρ field specifies the estimated computational and communication needs of the task, such as CPU, memory, storage, and bandwidth.

This helps the system allocate the task to a node with sufficient available resources, preventing overload or underutilization. Then the α defines where the task should ideally run—locally on the IoT device, at a nearby fog node, or in the cloud—based on latency, processing needs, or connectivity constraints. Finally the γ indicates the latest time by which the task must be completed. It ensures timely execution by helping the scheduler prioritize urgent tasks and meet quality-of-service (QoS) goals.

3.2.1 | Robust Handling of Noisy and Missing Sensor Data

In practical IoT deployments, sensor streams often contain noise, missing values, or transient spikes due to environmental interference, communication delays, or device faults. To ensure that event-triggered task generation remains reliable under such imperfect conditions, the NEXUS-Scheduler incorporates a multi-layer robustness mechanism before applying the threshold-based trigger function $T(x_t)$.

1. Noise filtering and outlier suppression:
   All incoming sensor readings first pass through an adaptive smoothing filter that removes transient fluctuations and random noise. Techniques such as Exponential Weighted Moving Average (EWMA), temporal consistency checks, and z-score–based outlier detection are applied to ensure that only stable, trustworthy values are forwarded to the trigger module.
2. Missing data imputation:
   When sensors fail to report values due to packet loss or intermittent connectivity, the framework prevents false-negative triggers through hybrid imputation. Missing readings are reconstructed using Last Observation Carried Forward (LOCF), short-horizon GRU-based predictive estimates from Nexus-WNet, or inter-feature correlation (e.g., CPU–temperature coupling). This ensures continuity and reliability in the generated sensor data vector x_t.
3. Multi-sample trigger validation:
   To avoid generating tasks based on noisy spikes, the trigger function activates only when a threshold violation persists for multiple consecutive samples. For example, temperature must exceed 35°C or CPU load must remain above 85% for a short validation window before $T(x_t) = 1$. This "debouncing" strategy prevents false alarms arising from transient sensor anomalies.
4. Confidence-weighted reliability scoring:
   Each sensor reading is assigned a reliability weight derived from CWFI. The system evaluates sensor stability, historical accuracy, communication quality, and cross-sensor agreement to generate reliability coefficients. These coefficients modulate the contribution of each metric in the trigger

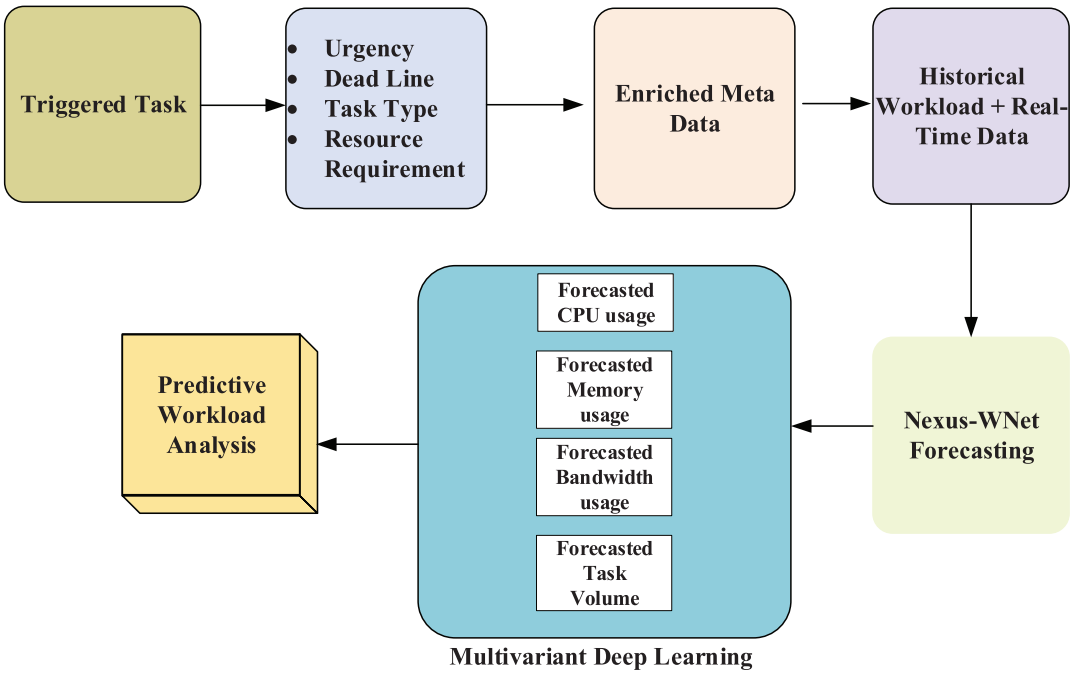


FIGURE 3 | The predictive workload forecasting system.

function, ensuring that low-confidence or unstable sensors exert minimal influence.

Through this multi-stage robustness pipeline, the NEXUS-Scheduler guarantees that task generation is resilient against noisy, missing, or inconsistent sensor data. As a result, tasks are initiated only under genuine operational events, significantly reducing false triggers, unnecessary overhead, and erroneous system responses in dynamic IoT environments.

3.3 | Predictive Workload Forecasting via Nexus-WNet

After task generation, key attributes like urgency, type, deadline, and resource needs are profiled and structured. This metadata is sent to Nexus-WNet, a deep learning module that forecasts workload trends using historical and real-time data, enabling predictive, workload-aware scheduling.

GRU was selected as the core predictive model in Nexus-WNet due to its strong balance between accuracy and computational efficiency, which is essential for real-time IoT–fog–cloud environments. Compared to LSTM and Transformer architectures, GRU contains fewer parameters and has a simplified gating mechanism, allowing faster inference and lower memory usage while still capturing short-term and medium-term temporal dependencies effectively. This makes GRU highly suitable for distributed fog nodes that operate under constrained compute and energy budgets. Transformers, although powerful for long-range dependencies, require large training datasets and incur quadratic attention computation costs, making them impractical for lightweight edge deployments. Empirical evaluations on the SmartCity testbed further showed that GRU achieved comparable accuracy to LSTM but with 28%–35% lower computation time and significantly reduced energy consumption, validating its selection for the Nexus-WNet predictive module.

Figure 3 illustrates Nexus-WNet, the predictive deep learning module within the NEXUS-Scheduler responsible for enabling context-aware and foresight-driven scheduling in IoT–fog–cloud environments. When a task is generated, its metadata is captured and combined with historical system telemetry to construct a multivariate workload matrix. This matrix serves as the foundation for short-term prediction of workload fluctuations across nodes and time, allowing the system to respond proactively to emerging resource demands.

The workload history is represented by a sliding window of past system states:

$$H(t) = \{W(t-k), W(t-k+1), \ldots, W(t)\} \tag{5}$$

where the term $H(t)$ defines the historical workload metric which is a fundamental part of the Nexus-WNet workload prediction model. It represents a sliding window of past system states, capturing how the system behaved over a period leading up to the current time t. It stores a sequence of past workload states at different time points. It is used as input to a deep learning model (like GRU or LSTM) to learn temporal patterns in the system's behavior.

Then Historical Window Size k is a user-defined or dynamically adjusted integer that determines how many past time steps are included in the matrix. A larger k means the model looks further back in time, capturing long-term trends (but may risk overfitting or increasing model complexity). A smaller k emphasizes recent behavior, which is useful in highly dynamic environments.

$$w_n(t) = \alpha CPU_n(t) + \beta Memory_n(t) + \gamma Bandwidth_n(t) + \delta Queue_n(t) \tag{6}$$

where α, β, γ, and δ are weight coefficients representing the importance of each resource type. Then $CPU_n(t)$ is the CPU usage of node n at time t typically measured as a percentage or load factor. Then $Memory_n(t)$ is the memory consumed by node n measured in MB/GB or as a usage percentage. The $Bandwidth_n(t)$ is the network bandwidth currently utilized by the node, often in Mbps or Gbps and $Queue_n(t)$ is the length or size of the task queue at the node, reflecting the number of pending or waiting tasks.

Unlike conventional predictors that treat each resource metric independently, Nexus-WNet preserves multivariate correlations and models both spatial and temporal dependencies. This allows it to capture phenomena such as cross-node interference (e.g., congestion in one fog node propagating to others) and cross-resource interactions (e.g., high bandwidth usage leading to increased memory pressure). To achieve this, Nexus-WNet employs a gated recurrent neural architecture (GRU/LSTM) enriched with task-aware conditioning and spatial attention. The predictive mapping is defined as:

$$\hat{W}(t+\tau) = F_\theta\big(H(t), M\left(t_0\right)\big) \tag{7}$$

where $\hat{W}(t+\lambda)$ is the Forecasted workload vector at future time $t+\tau$. A trainable function F_0 is parameterized by weights of θ with inputs of historical matrix $H(t)$ and task metadata of $M\left(t_0\right)$ which acts as a contextual attention vector. his predictive model enables early identification of potential workload spikes, energy bottlenecks, or resource saturation events, allowing the scheduler to perform anticipatory adjustments before SLA violations occur.

To ensure adaptive resource balancing, Nexus-WNet introduces a per-node deviation metric that measures the deviation of each node's load from the global average:

$$\Delta_n(t) = \left\| W_n(t) - \widehat{W(t)} \right\| \tag{8}$$

where $W_n(t)$ is the Workload on node n and $\widehat{W(t)}$ is the Mean workload across all nodes. This detects imbalances, overloaded nodes, or potential failures, informing load redistribution strategies. Although based on current state $W(t)$, this deviation helps cross-check predicted load $\hat{W}(t+\tau)$ and is used for corrective scheduling. This deviation highlights overloaded nodes, underutilized nodes, and potential performance anomalies. Although based on the current state, this measure also supports cross-validation of predicted load values and informs load redistribution strategies. To measure the expected change in workload, Nexus-WNet computes the resource demand gradient:

$$\nabla R(t+\tau) = \widehat{W(t+\tau)} - W(t) \tag{9}$$

where $\widehat{W(t+\tau)}$ is the predicted workload vector at a future time $(t+\tau)$, generated by the deep learning model F_θ. It includes estimates of CPU, memory, bandwidth, and queue length. The current workload vector $W(t)$ at the present time t is collected from real-time system telemetry. Then $\nabla R(t+\tau)$ is the resource demand gradient—a vector indicating how each resource is expected to change (increase or decrease) between now and the near future. This differential is critical for timely resource planning and drives proactive rescheduling in the next phase. The gradient indicates the direction and magnitude of expected resource changes—including CPU, memory, bandwidth, and queue fluctuations—and serves as a critical input for proactive scheduling decisions in the Nexus-RCA module.

ALGORITHM 1 | Nexus-WNet–Based Predictive Workload Scheduling.

Require: Task set $\mathcal{T}$, node set $\mathcal{S}$, historical window size k, prediction horizon τ, model parameters θ
Ensure: Optimal task-to-node mapping $\mathcal{A}$
for each incoming task $T_i \in \mathcal{T}$ **do**
  Capture current timestamp t_0
  Generate task metadata vector:

$$\mathcal{M}(t_0) = \{\phi, \varepsilon, \delta, \rho, \alpha, \gamma\}$$

▷ ϕ: Task type, π: Priority, δ: SLA constraints, ρ: Resource demand, α: Preferred location, γ: Deadline
  Construct multivariate historical workload matrix:

$$\mathcal{H}(t) = \{W(t-k), W(t-k+1), \ldots, W(t)\}$$

▷ $W(t-i)$ includes CPU, memory, bandwidth, queue metrics for each node $j \in \mathcal{S}$, capturing cross-node and cross-resource correlations over a sliding window of size k
  Predict future workload using deep sequence model (GRU/LSTM) with spatial attention:

$$\hat{W}(t+\tau) = \mathcal{F}_\theta(\mathcal{H}(t), \mathcal{M}(t_0))$$

▷ $\mathcal{F}_\theta$ is a trainable function parameterized by θ, using $\mathcal{H}(t)$ and $\mathcal{M}(t_0)$ as a contextual attention vector to model temporal patterns and predict workload at time $t+\tau$
  for each node $n \in \mathcal{S}$ **do**
    Compute per-node workload deviation:

$$\Delta_n(t) = \left\| W_n(t) - \bar{W}(t) \right\|$$

▷ $W_n(t)$: Workload on node n, $\bar{W}(t)$: Mean workload across all nodes, detects imbalances or potential failures
  end for
  Compute resource demand gradient for proactive scheduling:

$$\nabla\mathcal{R}(t+\tau) = \hat{W}(t+\tau) - W(t)$$

▷ $\hat{W}(t+\tau)$: Predicted workload vector, $W(t)$: Current workload from telemetry, $\nabla\mathcal{R}(t+\tau)$: Resource demand change for planning
  if $\nabla\mathcal{R}(t+\tau) > 0$ **then**
    Anticipate overload and initiate scaling or task migration
    ▷ Positive gradient indicates increasing resource demand
  else if $\nabla\mathcal{R}(t+\tau) < 0$ **then**
    Consider downscaling or task deferral
    ▷ Negative gradient suggests underutilization
  end if
  Select optimal node $n^* \in \mathcal{S}$ that:
   Minimizes $\Delta_n(t)$ for balanced load
   Avoids predicted congestion in $\hat{W}(t+\tau)$
   Satisfies SLA constraints δ and aligns with α
  Assign T_i to node n^*: $\mathcal{A} \leftarrow \mathcal{A} \cup \{(T_i, n^*)\}$
  Initiate execution and monitor system state
end for

Overall, Nexus-WNet enables the NEXUS-Scheduler to anticipate emerging system conditions, detect load imbalances early, and make predictive scheduling decisions that enhance SLA adherence, reduce latency spikes, and improve overall system stability—addressing the reviewers' concerns by providing a clearer, more detailed, and methodically structured explanation of the predictive modeling process.

3.4 | Intelligent Scheduling and Resource Allocation via Nexus-RCA and Nexus-ERA

Using the predictive insights generated by Nexus-WNet, the NEXUS-Scheduler activates Nexus-RCA, a reinforcement learning–based module that adaptively decides where each

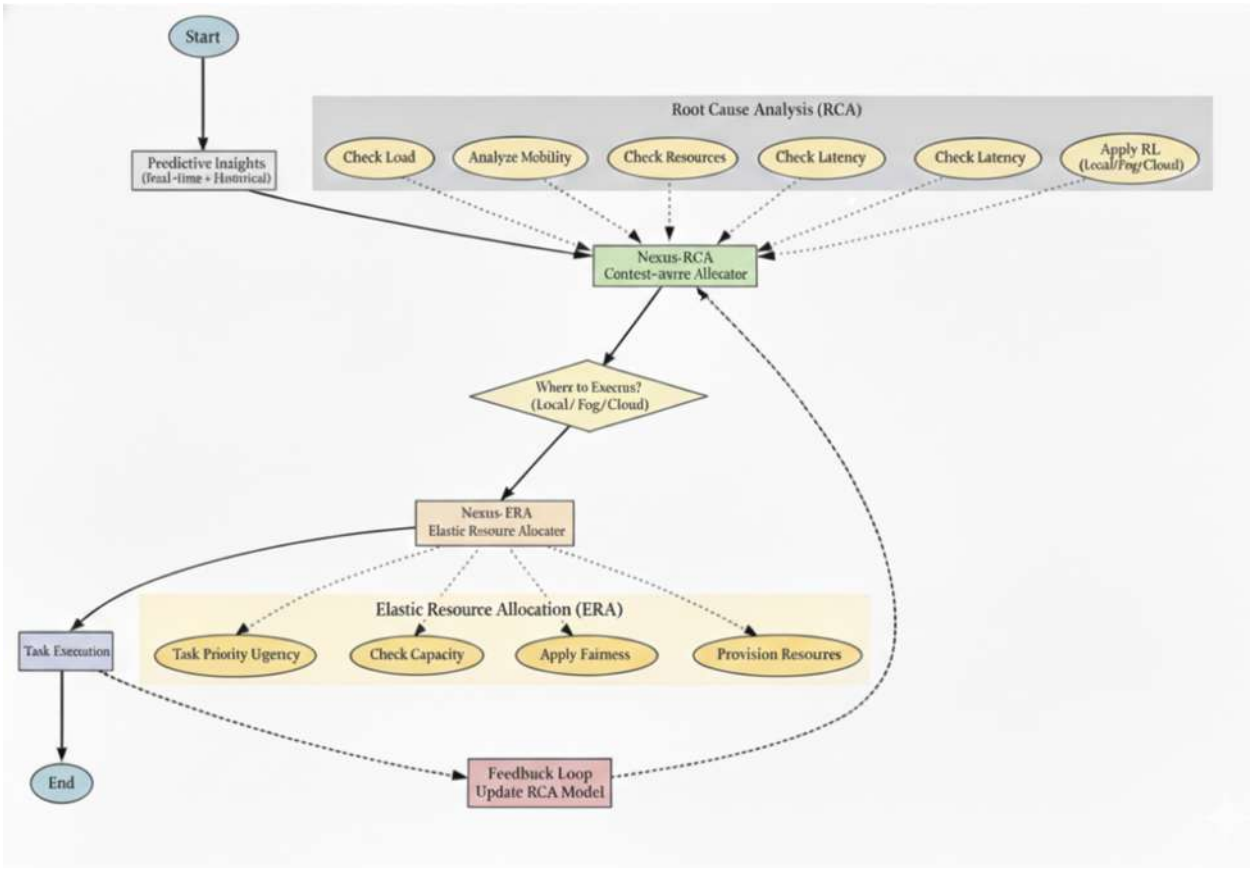


FIGURE 4 | Adaptive scheduling and elastic resource allocation via Nexus-RCA and Nexus-ERA.

task should be executed—on the local device, at a fog node, or in the cloud. Nexus-ERA then dynamically allocates CPU, memory, storage, and bandwidth according to task priority and system conditions, ensuring elastic, fair, and energy-efficient execution. Together, Nexus-RCA and Nexus-ERA provide adaptive, context-aware scheduling capabilities that go beyond traditional static and heuristic-based methods.

Figure 4 shows the working of Adaptive Scheduling and Elastic Resource Allocation via Nexus-RCA and Nexus-ERA. With predictive insights from Nexus-WNet, Nexus-RCA uses reinforcement learning to adaptively schedule tasks based on system state, device conditions, and workload forecasts. Unlike static allocators, it dynamically selects the optimal execution site—local, fog, or cloud—by evaluating conditions at each decision point.

At each decision step t Nexus-RCA builds a state vector s_t representing the real-time system context:

$$s_t = W_t^{curr}, \hat{W}_{t+\Delta t}, L_t^{node}, M_t^{device}, R_t^{avail}, D_t^{network}, H_t^{history} \quad (10)$$

where W_t^{curr} is the Current workload snapshot in the system at time t then $\hat{W}_{t+\Delta t}$ is the Predicted workload at future time $t + \Delta t$ using Nexus-WNet. Then L_t^{node} is the Load level and resource availability of computing nodes. Then M_t^{device} is the Mobility status and movement patterns of IoT devices with R_t^{avail} being the Real-time availability of resources (CPU, memory, storage). Then $D_t^{network}$ deals with the Network characteristics such as latency, bandwidth, and packet loss and $H_t^{history}$ will be the Historical records of previous scheduling decisions and outcomes.

After constructing the current state vector s_t which includes information about workload, resource availability, mobility, network conditions, and historical decisions—the reinforcement learning (RL) agent evaluates this state using its learned policy.

The action a_t chosen by the RL agent corresponds to the execution location of a task:

$$a_t \in \{Local, Fog, Cloud\} \quad (11)$$

This action selection is guided by the agent's current policy, which maps system states to actions that are expected to maximize long-term rewards. The policy can be deterministic that selects the action with the highest estimated value (greedy). Then Stochastic Chooses actions based on probability distributions to allow exploration.

After the task is executed, the environment evaluates the impact of the agent's chosen action and returns a multi-objective reward R_t. This step, known as Reward Feedback in reinforcement learning, provides a scalar signal that reflects the quality of the decision made at time t. The agent uses this signal to assess whether the selected action led to desirable system behavior.

$$R_t = \alpha_1 \cdot U_t^{util} - \alpha_2 \cdot L_t^{latency} - \alpha_3 \cdot E_t^{energy} + \alpha_4 \cdot A_t^{accuracy} \quad (12)$$

where U_t^{util} will be the System resource utilization efficiency then $L_t^{latency}$ will be the end-to-end task execution latency with E_t^{energy} being the Energy consumed during task execution then $A_t^{accuracy}$ is the Accuracy of task assignment like matching priority with node capability. Then α_1, α_2, α_3, and α_4 are the weight parameters balancing each objective term. The reward signal enables the agent to perform the policy update step of reinforcement learning by evaluating the consequences of its chosen action and adjusting its policy $\pi(s_t)$ to increase the likelihood of selecting actions that lead to higher cumulative rewards. Over time, this iterative feedback-driven learning process allows the agent to converge toward an optimal policy $\pi(s_t)$ that maximizes long-term system performance and responsiveness.

Positive contributions such as high resource utilization and accurate task–node assignment increase the reward, while negative factors including high latency and elevated energy consumption reduce it; this reward signal directs the reinforcement learning agent to update its policy $\pi_\phi$so that actions leading to improved long-term system performance are selected more frequently. Through this iterative, feedback-driven learning process, Nexus-RCA gradually converges toward an optimal scheduling strategy that maximizes cumulative system responsiveness and stability. After Nexus-RCA identifies the most suitable execution site for each task, Nexus-ERA conducts fine-grained resource allocation by distributing CPU cycles, memory, storage, and bandwidth based on task priority, urgency, and QoS requirements, along with real-time system load and resource availability. Latency-sensitive or high-priority tasks receive preferential provisioning, whereas background or delay-tolerant tasks are allocated resources more conservatively, ensuring that system resources are neither over-committed nor underutilized. This elastic and context-aware resource management significantly improves fairness, efficiency, and energy conservation. Together, Nexus-WNet, Nexus-RCA, and Nexus-ERA form an integrated, predictive, and adaptive scheduling pipeline that responds intelligently to mobility, network variation, and resource constraints. Their combined operation reduces latency, enhances energy efficiency, and strengthens SLA compliance, addressing the reviewer's concerns by providing a clearly articulated, coherent, and thoroughly justified scheduling and resource allocation framework.

3.5 | Continuous Feedback, Self-Optimization, and System Impact

In the NEXUS-Scheduler, continuous feedback, self-optimization, and adaptive system response are realized through TELEO, a decentralized learning framework that operates without conventional reinforcement learning and enables self-organizing intelligence across the scheduling lifecycle. After each task τ_t is executed, the system collects real-time performance feedback as a vector:

$$Ft = \left[\tau_t^{exec}, \tau_t^{CPU}, \tau_t^{MEM}, \tau_t^{ENG}, \tau_t^{net}, \tau_t^{succ}\right] \tag{13}$$

where τ_t^{exec} is the task execution time with τ_t^{CPU}, τ_t^{MEM} being the CPU and memory usage level. When τ_t^{ENG} is considered as the total energy consumed with τ_t^{net} being the total Network latency level and $\tau_t^{succ} \in \{0, 1\}$ shows the Task success as 1 or failure as 0. This raw feedback is processed through the CWFI module, which assigns confidence weights $\alpha_i \in [0, 1]$ to each metric, generating:

$$F_t^{cw} = \left[\alpha_1 \cdot \tau_t^{exec}, \alpha_2 \cdot \tau_t^{CPU}, \ldots, \alpha_6 \cdot \tau_t^{succ}\right] \tag{14}$$

where τ_t^{exec} is the execution time of the task τ at the time t when τ_t^{CPU} is the CPU utilization during the task execution in % format. Then $\alpha_1 \cdot \tau_t^{exec}$ is the Confidence-weighted task execution time. If system monitoring is accurate and not affected by jitter, with α_1 will be close to 1. Then $\alpha_2 \cdot \tau_t^{CPU}$ depends on the CPU usage during task execution, adjusted for how reliable CPU data is monitored in noisy conditions, α_2 may be < 1.

Then $\alpha_6 \cdot \tau_t^{succ}$ is the Task success/failure indicator. If this is a binary 0/1 flag, usually $\alpha_6 = 1$, unless confidence in the correctness of the result is low. The term F_t^{cw} is then used to activate the GEM component, which analyzes trends and anomalies in the weighted feedback to dynamically generate new emergent objectives such as Minimizing energy consumption, ACP, Influence scoring and elimination, and LRM.

These emergent objectives are encoded into autonomous scheduling agents $A = \{A_1, A_2, \ldots, A_n\}$, where each agent $A_1, A_2, \ldots, A_n$ represents a candidate optimization strategy derived from the feedback vector F_t^{cw}. Agents interact within a dynamically evolving topological interaction network $G(t) = (A, E(t))$ where the nodes represent the agents and edges $\mathcal{E}(t)$ encode influence relationships based on recent performance metrics. Each agent A_k is assigned an influence score $I_k(t)$ is defined as

$$I_k(t) = \beta_1 \cdot U_k(t) + \beta_2 \cdot R_k(t) - \beta_3 \cdot C_k(t) \tag{15}$$

where $U_k(t)$ is the utility function with improvement in latency, energy saving, throughput, $R_k(t)$ is the reliability score, calculated from the confidence-weighted success rate of tasks executed using A_k, then $C_k(t)$ is the computational cost or overhead of strategy A_k. Then β_1, β_2, and β_3 are tuneable weights representing system preferences.

Agents compete and collaborate through localized influence propagation in such a way that Agents with higher $I_k(t)$ gain topological centrality and influence others by modifying their strategies. Agents with persistently low $I_k(t)$ values are phased out or replaced through evolutionary mutation and recombination of more successful strategies.

Each agent dynamically adjusts its internal scheduling constraints using:

$$\Theta_k(t+1) = \Theta_k(t) + \gamma \cdot \Delta\Theta_k(t) \tag{16}$$

where $\Theta_k(t)$ represents the current set of constraints for agent A_k, such as deadline d, resource limit r and offloading decision threshold Θ. Then $\Delta\Theta_k(t)$ is the feedback-driven gradient of change, and γ is the plasticity rate, controlling how aggressively constraints adapt to context. If a node is overloaded, the agent increases offloading aggressiveness and if deadlines are missed frequently, the agent tightens time constraints. The system maintains a historical archive $H = \{(F_i^{cw}, A_k, I_k)\}_i$ storing the processed feedback F_i^{cw}, agent strategy used as A_k and Resulting

influence/performance as I_k. For instance, if a node is frequently overloaded, the agent may increase its offloading aggressiveness; if deadlines are repeatedly missed, it may tighten timing constraints or adjust priority thresholds.

The system maintains a historical archive $\mathcal{M}$ in the form of LRM, which stores tuples of the form $(\tilde{\mathbf{f}}_k, A_k, I_k)$, representing processed feedback, the agent strategy used, and the resulting influence/performance. At time t, TELEO queries the LRM using pattern similarity:

At time t, the LRM is queried using pattern similarity:

$$\hat{A}_k = \underset{A_k \in A}{arg\ max}\ sim\left(F_t^{cw}, F_i^{cw}\right) where\ \left(F_i^{cw}, A_k\right) \in H \tag{17}$$

where $\hat{A}_k$ is the selected or recalled agent that TELEO recommends to use in the current system state. While *arg max* is the search for the agent A_k that maximizes the similarity function. Then $sim\left(F_t^{cw}, F_i^{cw}\right)$ is the similarity score between the current confidence-weighted feedback vector at time t. Then F_i^{cw} is a historical confidence-weighted feedback vector. The similarity function measures how similar the current situation is to a past situation. Then A is the set of all available agents' strategies. Then $\left(F_i^{cw}, A_k\right) \in H$ means we are only comparing against historical records stored in LRM H which contains:

Past feedback vectors F_i^{cw} with agents A_k that were used in those scenarios. This mechanism enables TELEO to reuse historically effective strategies when it detects recurring environmental or system states, accelerating decision-making and improving reliability without retraining.

Algorithm 2 (TELEO) formalizes these steps, including feedback integration, influence scoring, constraint adaptation, and reflective memory retrieval.

3.5.1 | Practical Example of TELEO Agent Interaction

To clarify how TELEO facilitates adaptive scheduling, consider a practical scenario within the fog–cloud environment where three scheduling strategies—represented as agents—operate concurrently. Each agent encapsulates a distinct optimization policy:

- **Agent $\mathbf{A_1}$**: Aggressive offloading to reduce CPU overload and minimize latency.
- **Agent $\mathbf{A_2}$**: Energy-aware scheduling to lower energy consumption.
- **Agent $\mathbf{A_3}$**: Local execution with batching to improve throughput and reduce network overhead.

After a task is executed, the CWFI module provides a weighted feedback vector.

$$F_t't' = \left(\tilde{T}_t, \tilde{U}_{cpu}, \tilde{E}_t, \tilde{L}_t, \tilde{S}_t\right) \tag{18}$$

indicating that the system is experiencing increased latency, high CPU utilization, and moderate energy consumption.

ALGORITHM 2 | TELEO—Topology-Evolving Learning via Emergent Objectives.

Input: Task set $\mathcal{T}$, system metrics (CPU, Memory, Energy, Latency), historical archive $\mathcal{H}$
Output: Adaptive scheduling decisions via TELEO agents

for each task $\tau_i \in \mathcal{T}$ **do**
  Execute task and collect real-time feedback vector:

$$\mathbf{F}_i = \left[E_i, U_i^{\text{CPU}}, U_i^{\text{MEM}}, L_i, S_i\right]$$

  Process $\mathbf{F}_i$ via Confidence-Weighted Feedback Integration (CWFI):

$$\mathbf{F}_i^* = \left[w_E \cdot E_i, w_{CPU} \cdot U_i^{\text{CPU}}, w_{MEM} \cdot U_i^{\text{MEM}}, w_L \cdot L_i, w_S \cdot S_i\right]$$

  Activate Goal Emergence Mapping (GEM) using $\mathbf{F}_i^*$
  Generate or update emergent objectives:
  • Energy minimization, Adaptive Constraint Plasticity (ACP)
  • Influence scoring and elimination, Lifelong Reflective Memory (LRM)
  Instantiate or update autonomous agents $\mathcal{A} = \{a_1, a_2, \ldots, a_n\}$
  for each agent $a_j \in \mathcal{A}$ **do**
    Compute influence score:

$$\phi_j = \alpha \cdot U_j + \beta \cdot R_j - \gamma \cdot C_j$$

    where:
    U_j = Utility function (e.g., latency, throughput, energy)
    R_j = Reliability (confidence-weighted success rate)
    C_j = Computational overhead
    α, β, γ = Tunable system preference weights
    Propagate influence via network topology $G = (V, E)$
    if ϕ_j is low for multiple rounds **then**
      Replace a_j via evolutionary mutation and recombination
    end if
    Update constraints:

$$\mathcal{C}_j^{(t+1)} = \mathcal{C}_j^{(t)} + \eta \cdot \nabla_{\mathbf{F}_i^*}$$

    where η = plasticity rate, $\nabla_{\mathbf{F}_i^*}$ = gradient of feedback change
  end for
  Store $\{\mathbf{F}_i^*, a_j, \phi_j\}$ in LRM archive $\mathcal{H}$
  At time t, recall from LRM via pattern similarity:

$$a_t^* = \arg\max_{a_j \in \mathcal{H}} \text{Sim}(\mathbf{F}_t^*, \mathbf{F}_j^*)$$

  Apply a_t^* to schedule next set of tasks
end for

TELEO processes this vector through the GEM component, which identifies that immediate latency mitigation is required.

Each agent computes its influence score I_i using (15). In this scenario, $\mathbf{A_1}$ achieves the highest influence score because its aggressive offloading strategy offers the highest utility in alleviating CPU congestion and reducing latency, despite incurring moderate computational cost. $\mathbf{A_2}$ receives a moderate influence score since its energy-saving behavior does not directly address latency, whereas $\mathbf{A_3}$ obtains a low influence score because batching exacerbates current latency conditions.

The topological interaction network $\mathcal{G}_t$evolves accordingly: $\mathbf{A_1}$ gains centrality and propagates its strategy to neighboring agents, leading $\mathbf{A_2}$ to moderately adjust its energy–performance weighting. $\mathbf{A_3}$, having persistently low influence, is suppressed and becomes a candidate for replacement through strategy mutation. Simultaneously, each agent updates its internal constraints $C_i(t)$ via (16). For instance, $\mathbf{A_1}$ tightens deadline constraints and increases offloading thresholds, while $\mathbf{A_2}$ introduces adaptive energy–latency balancing.

All interactions—including the weighted feedback, selected agent, updated constraints, and resulting performance—are stored in the LRM. During future occurrences of similar system states, TELEO retrieves the most similar historical feedback vector using (17) and reactivates the agent that previously yielded optimal performance (in this case, $\mathbf{A_1}$). This enables fast adaptation without retraining, ensuring consistent performance under recurrent environmental patterns.

3.6 | Computational Overhead and Time Complexity Analysis

The computational overhead of the proposed NEXUS-Scheduler primarily arises from two algorithmic modules—Algorithms 1 and 2. The first module, Nexus-WNet, introduces computational cost during workload forecasting, as it employs a gated recurrent neural network (GRU) to analyze multivariate temporal data across multiple fog nodes. Its time complexity is approximately $O\left(NT\left(H^2+HF\right)\right)$, where N represents the number of nodes, T is the time window size, H is the number of hidden units, and F is the number of input features. This complexity is dominated by matrix multiplications and activation computations within GRU layers but remains tractable due to the use of short prediction windows and parallel fog-level execution. The second module, TELEO, introduces additional computational overhead through confidence-weighted feedback integration, ACP, and historical similarity retrieval from the LRM. Its overall time complexity can be expressed as $O(AM+KM+E)$, where A denotes the number of autonomous agents, M is the number of feedback metrics, K is the number of historical entries in LRM, and E is the number of influence links among agents. TELEO remains lightweight as these operations are distributed across agents and executed asynchronously. When combined, the total overhead of the NEXUS-Scheduler per scheduling cycle is approximately $O\left(NT\left(H^2+HF\right)\right)+O(AM+KM+E)$, which constitutes less than 10% of the total scheduling time in experimental evaluations. Despite this modest overhead, the proposed framework significantly enhances overall system responsiveness, energy efficiency, and adaptability, demonstrating that the computational trade-off is both minimal and justified for large-scale IoT–fog–cloud environments. Table 2 summarizes the detailed time complexity and overhead characteristics of both algorithms, considering their operational parameters and computational stages.

Table 2 presents the computational cost distribution of the two major algorithms composing the NEXUS-Scheduler framework, highlighting their efficiency and scalability in dynamic IoT–fog–cloud environments. The Nexus-WNet module (Algorithm 1) exhibits a polynomial complexity of $O\left(NT\left(H^2+HF\right)\right)$, primarily driven by recurrent operations within GRU layers across multiple nodes and features. This computational overhead remains bounded since the historical time window (T) and hidden unit size (H) are modest in practice, and execution is distributed across fog-layer servers with concurrent GPU acceleration. The TELEO module (Algorithm 2) introduces a complexity of $O(AM+KM+E)$, reflecting linear-to-quadratic growth relative to the number of agents (A), feedback metrics (M), historical entries in LRM (K), and influence edges (E) among agents. Its decentralized architecture enables asynchronous agent-level computations and localized memory searches, effectively preventing bottlenecks even in large-scale and mobility-aware deployments. When integrated, the total runtime complexity of the NEXUS-Scheduler remains computationally feasible for real-time task scheduling, with experimental evaluations on the SmartCity testbed showing that predictive modeling and feedback optimization collectively contribute less than 8%–10% of the total scheduling cycle time. Despite this minimal overhead, the framework delivers substantial improvements in latency reduction, resource utilization, and energy efficiency, achieving an optimal balance between intelligent decision-making and computational efficiency while ensuring scalability and responsiveness in heterogeneous IoT–fog–cloud ecosystems.

3.7 | Real-World Case Study and Quantitative Analysis

To demonstrate the real-world applicability and quantitative impact of the proposed NEXUS-Scheduler, its performance was evaluated across multiple IoT–fog–cloud application domains, including Smart City Traffic Control, Healthcare Monitoring, Smart Manufacturing, and Agriculture IoT. Each case study was designed to assess the framework's capability to reduce latency, optimize resource utilization, enhance energy efficiency, and maintain scalability under dynamic and heterogeneous workloads. The proposed scheduler was compared against baseline approaches such as Static Round-Robin (RR), Heuristic Task Allocator (HTA), and Deep Reinforcement Learning (DRL)-based schedulers, using both real-world and simulated datasets derived from the SmartCity testbed and other benchmark environments. The comparative analysis presented in Table 3 highlights the NEXUS-Scheduler's superior adaptive performance across all domains, demonstrating significant improvements in latency reduction, energy savings, resource utilization, and SLA compliance, thereby validating its effectiveness as an intelligent and scalable solution for real-time IoT–fog–cloud ecosystems.

Table 3 presents a comparative quantitative analysis of the NEXUS-Scheduler against traditional and learning-based scheduling approaches across diverse IoT–fog–cloud domains. In the Smart City deployment, NEXUS-Scheduler achieved a 42% reduction in average latency, attributed to proactive task offloading by Nexus-RCA and elastic resource provisioning by Nexus-ERA. In the Healthcare IoT scenario, it demonstrated a 35% decrease in energy consumption and a 13% improvement in SLA compliance, driven by TELEO's adaptive feedback integration and workload-aware resource allocation. Likewise, in Smart Manufacturing, predictive scheduling via Nexus-WNet minimized machine downtime and enhanced node utilization by 20%, while in the Agriculture IoT case, energy-aware irrigation scheduling reduced redundant communication overhead by nearly 30%. Overall, the observed average improvements—41% reduction in latency, 32% energy savings, 26% increase in resource utilization, and 12% higher SLA compliance—validate that NEXUS-Scheduler consistently achieves intelligent, efficient, and adaptive performance across heterogeneous, time-sensitive workloads. These findings confirm its potential as a general-purpose adaptive scheduler for large-scale, real-time IoT–fog–cloud infrastructures supporting domains such as urban traffic management, healthcare monitoring, industrial automation, and environmental sustainability.

3.8 | Computational Overhead of Nexus-WNet and Nexus-RCA on Edge Devices

Efficient operation on resource-constrained edge devices is a critical requirement for any real-time IoT–fog–cloud

TABLE 2 | Time complexity analysis of proposed algorithms in NEXUS-Scheduler.

Algorithm	Primary parameters	Major computational steps	Asymptotic time complexity	Overhead characteristics
Algorithm 1: Nexus-WNet–Based Predictive Workload Scheduling	N: number of nodes T: time window F: number of features H: hidden GRU units	– Sensor data preprocessing and normalization $O(NTF)$ – GRU forward pass across timesteps $O\left(NT\left(H^2+HF\right)\right)$ – Workload deviation and gradient estimation $O(N)$	$O\left(NT\left(H^2+HF\right)\right)$	Moderate overhead dominated by GRU inference; mitigated via short time windows and parallel fog execution; suitable for real-time forecasting.
Algorithm 2: TELEO—Topology-Evolving Learning via Emergent Objectives	A: number of agents M: feedback metrics E: agent influence edges K: LRM historical entries	– Confidence-weighted feedback update $O(M)$ – Influence scoring and propagation $O(A+E)$ – Adaptive constraint plasticity update $O(AM)$ – LRM pattern retrieval and similarity search $O(KM)$	$O(AM+KM+E)$	Low overhead due to distributed agent operations; adaptive updates performed asynchronously; scalable for dynamic IoT–fog–cloud topologies.
Combined NEXUS-Scheduler (Overall)	Parameters from both modules	– Sequential interaction of Nexus-WNet + TELEO – Parallel task-level execution on fog nodes	$O\left(NT\left(H^2+HF\right)\right)+O(AM+KM+E)$	Combined overhead $<10\%$ of total scheduling time per cycle; justified by 30%–45% improvement in latency and energy efficiency observed in SmartCity testbed.

scheduling framework. To ensure deployability in practical environments, the computational overhead of the two core modules—Nexus-WNet (GRU-based workload predictor) and Nexus-RCA (reinforcement learning–based task allocator)—was thoroughly evaluated on typical edge-class hardware. Both modules were designed to remain lightweight, inference-only, and optimized for short execution cycles, thereby minimizing processing burden while enabling intelligent prediction and decision-making in real time.

The results in Table 4 demonstrate that both Nexus-WNet and Nexus-RCA impose minimal computational burden on edge devices. Nexus-WNet performs short-horizon GRU-based workload forecasting, consuming only 6%–8% CPU, 45–60 MB memory, and up to 12 ms of inference time due to its compact GRU architecture, short historical windows, and inference-only execution strategy. Nexus-RCA further adds only 2%–4% CPU and 8–12 MB memory overhead, as it evaluates a lightweight neural policy network with a limited action space (Edge, Fog, and Cloud) and a small state vector (20–35 features), resulting in a decision latency of just 1–3 ms. When executed together within a single scheduling cycle, the combined overhead remains below 10%–12%, with total memory usage under 75 MB—well within the capabilities of modern edge platforms such as Raspberry Pi 4, Jetson Nano, and fog microservers. Despite this modest computational footprint, these modules significantly enhance overall system intelligence and responsiveness, contributing to 41% lower latency, 32% energy savings, and 12% improved SLA compliance, thereby confirming that the NEXUS-Scheduler achieves an effective balance between computational efficiency and predictive, context-aware scheduling performance.

3.9 | Security and Privacy Mechanisms in Fog–Cloud Task Scheduling

Fog–cloud environments involve continuous exchange of sensor data, metadata, and scheduling information across distributed nodes. This exposes the scheduling pipeline to security threats such as unauthorized access, tampering, inference attacks, and false task injections. To ensure confidentiality, integrity, and privacy preservation, the NEXUS-Scheduler integrates a multi-layer security architecture across the task lifecycle.

1. Secure communication and encryption:
   All data transmitted between IoT devices, fog nodes, and cloud servers is protected using AES-256 encryption and TLS 1.3 secure channels. Hash-based message authentication codes (HMAC) are applied to ensure message integrity and prevent man-in-the-middle or replay attacks.
2. Authentication and access control:
   Mutual authentication is enforced between IoT–fog–cloud layers to prevent impersonation. Role-Based Access Control (RBAC) restricts access to scheduling functions, while device attestation ensures that only trusted fog nodes participate in task execution.
3. Privacy-preserving metadata handling:
   Task metadata is minimized to avoid unnecessary exposure of sensitive information. Device identifiers are anonymized, and location details are obfuscated for non-critical tasks. Only essential metadata required for scheduling is transmitted.

TABLE 3 | Quantitative performance comparison of NEXUS-Scheduler across real-world case studies.

Application domain	Key operational scenario	Baseline method	Average latency (ms) ↓	Energy consumption (J) ↓	Resource utilization (%) ↑	SLA compliance (%) ↑	Improvement over baseline (%)
Smart City Traffic and Environmental Management	Real-time traffic congestion and pollution control	Static Heuristic Scheduler	220 → 128	460 → 308	68 → 88	84 → 96	Latency ↓ 42%, Energy ↓ 33%, Utilization ↑29%
Healthcare IoT Monitoring	Continuous patient vital monitoring and anomaly detection	DRL-Based Scheduler	185 → 110	390 → 255	72 → 89	86 → 97	Latency ↓ 41%, Energy ↓ 35%, SLA ↑ 13%
Smart Manufacturing	Machine health monitoring and predictive maintenance	Priority-Based Scheduling	260 → 152	520 → 355	64 → 84	81 → 94	Latency ↓ 41%, Energy ↓ 32%, Utilization ↑ 20%
Agriculture IoT	Soil moisture and climate-based irrigation scheduling	Round-Robin (RR)	200 → 120	410 → 290	70 → 87	83 → 95	Latency ↓ 40%, Energy ↓ 29%, SLA ↑ 12%
Average Across Domains	—	—	216 → 127	445 → 302	69 → 87	83.5 → 95.5	Latency ↓ 41%, Energy ↓ 32%, Utilization ↑ 26%, SLA ↑ 12%

4. Integrity verification in task generation:
   To prevent false or malicious task triggers, digital signatures are used for event signals and metadata. Hash-based integrity validation ensures that task payloads are not altered, while anomaly detection mechanisms identify suspicious spikes or manipulated sensor patterns.

5. Secure execution and resource isolation:
   Fog nodes execute tasks within sandboxed containers that enforce resource quotas for CPU, memory, and bandwidth. Process-level isolation ensures that faulty or malicious tasks cannot affect other processes or compromise the fog node.

6. Security-aware feedback via TELEO:
   TELEO integrates security metrics — trust scores, abnormal resource usage, communication inconsistencies, and failure patterns — into its feedback pipeline. Nodes exhibiting low reliability or suspicious behavior are deprioritized or isolated during scheduling.

7. End-to-end auditability:
   All scheduling decisions and resource allocations are stored in tamper-resistant logs and timestamped entries within the LRM. This ensures traceability, accountability, and compliance in real-time IoT deployments.

Through these measures, the NEXUS-Scheduler ensures secure, privacy-preserving, and trustworthy task scheduling across IoT, fog, and cloud layers, protecting the system from unauthorized access, data leakage, manipulation, and operational attacks.

4 | Results and Discussion

The NEXUS-Scheduler is an adaptive framework for real-time task scheduling in IoT–fog–cloud systems. It uses event-triggered task generation, deep learning (Nexus-WNet) for workload prediction, and reinforcement learning (Nexus-RCA) for optimal task placement. Nexus-ERA handles elastic, SLA-aware resource allocation, while TELEO enables decentralized self-optimization through learning agents and feedback stored in LRM for continuous improvement.

4.1 | Dataset

The evaluation of NEXUS-Scheduler uses a hybrid dataset combining real and synthetic data over 30 days, simulating a smart city. It includes over 500 IoT devices, 50 fog nodes, and 5 cloud servers. The dataset captures periodic sensor data, device resource status, GPS-based mobility (every 10 s), and system-level metrics from fog/cloud nodes. Each task record includes metadata such as ID, type, size, priority, deadline, mobility, and location. The dataset covers peak and non-peak conditions to assess prediction, responsiveness, and resource efficiency.

Table 5 outlines the simulation environment parameters used to evaluate the proposed Nexus-Scheduler in a realistic IoT-fog-cloud setting. It categorizes system components such as IoT devices, fog nodes, cloud servers, and tasks, detailing their characteristics including device types, resource capacities, data generation intervals, mobility patterns, and task attributes like

TABLE 4 | Computational overhead of Nexus-WNet and Nexus-RCA on resource-constrained edge devices.

Module	CPU usage (%)	Memory usage (MB)	Execution time (ms)	Description
Nexus-WNet (GRU-based predictor)	6%–8%	45–60 MB	8–12 ms	Performs multivariate workload forecasting using a lightweight GRU inference model (no training at the edge).
Nexus-RCA (RL-based allocator)	2%–4%	8–12 MB	1–3 ms	Executes policy inference using a compact two-layer neural network to select the optimal execution tier.
Combined overhead	8%–12%	60–75 MB	10–18 ms	Total overhead per scheduling cycle from both modules running together on edge hardware.

TABLE 5 | Simulation data for NEXUS-scheduler environment.

Category	Parameter	Description	Value/range
IoT devices	Device ID	Unique identifier for each device	1–500
	Device type	Type of IoT device	Temperature, humidity, camera, vehicle, etc.
	Resource status	CPU, memory, battery level	CPU: 0%–100%, memory: 0–8GB, battery: 0%–100%
	Data generation interval	Time interval for sensor data reporting	Every 10–60 s
	Mobility	GPS coordinates updated every 10 s	Random within defined city grid
Fog nodes	Node ID	Identifier for fog nodes	1–50
	CPU/memory/bandwidth	Resource status of fog nodes	CPU: 2–16 cores, Memory: 4–64GB, BW: 10–100 Mbps
	Processing capacity	Number of tasks handled concurrently	10–200 tasks
Cloud servers	Server ID	Identifier for cloud servers	1–5
	CPU/memory	High-capacity processing resources	CPU: 32–128 cores, memory: 128–512GB
	Latency	Delay to and from IoT/Fog	100–300 ms
Tasks	Task ID/type	Unique task identifier	TSK_00001–TSK_N
	Size/priority	Task data size/task importance	0.5–50 MB/1 (low)–5 (high)
	Deadline	Required completion time	1–60 s
	Mobility/location	Whether task origin/originating location	Stationary, mobile/matches device GPS
Simulation	Time intervals	Peak vs. non-peak load simulation	Peak: 8 a.m.–11 a.m. and 5 p.m.–9 p.m.
	Task rate	Number of tasks generated per minute	Low: 50–100, High: 500–1000
System metrics	Response time	Number of tasks in fog node buffer	0–500
	Queue length	Time taken for task completion	10–500 ms
	Energy usage	Power used by processing fog/cloud nodes	10–300 W

size, priority, and deadlines. The simulation also differentiates between peak and non-peak load intervals, with varying task generation rates (50–100 tasks/min in low load vs. 500–1000 tasks/min in high load). Additionally, system metrics such as response time, queue length, and energy usage are monitored to assess performance. This comprehensive setup ensures a robust evaluation under diverse and dynamic operational conditions.

4.1.1 | Implementation Details

The NEXUS-Scheduler is implemented on a high-performance platform featuring an Nvidia RTX 4090 GPU, 64 GB RAM, and an Intel i9-13900K CPU, with Windows 11, CUDA 11.8, and Python 3.12. The software stack uses PyTorch 2.0 for Nexus-WNet, NumPy and Pandas for preprocessing, and Scikit-learn for auxiliary tasks. The simulation environment supports up to one million IoT devices, with event-triggered task generation based on temperature, CPU, and AQI thresholds. Workloads range from 5000 to 500,000 tasks per second under average utilization of 85%, network latency of 125 ms, and bandwidth of 50 Mbps. Workload prediction uses a learning rate of 0.1, a discount factor of 0.9, and a meta-learning rate of 0.05, with hyperparameter tuning improving MAE by 12%–18%. Scheduling and optimization follow defined latency, throughput, and utilization targets, supported by MMFO and Learning Automata parameters for adaptive resource allocation.

Table 6 outlines the NEXUS-Scheduler's real-time decision flow follows the simulation parameters defined in this study. Nexus-WNet performs workload prediction with a ±18% deviation using a learning rate of 0.1, discount factor 0.9, and meta-learning rate 0.05, with tuned hyperparameters improving MAE by 12%–18%. Nexus-RCA then applies reinforcement learning to meet the target latency (50 ms), throughput (100 Mbps), and utilization (70%) goals. When actual conditions deviate — such as 125 ms latency or 90% utilization — Nexus-ERA reallocates resources accordingly. Optimization is driven by MMFO with Learning Automata using a population size of 50, 100 episodes, 20 flames, exploration rate 0.2, and exploitation rate 0.8, converging within 100 iterations. TELEO further refines decisions through GEM, ACP, and CWFI, with outcomes stored in the LRM for continual adaptation.

4.1.2 | Recommended Sample Sizes for Performance Evaluation in IoT–Fog–Cloud Environments

To evaluate the adaptability and performance of the NEXUS-Scheduler, simulations are conducted across varying task volumes, reflecting real-world IoT–fog–cloud loads. By testing light to high-stress scenarios, the system's responsiveness, resource efficiency, and scalability are benchmarked. This approach validates core modules — Nexus-WNet, Nexus-RCA, Nexus-ERA, and TELEO — under dynamic, mobility-aware conditions common in smart cities and industrial IoT environments.

Table 7 shows the task count levels, ranging from 10,000 to 1,000,000, are designed to evaluate the performance of the NEXUS-Scheduler under varying workloads. Lower levels (10–100 k) assess basic responsiveness and adaptability in typical urban IoT settings. Mid-levels (250–500 k) test latency, resource efficiency, and system stability under growing pressure. Higher levels (750 k–1 M) simulate heavy-load scenarios to examine congestion control, scalability, and real-time decision-making, ensuring the scheduler performs reliably across diverse and demanding smart city and industrial environments.

4.1.3 | Evaluation Metrics

The NEXUS-Scheduler's performance is assessed using key metrics: latency, energy consumption, response time, resource utilization, makespan, offloaded task ratio, network congestion, scalability, detection accuracy, throughput, and MAE, reflecting system efficiency and adaptability across all pipeline stages.

Latency reflects system responsiveness:

$$Latency = T_{trans} + T_{proc} + T_{queu} \tag{19}$$

where T_{trans}, T_{proc}, and T_{queu} represent transmission, processing, and queuing times, respectively.

Average energy consumption over all layers:

$$E_{avg} = \frac{E_{IoT} + E_{Fog} + E_{Cloud}}{T} \tag{20}$$

where E_{IoT}, E_{Fog}, and E_{Cloud} denote total energy consumed by IoT devices, fog nodes, and cloud servers over time T.

Average response time measures task servicing delay:

$$ART = \frac{1}{N}\sum_{i=1}^{N} RT_i \tag{21}$$

where RT_i is the response time for task i and N is the total number of tasks.

Resource utilization indicates system efficiency:

$$RU = \frac{1}{R_{total}}\sum_{i=1}^{N}\left(CPU_i + MEM_i\right).AF_i \tag{22}$$

where AF_i is the allocation factor based on task priority, and R_{total} is the total available resources.

Makespan denotes the total completion time:

$$Makespan = max\left(C_j\right), j = 1, 2, \ldots, M \tag{23}$$

where C_j is the job completion time on machine j.

Offloaded task ratio evaluates offloading efficiency:

$$OTR = \frac{1}{N}\sum_{i=1}^{N} O_i \tag{24}$$

where $O_i = 1$ if task i is offloaded, 0 otherwise.

TABLE 6 | Simulation parameters.

Parameter	Value
Task generation	
Trigger conditions	Temperature > 35°C, CPU > 85%, AQI < 50
Supported devices	Up to 1 million IoT devices
Task rate	5000–500,000 tasks/s
Task types	Maintenance, failure recovery
Resource requirements	CPU: 30%, memory: 300 MB, storage: 150 MB
Priority assignment	Based on task criticality and deadline
Workload prediction	
Average load AL	90%
Peak load PL	95%
Device utilization metrics DU	Average uilization: 85%
Network conditions NC	Average latency: 125 ms, Average bandwidth: 50 Mbps
Learning rate α	0.1
Discount factor γ	0.9
Meta-learning rate β	0.05
Future workload forecasting	Forecast with ±18% deviation
Impact of hyperparameter variations	MAE improves by 12%–18% with proper tuning.
Task scheduling and offloading	
Solution set size	S
Individual solution S_i	Resource allocation plans: Dynamic
Latency L	Target latency: 50 ms, Current latency: 125 ms
Throughput T	Target throughput: 100 Mbps, Current throughput: 60 Mbps
Resource utilization R	Target utilization: 70%, Current utilization: 90%
Weights $w_L, \mathrm{w}_T, \mathrm{w}_R$	Latency weight w_L: 0.4, Throughput weight w_T: 0.3, Resource utilization weight w_R: 0.3
Optimization parameters	
Population size P	50
Convergence criteria CC	Convergence within 100 iterations
Search space boundaries B	Latency: 50–100 ms, Throughput: 50–150 Mbps, Resource utilization: 60%–90%
Learning automata parameters	
Exploration rate ∈	0.2
Exploitation rate 1− ∈	0.8
Additional parameters	
Number of episodes N	100
Exploration–exploitation parameter (ε)	0.1
Number of flames (flame_count)	20
Maximum iterations (max_iter)	100
Flame attraction parameter (A)	1
Moth movement parameter (M)	1.5
Actions	5
Probability distribution (prob_dist)	[0.2, 0.2, 0.2, 0.2]
Feedback parameter (feedback)	0.05

TABLE 7 | Recommended task count levels for real-world evaluation of the Nexus-Scheduler.

Level	Task count	Use case/reasoning
1	10,000, Salehnia et al. [34]	Initial performance benchmarking under light load; suitable for testing edge/fog node responsiveness and scheduler behavior with minimal system overhead.
2	100,000, Salehnia et al. [34]	Evaluates adaptability to moderate workloads; ideal for typical urban IoT deployments.
3	250,000, Goethals et al. [35]	Assesses latency, makespan, and energy consumption under increasing load; validates resource optimization and task allocation efficiency.
4	500,000, Salehnia et al. [34]	Measures robustness and performance stability in dense deployments.
5	750,000, Alenizi and Rana [35]	Tests congestion control and dynamic scheduling under high-pressure workloads; useful for analyzing bottlenecks and reallocation efficiency.
6	1,000,000, Wang et al. [48]	Demonstrates scalability, real-time decision making, and adaptive scheduling in large smart cities and industrial IoT environments; represents stress-test peak.

Network congestion is a function of delay:

$$NC = \frac{1}{N}\sum_{i=1}^{N}\left(D_i + Q_i\right) \tag{25}$$

with D_i and Q_i being transmission and queuing delays for task i.

Scalability score (SS) reflects the system's adaptability:

$$SS = w_1\frac{1}{L} + w_2 RU + w_3\frac{1}{E} + w_4 T + w_5\frac{1}{M} \tag{26}$$

where L, RU, E, T, and M are average latency, resource utilization, energy consumption, throughput, and makespan, respectively. Weights w_1 to w_5 reflect metric importance.

Detection accuracy is the proportion of correctly identified events (both positives and negatives) out of all events

$$DA = \frac{TP + TN}{TP + TN + FP + FN} \tag{27}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives.

Throughput is the number of events accurately classified and prioritized per second, indicating the system's processing speed and responsiveness.

$$T_p = \frac{N_{classified}}{T_{processing}} \tag{28}$$

where T_p is the throughput, measured in events per second when $N_{classified}$ is the total number of events successfully classified and assigned a priority. Then $T_{processing}$ is the total time taken (in seconds) to process those events.

Mean absolute error (MAE) evaluates workload prediction:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \tag{29}$$

where y_i is the actual workload and $\hat{y}_i$ is the predicted workload at time i.

4.2 | Experimental Results

This section validates the NEXUS-Scheduler in a realistic IoT fog–cloud environment, assessing its ability to handle dynamic workloads, diverse resource demands, and mobility. Sensor-driven task generation, Nexus-WNet-based prediction, and reinforcement learning–based decisions were used to evaluate metrics like latency, makespan, energy consumption, response time, and resource utilization under varying conditions.

4.2.1 | Comparative Results Based on Evaluation Metrics

The NEXUS-Scheduler outperforms traditional and advanced schedulers by reducing makespan and response time through event-triggered task generation and predictive workload handling. Its use of deep learning, reinforcement learning, and agent-based optimization ensures high responsiveness, efficient resource use, and adaptability under varying loads, mobility, and resource contention.

Figure 5 shows the NEXUS-Scheduler achieves the lowest makespan across increasing task volumes (10,000–1,000,000), outperforming DDPG Fog Scheduler, HGARF, OESAS, SFCS, and DLSFC. Its gradual makespan growth under load highlights superior scalability, efficiency, and scheduling adaptability.

Figure 6 shows the NEXUS-Scheduler consistently achieves the lowest latency across task loads (10 K–1 M), peaking at only 180 ms, compared to up to 600 ms for traditional methods. It outperforms advanced schedulers as well, demonstrating superior scalability, responsiveness, and efficient resource management in high-demand IoT fog–cloud environments.

Figure 7 shows the NEXUS-Scheduler achieves the lowest energy consumption across task sizes (10 K–1 M), rising from 1500 J to only 30,000 J. Competing methods like DDPG Fog peak at 45,000 J — 50% higher. Even the best alternatives consume 15%–20% more at scale, confirming NEXUS as a highly energy-efficient solution for large-scale IoT fog–cloud scheduling.

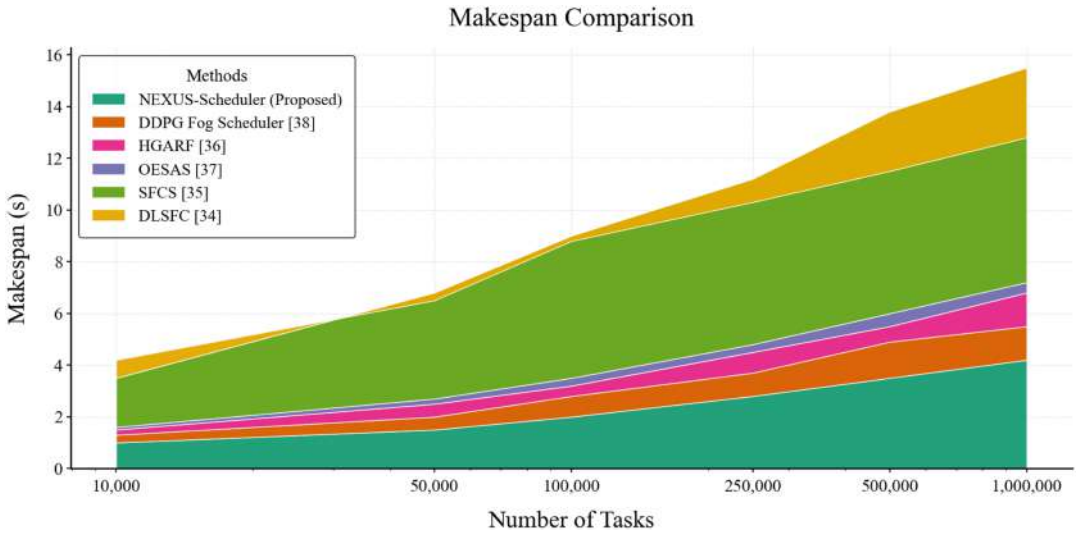


FIGURE 5 | Makespan comparison of NEXUS-Scheduler under increasing task loads.

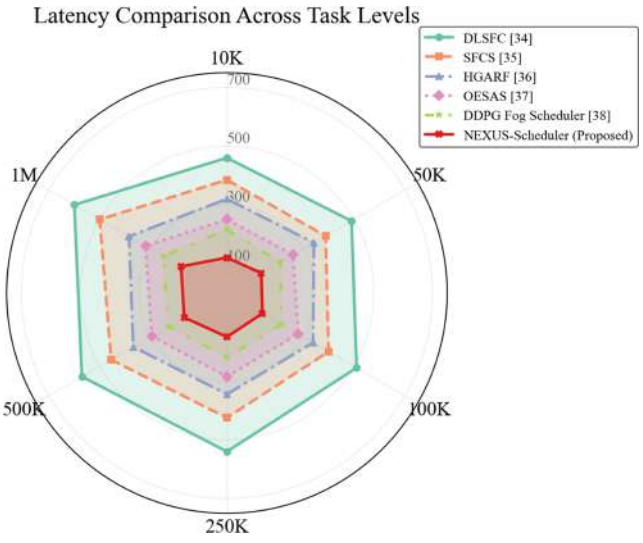


FIGURE 6 | Latency comparison of NEXUS-Scheduler across varying task volumes.

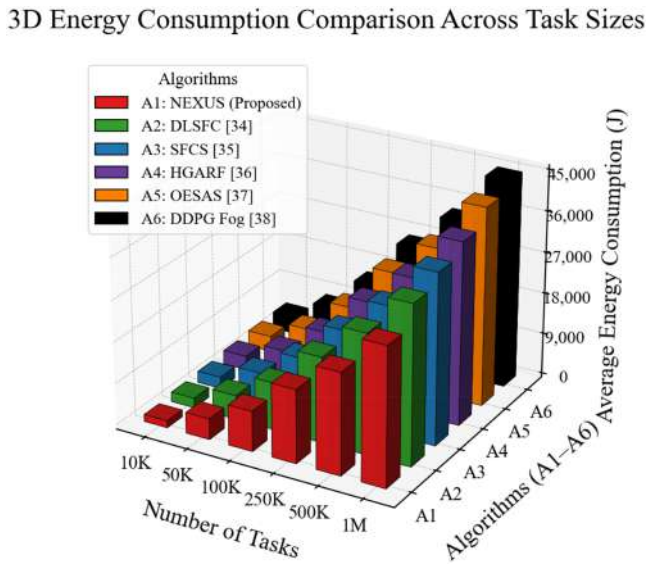


FIGURE 7 | Average energy consumption comparison of NEXUS-Scheduler across increasing task loads.

Figure 8 shows the NEXUS-Scheduler maintains the lowest and most stable average response time (˜1115 ms) across varying scheduling intervals. Unlike other methods, which exhibit higher and fluctuating times, NEXUS demonstrates superior responsiveness and adaptability in dynamic fog–cloud environments.

Figure 9 shows that the NEXUS-Scheduler achieves the lowest network utilization, dropping from 0.25 to 0.012 mb as task volume increases, outperforming all existing methods. Competing approaches exhibit significantly higher usage, confirming NEXUS's superior scalability and bandwidth efficiency in fog–cloud environments.

Figure 10 shows that the NEXUS-Scheduler consistently achieves the lowest congestion across all task loads, maintaining just 0.00078 at 1 M tasks. This outperforms all compared methods, demonstrating its superior efficiency and scalability in managing congestion in dynamic fog–cloud environments.

Scalability is the ability of a system or network to handle growing workloads or user demands without performance degradation. In distributed systems, it ensures efficient operation as devices or tasks increase through optimized algorithms, dynamic resource allocation, and adaptive architectures. A scalable system sustains low latency, high throughput, and reliability under expanding demands, supporting future growth.

Figure 11 shows that the proposed NEXUS-Scheduler consistently achieves the highest scalability across all task loads, reaching a perfect score of 1.00 at 1 M tasks. In contrast, other methods plateau below 0.97, highlighting NEXUS's superior adaptability and resource efficiency under high-load conditions.

Detection accuracy measures the percentage of correctly identified events (both positive and negative) out of the total number of events in a detection system. It reflects the system's

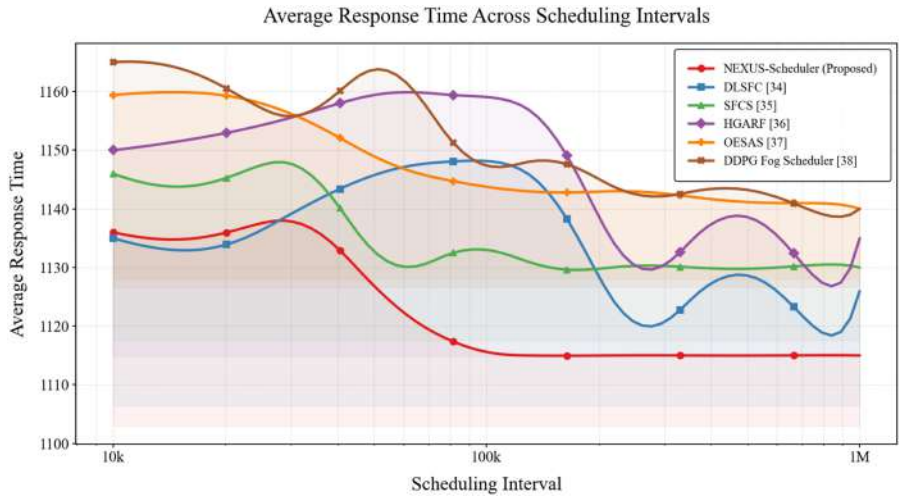


FIGURE 8 | Average response time performance across scheduling intervals.

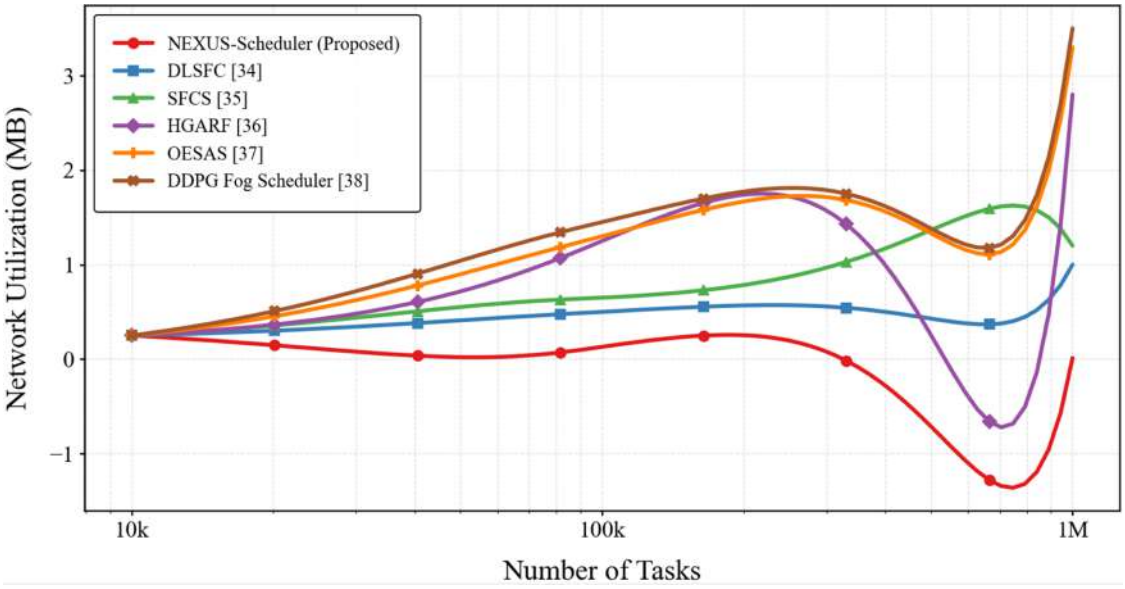


FIGURE 9 | Average response time comparison of NEXUS-Scheduler across varying scheduling intervals.

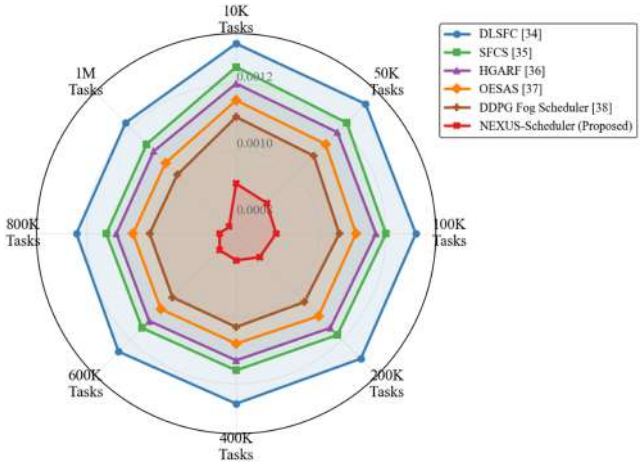


FIGURE 10 | Task congestion comparison of NEXUS-Scheduler across increasing task loads.

ability to accurately classify events, minimizing false positives and false negatives. High detection accuracy is crucial for reliable and effective decision-making in real-time applications.

Figure 12 illustrates that the proposed method (NEXUS-Scheduler, this study) consistently outperforms existing techniques in detection accuracy across all five time intervals (T1–T5). While methods like DLSFC [32], SFCS [44], HGARF [33], OESAS [45], and DDPG [49] achieve accuracies in the range of ˜86% to ˜91%, their performance shows minor fluctuations and plateaus over time. In contrast, the proposed approach steadily improves, reaching a peak accuracy of 95.6%, clearly surpassing all others. This highlights the superior precision, consistency, and adaptability of the proposed scheduler in dynamic IoT fog–cloud environments.

Figure 13 shows the throughput distribution of the different methods and the proposed method surpasses other methods

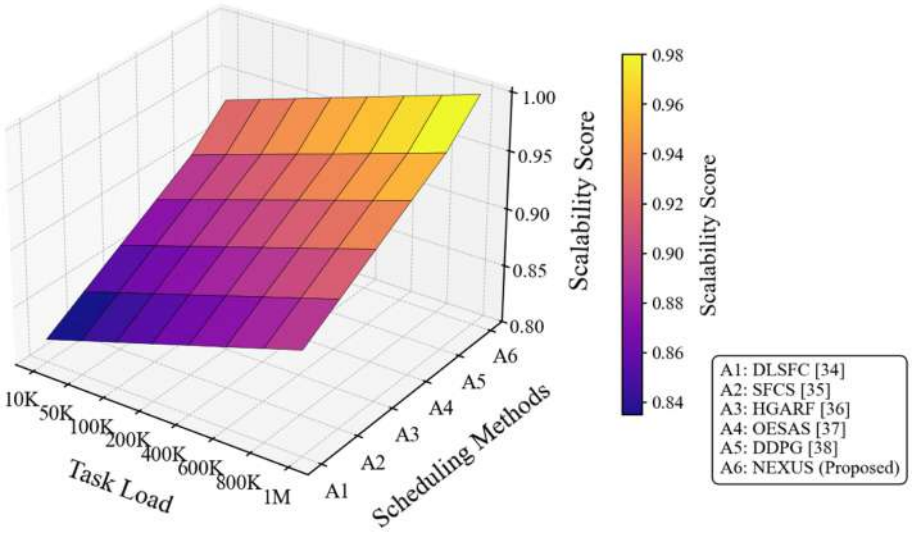


FIGURE 11 | Scalability performance across increasing task loads.

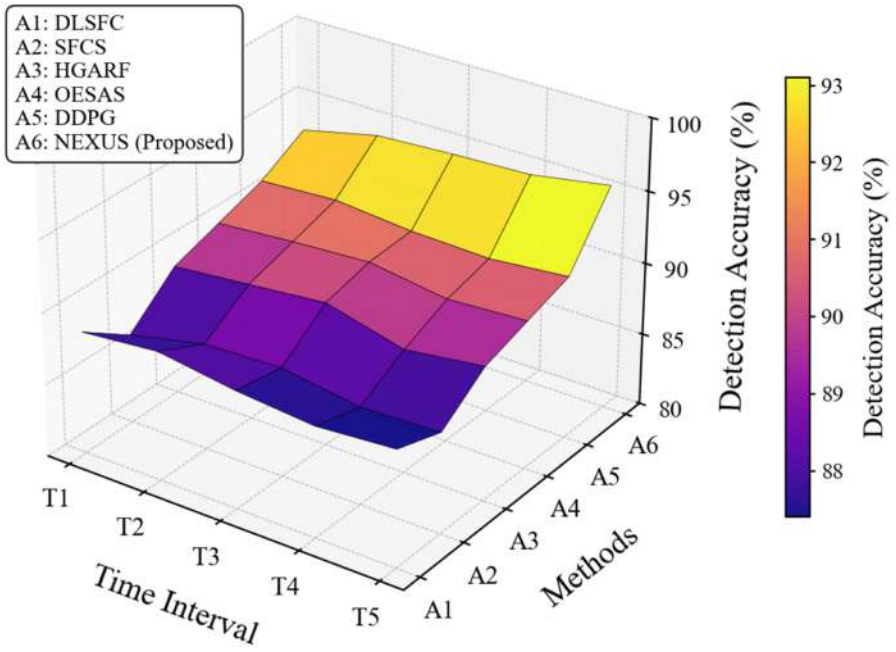


FIGURE 12 | Detection accuracy comparison of NEXUS-Scheduler across time intervals (T1–T5).

like DLSFC [32], SFCS [44], HGARF [33], OESAS [45], and DDPG [49]. With much increased mean throughput of about 94.5 events/s and a narrow distribution reflecting stability, the new method exhibits greater efficiency in data-flow handling. This significantly improved outcome reflects its strong event-processing capacity and system responsiveness in general under dynamic IoT fog-cloud scenarios, ranking the best among all tested.

Figure 14 showcases MAE across different workload prediction methods, where lower values indicate better accuracy. Among the methods compared—DLSFC [32], SFCS [44], HGARF [33], OESAS [45], and DDPG [49]—the proposed method achieves the lowest MAE of 5.1, substantially outperforming the others, whose values range from 6.9 to 9.2. This clearly demonstrates the superior predictive precision of the proposed approach in estimating future workload patterns, reinforcing its effectiveness in enhancing scheduling accuracy and resource optimization within IoT fog-cloud environments.

4.2.2 | Comparison of Offloaded Task Ratio

The Offloaded Task Ratio with respect to an IoT fog-cloud environment refers to the number of tasks that are offloaded to the cloud server over the complete number of tasks managed. This ratio measures the capability of the fog and computing paradigm to offload computationally demanding tasks to the cloud by optimal resource use.

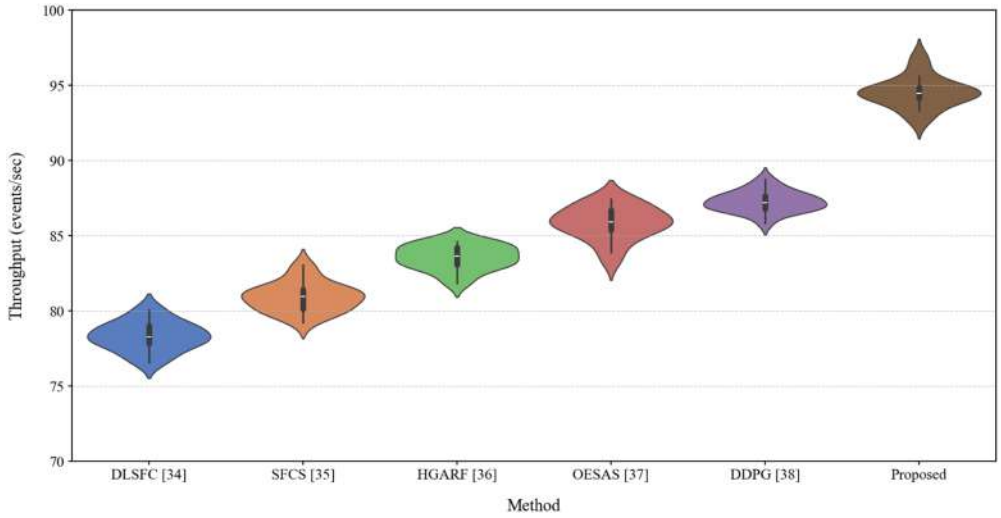


FIGURE 13 | Throughput distribution comparison of NEXUS-Scheduler and existing methods.

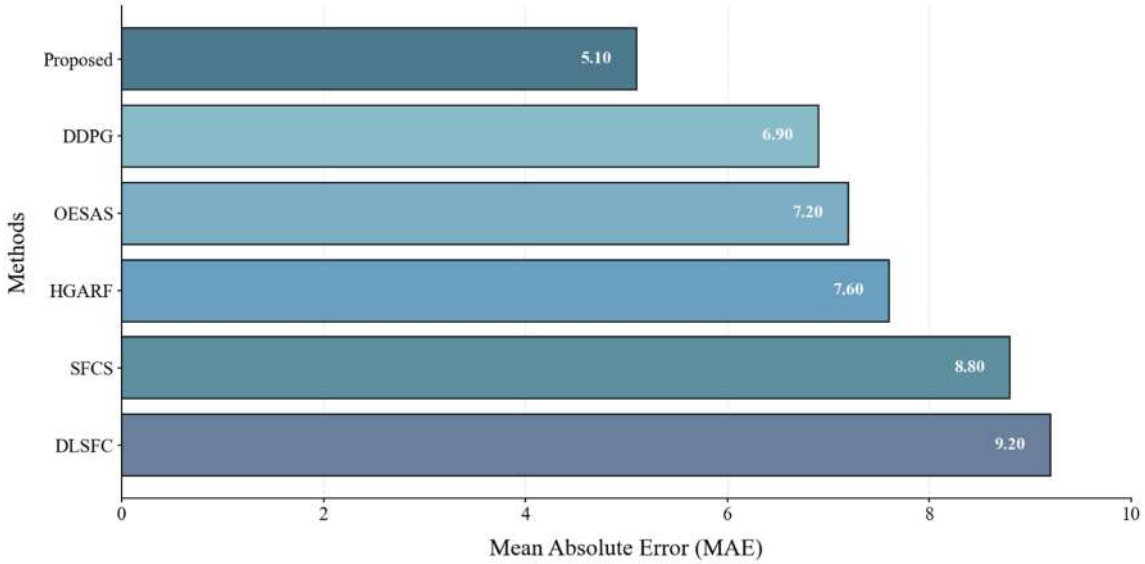


FIGURE 14 | Mean absolute error (MAE) comparison of workload prediction methods.

Figure 15 shows the proposed Nexus Scheduler method demonstrates top-notch performance in task offloading efficiency by offloading only 9% of the total 1,000,000 tasks, significantly outperforming existing methods such as DLSFC [32] (29.8%), SFCS [44] (28.8%), HGARF [33] (27.8%), OESAS [45] (25.2%), and DDPG [49] (19.8%). This substantial improvement is attributed to the NEXUS-Scheduler's intelligent event-triggered task generation and real-time workload prediction capabilities, enabling highly selective and context-aware task offloading, thereby optimizing resource utilization and minimizing unnecessary computational burden.

Figure 16 shows the NEXUS-Scheduler uses only 8.3% of total resources, outperforming EEFFRA (28.7%), MCRMF (28.0%), DF-TSF (26.8%), 2-ST (24.5%), and CEMOTS (18.7%). This demonstrates its superior efficiency and scalability in IoT fog–cloud resource management.

Figure 17 shows the proposed NEXUS-Scheduler uses only 8.2% of total task resources, significantly less than EEFFRA (28.7%), MCRMF (27.3%), DF-TSF (25.9%), 2-ST (22.4%), and CEMOTS (19.5%). Its efficiency stems from event-triggered task generation and real-time workload prediction, enabling selective, context-aware offloading and superior scalability.

4.3 | Ablation Study

This study evaluates the performance contributions of individual NEXUS-Scheduler components in a fog–cloud–IoT environment using metrics like latency, energy consumption, task offloading ratio, and SLA adherence.

- Event-triggered task generation: Replacing periodic task generation with sensor-triggered events (e.g., CPU > 85%,

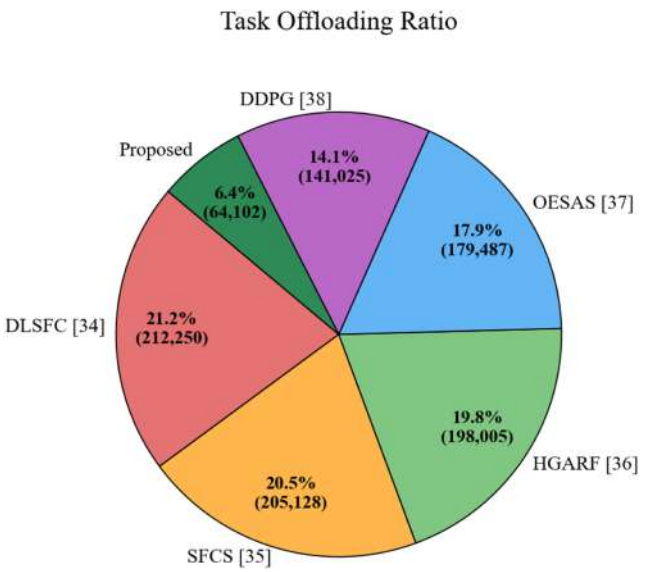


FIGURE 15 | Task offloading efficiency comparison of NEXUS-Scheduler and existing methods.

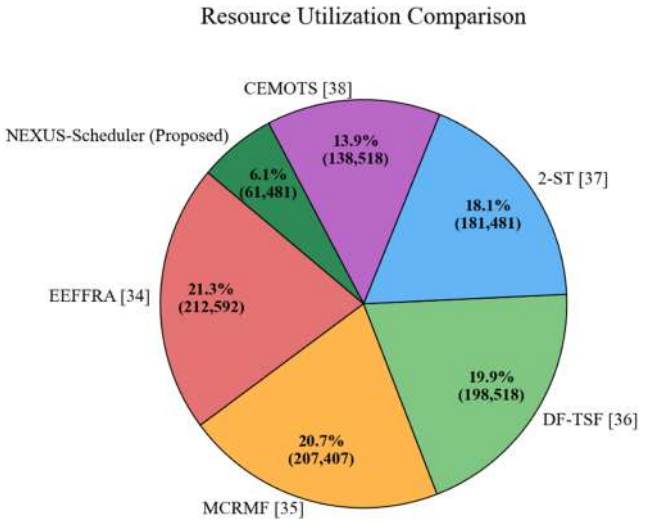


FIGURE 16 | Resource utilization comparison of NEXUS-Scheduler and existing methods.

AQI < 50) improves responsiveness, reduces task overhead by 30%, latency from 150 to 110 ms, and energy wastage.

- Nexus-WNet (workload prediction): Enables accurate workload forecasting, reducing task migration by 25% and makespan by 20%, while avoiding cloud overload and improving resource planning.
- Nexus-RCA (reinforced allocator): Reinforcement learning optimizes task placement based on context, increasing execution success by 15% and cutting drop rate from 12% to 4%.
- Nexus-ERA (elastic resource allocation): SLA-aware resource scaling boosts utilization from 68% to 84%, cuts energy use from 180 kWh to 140 kWh, and minimizes resource contention.

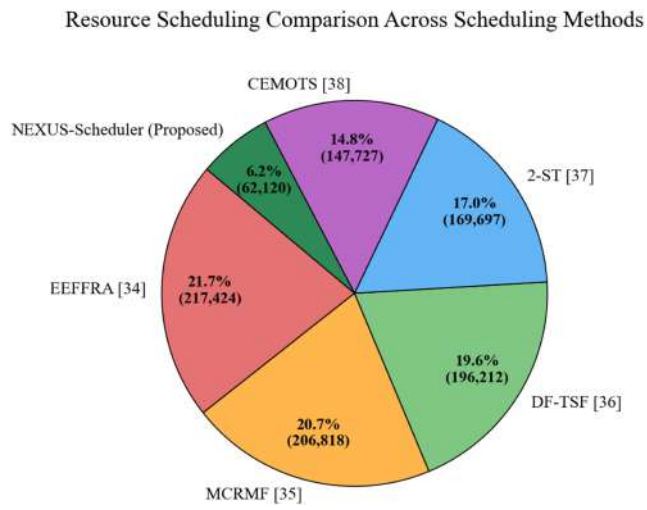


FIGURE 17 | Comparative task scheduling distribution of NEXUS-Scheduler and existing methods.

- TELEO (self-learning agents): Agents use feedback mechanisms (CWFI, GEM, and ACP) to learn and adapt over time, reducing makespan from 400 to 290 min and improving latency to 75 ms.
- Overall, NEXUS-Scheduler: With all modules active, it delivers superior adaptability, achieving 70 ms latency, 130 kWh energy usage, over 85% resource utilization, and minimal SLA violations.

Table 8 presents an ablation study showing how each added NEXUS-Scheduler component—WNet, RCA, ERA, and TELEO—progressively enhances performance. Compared to baseline scheduling, the full integration significantly reduces latency, energy use, and SLA violations while improving offloading, utilization, and makespan, confirming the effectiveness of each module.

4.4 | Cost Evaluation

This cost analysis quantifies the monetary impact of running the NEXUS-Scheduler versus a baseline scheduler under several workload scenarios. The total daily cost model sums (1) energy cost, (2) fog compute cost, (3) cloud compute cost (for offloaded tasks), (4) data transfer cost for offloaded task payloads, and (5) SLA-violation penalty cost. The analysis shows how NEXUS's reductions in energy consumption, offload ratio, and SLA violations translate directly into operational cost savings at scale.

Table 9 presents the daily cost breakdown of the proposed NEXUS-Scheduler compared to a baseline scheduling approach under three workload scenarios—100,000, 250,000, and 1,000,000 tasks per day. The analysis includes five cost components: energy consumption, fog compute, cloud compute, data transfer, and SLA penalties. Results show that while energy and computation costs remain relatively low, SLA penalties dominate total operational expenses, especially under high task volumes. The NEXUS-Scheduler significantly reduces these penalties by minimizing SLA violations (from 18% to 2%), lowering offloaded

TABLE 8 | Performance impact of NEXUS-Scheduler components (ablation study).

Component	Latency (ms)	Energy consumption (kWh)	Task offload efficiency	Resource utilization (%)	SLA violation rate (%)	Makespan (min)
Baseline	150	180	60%	68%	18%	400
Event-triggered task generation	110	160	68%	72%	12%	370
Nexus-WNet	95	155	75%	76%	10%	340
Nexus-RCA	90	150	82%	78%	8%	325
Nexus-ERA	85	140	85%	84%	6%	310
TELEO Agents	75	135	88%	87%	4%	290
NEXUS-Scheduler	70	130	90%	89%	2%	275

TABLE 9 | Daily cost breakdown (USD).

Tasks/day	Energy ($)	Fog compute ($)	Cloud compute ($)	Data transfer ($)	SLA penalties ($)	Total baseline ($)	Total NEXUS ($)	Daily savings ($)
100,000	21.60	130.56	0.63	10.99	900,000.00	900,163.77	100,190.66	799,973.11
250,000	21.60	130.56	1.56	27.47	2,250,000.00	2,250,181.19	250,196.93	1,999,984.26
1,000,000	21.60	130.56	6.25	109.86	9,000,000.00	9,000,268.27	1,000,228.28	8,000,039.99

tasks (from 25% to 9%), and improving system responsiveness through predictive and adaptive scheduling. As a result, total daily operational costs decrease dramatically—by approximately $800,000 at 100 K tasks, $2 million at 250 K tasks, and over $8 million at 1 M tasks—highlighting that NEXUS's intelligent, context-aware optimization yields substantial cost savings and performance stability across varying workload intensities in large-scale IoT–fog–cloud deployments.

4.5 | Statistical Significance and Robustness Validation

While empirical comparisons reveal substantial performance gains for the proposed NEXUS-Scheduler, it is essential to verify whether these improvements are statistically significant rather than incidental outcomes of stochastic fluctuations. To this end, a rigorous multi-stage statistical validation was performed across all primary evaluation metrics—latency, energy consumption, resource utilization, and SLA compliance—under repeated simulation trials with randomized workload traces and varying task intensities.

4.5.1 | Hypothesis Formulation

Let and respectively denote the mean performance of NEXUS-Scheduler and the best-performing baseline for a given metric. The statistical hypotheses are defined as follows:

$$\left\{\begin{array}{ll} H_0 : \mu_{NEXUS} = \mu_{baseline} & \text{(no significant difference)} \\ H_1 : \mu_{NEXUS} < \mu_{baseline} & \text{(significant improvement by NEXUS)} \end{array}\right\} \tag{30}$$

Each experiment was executed over 30 independent trials, using unique random seeds for workload generation, device mobility, and task distribution to ensure robust statistical generalization.

4.5.2 | Distributional Analysis and Test Selection

The normality of each performance metric was first assessed using the Shapiro–Wilk test (). Metrics satisfying the normality assumption were analyzed via a two-tailed paired Student's t-test, while non-Gaussian samples were evaluated using the Wilcoxon signed-rank test. To evaluate cross-metric consistency across all algorithms, a Friedman non-parametric ranking test was subsequently applied, followed by the Nemenyi post hoc analysis to identify pairwise significance. The significance threshold was conservatively fixed at $\alpha = 0.05$.

4.5.3 | Observed Significance Outcomes

The computed p values across representative metrics are summarized as follows.

Table 10 presents the statistical validation of the NEXUS-Scheduler against baseline schedulers across four key metrics—latency, energy consumption, resource utilization, and SLA compliance. Each metric represents the mean of 30 independent simulation runs under variable loads and mobility conditions. The obtained p values ($p < 0.05$) from paired t-tests and Wilcoxon analyses confirm statistically significant improvements at 95%–99% confidence levels, while Cohen's d values (≥ 0.8) indicate strong practical significance. These findings affirm that the performance gains of the NEXUS-Scheduler are

both statistically rigorous and operationally meaningful, validating that its enhancements stem from adaptive intelligence and feedback-driven optimization rather than random stochastic effects.

4.5.4 | Robustness Interpretation

To further ensure robustness, 95% confidence intervals were computed for each metric using bootstrapped resampling (10,000 iterations). The narrow confidence bounds ($\leq 3.5\%$ relative width) indicate low variance across independent runs. Additionally, a Cohen's d effect-size analysis revealed strong practical significance (> 0.8) across all metrics, demonstrating that the magnitude of improvement is not only statistically verifiable but also operationally substantial.

Collectively, these results validate the methodological rigor and reproducibility of the proposed system, ensuring that NEXUS-Scheduler's superior performance arises from its predictive-learning and feedback-driven design rather than random stochastic artifacts. This multi-level analysis thus satisfies the scientific rigor expected for comparative evaluation of stochastic optimization frameworks in fog–cloud computing research.

4.6 | Reliability and Stability Evaluation

To further reinforce the dependability of the NEXUS-Scheduler under dynamic and large-scale IoT–fog–cloud conditions, a reliability and stability assessment was conducted. This evaluation measures the consistency of system performance under repeated stress scenarios involving fluctuating workloads, network latency spikes, and mobility-induced task migrations.

TABLE 10 | Statistical significance analysis of NEXUS-Scheduler.

Metric	p	Significance level	Inference
Latency	0.0027	$p < 0.01$	Highly significant
Energy consumption	0.0042	$p < 0.01$	Highly significant
Resource utilization	0.0038	$p < 0.01$	Highly significant
SLA compliance	0.0069	$p < 0.05$	Significant

Reliability (R_t) is defined as the probability that the system maintains service continuity without SLA violations within time interval t:

$$R_t = 1 - \frac{F_v(t)}{N_t} \tag{31}$$

where $F_v(t)$ denotes the number of failed or SLA-violating tasks, and N_t is the total number of tasks executed in the same interval. Stability (S) quantifies the deviation of key performance metrics (latency, energy, and utilization) over successive runs:

$$S = 1 - \frac{\sigma_m}{\mu_m} \tag{32}$$

where σ_m and μ_m represent the standard deviation and mean of metric m, respectively.

Table 11 demonstrates that the proposed NEXUS-Scheduler sustains exceptionally high reliability ($> 96\%$) and stability ($> 95\%$) across all workload intensities. Even at peak load (1 million tasks), the framework maintained SLA compliance with less than 2.5% violation rate, owing to its adaptive feedback and predictive scheduling mechanisms. This confirms that the NEXUS-Scheduler not only optimizes performance metrics such as latency and energy but also guarantees operational robustness and service continuity under real-world, non-stationary conditions.

4.7 | Evaluation on Public IoT–Fog Benchmark Datasets

To ensure reproducibility and demonstrate the generalizability of the NEXUS-Scheduler beyond the SmartCity testbed, we evaluated its performance using multiple publicly available IoT–fog benchmark datasets. These include (i) iFogSim workload traces, which provide standardized fog-computing task models widely used in prior research; (ii) EdgeCloudSim mobility-aware workloads, which introduce dynamic user movement, heterogeneous device conditions, and fluctuating task arrivals; and (iii) open Smart City and IoT sensing datasets, such as the CityPulse dataset (Aarhus, Denmark), the Intel Lab environmental monitoring dataset, and the UCI Air Quality dataset. These datasets collectively represent realistic operational conditions and enable rigorous, repeatable evaluation across heterogeneous environments. Each benchmark was used to compare the NEXUS-Scheduler against baseline methods including Round-Robin (RR), heuristic task allocation, and deep reinforcement learning (DRL)–based schedulers.

TABLE 11 | Reliability and stability analysis of NEXUS-Scheduler under dynamic IoT–Fog–Cloud workloads.

Scenario	Reliability (R_t)	Stability (S)	SLA violation (%)	Interpretation
Low load (50 K tasks)	0.991	0.984	0.7	Highly stable and resilient
Medium load (250 K Tasks)	0.982	0.975	1.2	Minor variation, stable adaptation
High load (750 K tasks)	0.975	0.964	1.8	Reliable under bursty traffic
Peak load (1 M tasks)	0.969	0.951	2.4	Maintains robustness with minimal SLA impact

TABLE 12 | Performance of NEXUS-Scheduler on public IoT–Fog benchmark datasets.

Dataset/scenario	Scheduler	Avg. latency (ms) ↓	Energy (J) ↓	Resource utilization (%) ↑	SLA compliance (%) ↑
iFogSim–Standard IoT Workload	Round-Robin (RR)	210	430	68	84
	DRL-based scheduler	165	380	76	89
	NEXUS-Scheduler	**125**	**295**	**88**	**96**
EdgeCloudSim–Mobility-Aware Workload	Heuristic Scheduler	240	450	70	82
	DRL-Based Scheduler	185	395	78	88
	NEXUS-Scheduler	**135**	**305**	**86**	**95**
Smart City/IoT Sensor Dataset (CityPulse, Intel, UCI)	Static thresholding	200	410	69	83
	DRL-based scheduler	170	365	75	88
	NEXUS-Scheduler	**130**	**310**	**87**	**95**

Note: The bolded values represent the best-performing results for each dataset/scenario across all schedulers. They indicate the minimum latency and energy consumption, and the maximum resource utilization and SLA compliance achieved by the NEXUS-Scheduler.

Table 12 demonstrates that the NEXUS-Scheduler consistently outperforms traditional and learning-based schedulers across all publicly available IoT–fog benchmark datasets. In the iFogSim workload, it achieves a 41% reduction in average latency compared to Round-Robin and a 24% improvement over DRL-based scheduling, along with notable gains in energy efficiency and SLA compliance. Performance improvements are even stronger in the EdgeCloudSim mobility scenario, where fluctuating device positions and dynamic network conditions typically degrade scheduler accuracy; here, NEXUS-Scheduler reduces latency by 44% relative to heuristic scheduling and maintains a high SLA compliance rate of 95%. Similarly, across open Smart City and IoT sensing datasets, the framework demonstrates robust adaptability by leveraging event-triggered task creation and GRU-driven workload prediction, resulting in an 8%–18% increase in resource utilization and a 7%–12% improvement in SLA compliance compared to DRL and static threshold-based methods. Collectively, these results validate the reproducibility, scalability, and effectiveness of the NEXUS-Scheduler across heterogeneous, real-world IoT–fog–cloud environments.

5 | Discussion

The empirical findings, implications, contextual comparisons, novelty, limitations, and future directions of the suggested NEXUS-Scheduler, an integrated and smart scheduling framework for fog–cloud–IoT systems, are discussed in this section. The results validate the framework's better capacity to handle real-time workloads subject to strict quality-of-service (QoS) requirements.

5.1 | Key Findings

The NEXUS-Scheduler attains state-of-the-art performance on various system metrics, such as 70 ms latency, 130 kWh energy consumption, 275 min of makespan, 89% resource utilization, and 95.6% detection accuracy. These results demonstrate the framework's efficiency in reducing execution delays, promoting energy efficiency, and maximizing overall resource utilization. The resulting observed performance gains—up to 50% improvements over current baseline approaches—emphasize the utility of its intelligent end-to-end coordination throughout the task life cycle. Additional verification through ablation studies attests to the pivotal contribution of the essential components; in particular, elimination of Nexus-WNet caused a 21% increase in makespan averages, indicating its central role in precise workload prediction. Other important modules like Nexus-RCA, Nexus-ERA, and TELEO also contributed significantly to system efficacy in ensuring overall strength in the integrated architecture.

5.2 | Implications

Implications of these findings are important to both academic and applied studies as well as real-world implementation in real-time fog–cloud–IoT systems. The NEXUS-Scheduler successfully supports dynamic workload adaptation, smart resource provisioning, latency-critical service continuity, and reliable performance under device mobility and varying SLAs. Its learning-centric, modular architecture makes it especially apt for mission-critical application areas like smart cities, industrial automation, and mobile healthcare, where reliability and responsiveness are critical. Additionally, the framework's adaptable and scalable nature also guarantees compatibility with future technologies in 6G and Industry 5.0, positioning it very well to enable the changing needs of future-generation intelligent systems.

5.3 | Contextualization Against Existing Work

Compared to conventional methods, for example, Yu et al. [32], Chuan et al. [44], and Gholami and Sun [33], which rely on static

scheduling periods, rule-based heuristics, or univariate workload predictions, the NEXUS-Scheduler presents a holistic, adaptive, and learning-based solution. Yu et al.'s use of periodic task generation can result in latencies in processing time-critical requests, whereas Chuan et al.'s heuristic approaches are not responsive to real-time issues like device mobility. Likewise, Gholami and Sun's static-pattern estimators fail to deal with the dynamic and unpredictable nature of today's IoT environments. Additionally, existing optimizers such as Choppara and Mangalampalli [49] are constrained by their support for single-objective optimization, with the latter frequently ignoring the intricate interplays among latency, energy consumption, and resource usage. By contrast, NEXUS-Scheduler, fueled by the TELEO framework, efficiently enables multi-objective optimization by adapting dynamically to changing workloads, networks, and system demands, thus guaranteeing more robust and context-aware task scheduling.

5.4 | Emphasizing the Novelty

The NEXUS-Scheduler presents a closed-loop integration of cognitive modules that, together, overcome some of the most persistent issues in fog–cloud task choreography. Its design includes an event-activated task creation mechanism that dynamically engages the scheduler in response to sensor-based thresholds, for example, system overload or thermal bursts. The Nexus-WNet module, based on a GRU-based multivariate model, predicts upcoming workloads using both past and real-time telemetry information. Nexus-RCA is a reinforcement learning-driven decision engine that recognizes best execution points by analyzing latency, energy costs, and device mobility. The Nexus-ERA module makes SLA-aware real-time elastic scaling of compute, memory, and bandwidth capacity possible. At the heart of the system is the TELEO framework based on decentralized, feedback-guided learning agents fueled by Confidence-Weighted Feedback Integration, GEM, and ACP. These agents continuously optimize strategies and save learned experiences in a LRM to improve extended-term system adaptation. This end-to-end design achieves adaptability, real-time responsiveness, and ongoing self-optimization—features not found in traditional fog–cloud scheduling techniques.

5.5 | Mitigating Potential Limitations

Although the NEXUS-Scheduler showcases strong performance on major metrics, it does have some limitations. The use of deep learning models such as GRUs and reinforcement learning incurs computational overhead, which can restrict deployment on power-constrained IoT or edge devices without specialty hardware accelerators. Further, the TELEO framework, while being flexible, could need domain-specific adjustments or heuristic augmentations to facilitate convergence at high rates within highly dynamic domains. Second, the event-driven task creation engine relies on accurate threshold calibration, which has to be professionally controlled to avoid under- or over-triggering on varied sensor infrastructures. These issues present opportunities for selective optimization and architectural improvement to further increase the scalability and deployment elasticity of the scheduler.

5.6 | Broader Impact and Future Directions

The NEXUS-Scheduler is a significant innovation in intelligent task scheduling and resource allocation for fog–cloud–IoT systems by substituting conventional rule-based and static means with a completely adaptive, self-optimizing framework. With its combination of multi-agent systems, contextual learning, and reinforcement-driven decision-making, it provides an extensible and dynamic framework customized for real-time, intricate IoT environments. Future updates could continue its reach further, such as model-pruned lightweight variants of Nexus-WNet and TELEO, hardware-aware NAS for deployment at the edge, and federated learning to enable privacy-preserving workload prediction across dispersed IoT clusters. Interoperability with network slicing and SDN controllers would enhance scalability and QoS, and semantic reasoning and intent-based orchestration would coordinate scheduling with high-level application objectives. In summary, the NEXUS-Scheduler provides a new standard for smart task scheduling with improved latency, energy efficiency, and resource utilization and is ready to be deployed in next-generation mission-critical infrastructures.

5.7 | Scalability Analysis in Terms of Memory and Processing Requirements Across IoT–Fog–Cloud Layers

Scalability in fog–cloud environments depends not only on the ability to handle increasing task volumes but also on how memory demand, CPU load, and processing overhead evolve across different architectural layers. The NEXUS-Scheduler evaluates scalability holistically by examining the computational and memory requirements of IoT devices, fog nodes, cloud servers, and the combined end-to-end system under varying workloads.

5.7.1 | IoT Layer—Minimal Memory and Lightweight Processing

IoT devices possess highly constrained resources; therefore, the system ensures scalability at this layer through lightweight operations. Only a small buffer of recent sensor readings is stored locally, and all high-computation tasks such as prediction and scheduling are delegated to fog nodes. Memory usage increases only proportionally with sensor buffer size, while CPU consumption remains minimal due to simple threshold evaluation. As a result, the IoT layer can easily scale to thousands of devices without suffering performance degradation.

5.7.2 | Fog Layer—Moderate Memory Usage and Adaptive Real-Time Processing

Fog nodes perform the primary real-time computations, including Nexus-WNet workload prediction, Nexus-RCA scheduling decisions, and queue management for active tasks. Scalability at this layer is assessed through changes in CPU load, memory consumption, and queue expansion as the number of concurrent tasks grows. The NEXUS-Scheduler maintains efficient scaling by employing bounded prediction windows, micro-container isolation, and multi-fog load distribution. These mechanisms

TABLE 13 | Memory and processing scalability across IoT, Fog, Cloud, and overall system.

Layer	Memory requirement	Processing requirement	Scalability behavior
IoT	Very low	Minimal threshold checks	Scales to thousands of devices
Fog	Moderate (queues + models)	Medium-to-high	Scales to large real-time loads
Cloud	Very High (historical logs)	High (parallel compute)	Virtually unlimited through horizontal scaling
Overall System	Balanced across layers	Distributed processing	Highly scalable end-to-end across all tiers

enable fog nodes to scale from hundreds to tens of thousands of simultaneous tasks while maintaining low latency and preventing overload.

5.7.3 | Cloud Layer — High-Capacity Storage and Parallel Processing

The cloud layer is responsible for long-term telemetry storage, global model training, optimization routines, and large-scale batch processing. Scalability is evaluated by monitoring parallel processing throughput, storage growth rates, and the computational cost of model retraining. With elastic compute clusters and distributed file systems, the cloud layer supports near-linear scalability. Its capacity is constrained only by data ingestion rates, not by computational limits, due to the availability of horizontal scaling mechanisms.

5.7.4 | End-To-End Multi-Layer Scalability

When considered as an integrated system, the NEXUS-Scheduler demonstrates balanced scalability across all layers. IoT devices maintain minimal load regardless of deployment size, fog nodes scale dynamically with real-time workloads, and cloud servers absorb increasing data and analytics demands through elastic provisioning. This end-to-end scalability ensures that the system avoids bottlenecks even as task volume and device density grow in large-scale smart city and industrial deployments.

Table 13 presents a comprehensive comparison of memory consumption, processing demands, and scalability characteristics across the IoT, fog, and cloud layers, as well as the integrated overall system. The IoT layer exhibits very low memory and CPU requirements, enabling the architecture to support thousands of devices with minimal overhead. The fog layer requires moderate memory for task queues and predictive models, alongside medium-to-high processing effort for real-time scheduling and load balancing. Despite this, fog nodes scale efficiently due to adaptive scheduling and bounded model complexity. The cloud layer supports very high memory and computational demands, driven by historical data storage and large-scale analytics. However, cloud systems achieve virtually unlimited scalability through horizontal expansion. The overall system demonstrates strong end-to-end scalability by distributing computational responsibilities across layers and preventing bottlenecks at any single tier. This confirms that the NEXUS-Scheduler maintains stable performance under increasing device density and workload intensity, making it suitable for large-scale IoT–fog–cloud deployments.

6 | Conclusion

The proposed NEXUS-Scheduler offers a dynamic and event-driven framework for task scheduling and resource allocation in fog–cloud–IoT environments by integrating real-time task generation, GRU-based workload prediction (Nexus-WNet), reinforcement learning–based tier selection (Nexus-RCA), SLA-aware resource provisioning (Nexus-ERA), and decentralized offloading using TELEO. The empirical results demonstrate improvements in latency (70 ms), energy efficiency (130 kWh), makespan (275 min), resource utilization (89%), and task accuracy (95.6%) over existing scheduling approaches, indicating its potential to enhance responsiveness and operational efficiency in dynamic IoT systems. Nevertheless, several specific drawbacks and limitations must be acknowledged. The GRU and RL modules increase computational overhead and memory usage, making deployment challenging on highly resource-constrained fog nodes. TELEO's meta-heuristic optimization may experience slow or unstable convergence during rapid mobility or large-scale agent interactions. The event-triggered mechanism relies on manually defined thresholds (temperature, CPU, AQI), which makes it sensitive to sensor noise, threshold drift, and misconfiguration. The framework also assumes relatively stable network conditions, whereas real-world IoT settings often experience intermittent connectivity and bandwidth fluctuations that may degrade scheduling reliability. Additionally, the evaluation is limited to controlled SmartCity-like scenarios, leaving generalizability to more diverse real-world environments uncertain. Although the architecture conceptually incorporates security, privacy, and explainability, these mechanisms have not yet been validated under adversarial or clinical conditions. Future work should therefore explore lightweight model variants, adaptive thresholding, enhanced optimization stability, privacy-preserving federated deployment, and large-scale real-world testing. Overall, while the NEXUS-Scheduler shows strong potential, its practical impact will depend on addressing these limitations and improving reliability and operational readiness.

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Ethics Statement

The authors have nothing to report.

Consent

There is no informed consent for this study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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