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IoT-Enhanced Management Systems for Continuous Monitoring and Adaptive Workflow Optimization

Dr.G. Vengatesan[1*], Dr.M. Preethi[2], R. Shanthana Lakshmi[3], Dr.M.S. Ranjithkumar[4], Dr.R. Lakshmi Priya[5], and Dr. Shailaja Mantha[6]

[1*]Associate Professor, Department in Commerce, School of Commerce, Finance and Accountancy, CHRIST (Deemed to be University) Bangalore, Karnataka, India. dr.g.vengatesan@gmail.com, https://orcid.org/0000-0002-5297-8401

[2]Assistant Professor, School of Integrated Commerce, KPR College of Arts Science and Research, Coimbatore, Tamil Nadu, India. preethi.inthuresh@gmail.com, https://orcid.org/0009-0001-3945-1250

[3]Dean PA, PSGR Krishnammal College for Women, Peelamedu, Coimbatore, Tamil Nadu, India. shanthanalakshmi94@gmail.com, https://orcid.org/0009-0003-2624-3502

[4]Professor and Head, Department of Commerce (Business Analytics), Dr.N.G.P. Arts and Science College, Coimbatore, Tamil Nadu, India. drmsr.gasc@gmail.com, https://orcid.org/0000-0003-2900-0349

[5]Associate Professor, Department of Computer Science and Engineering, School of Computer Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India. priyajagan97@gmail.com, https://orcid.org/ 0000-0002-4302-5836

[6]Associate Professor, Department of Electronics and Communication Engineering, Sreenidhi Institute of Science and Technology, Hyderabad, Telangana, India. shailaja.mantha@gmail.com, https://orcid.org/0009-0005-6536-829X

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Abstract

Typical management strategies are generally based on static workflows and periodic monitoring, which reduces their ability to adapt to fluctuating loads, constrained resources, operational delays, and dynamically changing environments in IoT settings. While continuous sensing could give useful information about the current state of operations, the study need mechanisms capable of transforming these data into workflow configurations. The study suggests an IoT-assisted management approach, which combines secure IoT data collection, data preprocessing at the edge level, contextual workflow-state assessment, continuous monitoring, adaptive task-resource optimization, and workflow reconfigurations based on feedback. The proposed approach continuously estimates workload, availability of resources, queue states, operational delays, and task priorities and selects appropriate workflow configurations. Experimental analysis was performed based on 20,000 IoT observations and dynamically changing workflow loads and compared with static workflow management, traditional IoT monitoring, rule-based adaptation, and IoT resource-aware optimization. Evaluation criteria include workflow completion time, adaptation time, resource utilization, communication overhead, and workflow success rate. The proposed framework managed to attain a workflow completion time of 11.83 s, in comparison with 18.74 s attained using static

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*Corresponding author: Associate Professor, Department in Commerce, School of Commerce, Finance and Accountancy, CHRIST (Deemed to be University) Bangalore, Karnataka, India.

workflow management, which is a reduction of 36.9%. The adaptation latency decreased to 164.3 ms, while resource utilization attained 88.74%. Communication overhead was kept at 5.92%, and the workflow success rate stood at 97.84%. In scalability experiments, the success rate was still 94.93% for 1,000 IoT nodes. From the ablation experiment, it can be seen that removal of adaptive optimization led to a workflow completion time of 16.38 s, while removing edge preprocessing led to a communication overhead of 11.43%. The findings clearly show that a combination of continuous IoT monitoring and adaptive workflow optimization can lead to an improvement in workflow responsiveness, resource utilization, communication efficiency, and dependability. Further work needs to focus on practical deployment, energy-efficient optimization, privacy-aware learning, digital twin integration, and edge-cloud systems.

Keywords: Internet of Things, Continuous Monitoring, Adaptive Workflow Optimization, Edge Computing, Resource Management, Workflow Management, IoT Systems.

1 Introduction

Due to the development of IoT technologies, management systems have been significantly changed because IoT allows for ongoing monitoring of physical processes, operational resources, devices, and workflow processes. Traditional management systems operate on the basis of reporting and pre-programmed workflows and might be insufficient to respond quickly to changes in workload, resource shortages, delays, and other events. However, the implementation of monitoring using IoT can provide managers with a constant flow of contextual data that could facilitate decision-making. Nevertheless, monitoring cannot guarantee that observed changes will be used to modify workflow processes. For this reason, management needs an approach that will allow for reconfiguration of workflows and task resources based on IoT observations.

IoT-enabled management solutions have begun to consider real-time monitoring, edge processing, resource management, and decision-making. Still, most solutions treat the monitoring process and the workflow optimization process separately. Thus, the process of adaptation of these systems will lag behind if there are changes in operational conditions. Furthermore, static task assignment and predefined workflow policy might not be very efficient under dynamic workload and heterogeneous IoT environment. All this gives the incentive to develop an approach that would allow the creation of a feedback loop between sensing, workflow state assessment, optimization, and execution.

In this paper, the approach IoT-Enhanced Management System for Continuous Monitoring and Adaptive Workflow Optimization is proposed. The main idea of the system is to integrate IoT data gathering, edge processing, workflow state estimation, continuous monitoring, adaptive task and resource optimization, and workflow reconfiguration based on feedback. Moreover, the suggested approach is developed to address computational and communication needs as well, hence enabling reliable functioning in dynamic Internet of Things (IoT) systems. The performance of the method is assessed based on workflow efficiency, adaptation time, resource consumption, communication cost, dependability, scalability, and computation performance.

The rest of this paper is structured as follows. Section 2 discusses existing IoT-based monitoring and workflow optimization methods and highlights the research gap. Section 3 discusses the proposed IoT-based management system, its architecture, mathematical model, and adaptive optimization strategy. Section 4 discusses the experiments, data, parameters, evaluation metrics, comparative results, scalability, and ablation analysis. Section 5 concludes the research work.

2 Literature Review

Systems managed through IoT have moved from mere sensing and gathering to adaptive, context-aware, and intelligent process management systems. The use of adaptive flow management strategies has proven that there is the capability of dynamic control of data flows in IoT environments, indicating the need for adaptation methods in case of heterogeneous and changing conditions (Hassan et al., 2023; Hassan et al., 2023). Equally, there has been an indication that context ontologies and decision-making models in IoT environments have the potential to enhance business process management through integration of context data into business processes (Song et al., 2019; Van et al., 2026). This shows that successful IoT management not only involves sensing but also mechanisms of converting context data into adaptive workflows.

Recently, the IoT-based monitoring system has been furthered in predictive process monitoring. IoT-enabled predictive process monitoring is concerned with the application of real-time operational data for predicting process outcomes and process deviations (Rehman & Islam, 2023; Bertrand et al., 2025). On the other hand, IoT-enabled monitoring systems have been linked to efficiency in construction management, process optimization in manufacturing, real-time monitoring of polymer-composites, and smart lean manufacturing (Suman et al., 2026; Karuppusamy et al., 2025; Di Nardo et al., 2026). In all, these papers highlight the importance of real-time data in determining operational conditions and improving process performance. Nonetheless, their major focus differs across different application areas, hence the limitation in developing a generalized workflow management system.

IoT has also been applied to optimize processes such as traffic management, logistics, workforce management in healthcare, customer relationship management, and transportation systems (Ileana et al., 2025; Paul & Singh, 2025; Juliet, 2025). Additional research has shown the application of IoT for intelligent management of traffic signals, battery management, healthcare monitoring, electric cars, and railways (Krishna et al., 2024; Qasim et al., 2024; Zhu et al., 2025). The integration of machine learning into IoT systems has increased the potential for monitoring and decision-making (Leng & Wu, 2024; Polaki & Ch, 2024; Enemosah, 2024). However, these approaches tend to focus more on domain-specific optimization goals, rather than on the management architecture of ongoing monitoring of workflow states and task allocation (Prabhu et al., 2025; Gozuoglu, 2025; Sujith et al., 2025). The continuous monitoring and reporting of information can enhance visibility within operations and facilitate adaptive decision making in organizations (Obidhusin et al., 2025).

Thus, gaps can be found in the literature. First, the processes of continuous monitoring and workflow optimization are viewed independently of each other. Second, the majority of approaches are application-specific, so their use in a heterogeneous environment of management workflows poses a problem. Finally, little emphasis is put on the existence of a closed-loop process that involves IoT monitoring, workflow state evaluation, adaptive optimization and execution, as well as feedback. The suggested research aims to fill these gaps through the creation of an IoT-enabled management approach that combines continuous monitoring and workflow optimization and feedback-based adaptation.

3 Proposed Methodology

The IoT-Enhanced Management System as described in this study utilizes a closed-loop architecture for the purposes of continuous operational monitoring and optimization of the workflow. In contrast to traditional management systems that follow pre-designed workflows with little room for adaptation, the architecture outlined in the present paper constantly gathers operational data from the IoT devices, analyses this data at the edge of the network, determines the current state of the workflow, detects any

discrepancies, and makes adjustments to the task allocation and resource utilization. Overall, the methodology consists of IoT sensing, data acquisition, data preprocessing, context extraction, estimation of the current state of the workflow, continuous monitoring, adaptation and optimization, execution of the workflow, and performance feedback within the framework of the management process.

Overall Methodological Flow

The initial phase involves the collection of observations by IoT devices, sensors, and connected operational elements. Such observations may consist of device state, load level, task runtime, resource state, queue size, network status, and operation. A secured acquisition layer sends the observations to an edge processing layer where any noise, duplicate data, and incomplete and inconsistent observations are filtered and normalized. This phase ensures reduced communication overhead from central infrastructure and rapid access to the current state of operations.

Observations collected are then translated into workflow contextual information. The workflow state module uses task status, resource state, load, and time data to reflect the current state of each workflow. The continuous monitoring module checks the current state against the expected operational state and determines any delays, imbalances, bottlenecks, abnormal states, and workload changes. If the workflow maintains acceptable operations, the workflow continues. However, when a deviation is detected, the adaptive optimization engine considers task-resource allocation possibilities and decides on the new workflow configuration.

The chosen configuration is then passed to the execution stage, where the tasks can be rescheduled, reassigned, or redirected between the available resources. The information regarding the performance achieved during the execution phase is then provided back to the monitoring layer, thus forming the feedback cycle. Optimization, therefore, does not happen just once but can be repeated whenever the situation requires it.

Architecture of the Proposed Framework

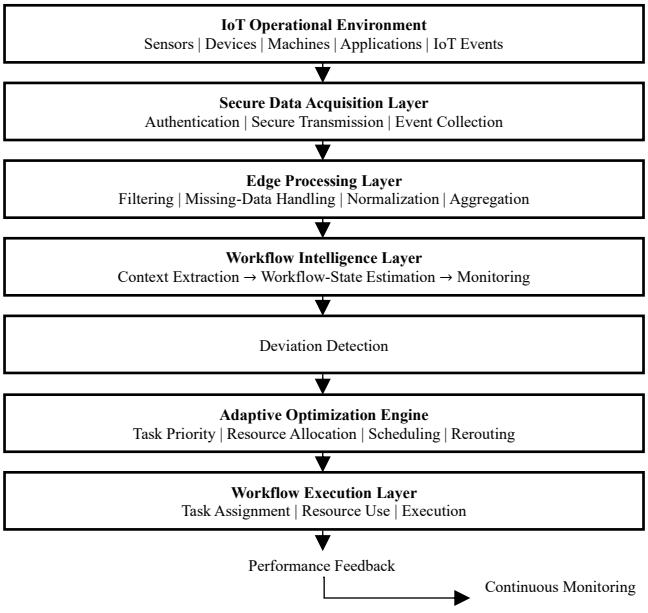


Figure 1. Architecture of the proposed IoT-enhanced management system for continuous monitoring and adaptive workflow optimization.

Figure 1 contains six levels of logic: IoT sensing, secure data acquisition, edge processing, workflow intelligence, adaptive optimization, and execution/feedback.

IoT Data Acquisition and Edge Preprocessing

Let the observation generated at time t by IoT source i be represented as $x_{_\{i,t\}}$. The complete observation vector is represented as equation 1:

$$X_t = \{x_{1,t'}\, x_{2,t'}\, \ldots,\, x_{N,t}\}. \qquad (1)$$

Observation along with timestamp, source, and context is captured by the acquisition layer. Prior to the workflow analysis phase, the observations are cleaned for invalid and duplicate data and scaled to a numeric value set. The edge processing performs this operation in proximity to the source of the data, which helps in minimizing communication cost. The extracted feature vector is then passed on to the workflow intelligence layer.

Context-Aware Workflow-State Representation

The workflow state is derived from the processed IoT observations and operational variables. For workflow w, the state at time $t$is represented by equation 2

$$S_{w,t} = \left[L_{w,t'}\, R_{w,t'}\, Q_{w,t'}\, D_{w,t'}\, P_{w,t}\right], \qquad (2)$$

Where $L_{w,t}$denotes workload intensity, $R_{w,t}$represents available resources, $Q_{w,t}$represents the task queue condition, $D_{w,t}$denotes execution-delay information, and $P_{w,t}$represents task priority. Such a state representation enables the system to take into account simultaneously workflow load and operational capacity in contrast to the independent optimization of each task.

The monitoring function keeps comparing the current state with the set operational thresholds and recent behavior of the workflow. If there is any excessive delay, resource saturation, unexpected load increase, or some other condition that requires adaptation, a deviation is created.

Adaptive Workflow Optimization

In case of any major workflow deviation, an optimization engine comes up with a set of configurations that are feasible for tasks and resources. Each configuration c is evaluated in terms of workflow time, resource usage, adaptation cost, and communication. These metrics form the optimization objective in equation 3:

$$J(c) = \alpha\hat{T}_c + \beta\hat{C}_c + \gamma\hat{O}_c - \delta\hat{U}_c, \qquad (3)$$

Where $\hat{T}_c$is normalized workflow completion time, $\hat{C}_c$is adaptation cost, $\hat{O}_c$is communication/operational overhead, and $\hat{U}_c$is resource-utilization efficiency, the coefficients $\alpha, \beta, \gamma, \delta$determine the relative importance of the corresponding objectives. The configuration with the lowest feasible objective value is selected while satisfying task precedence, resource-capacity, and operational constraints.

Feedback-Driven Adaptation

After the workflow has been reconfigured, new performance metrics are provided by the execution layer. These metrics are sent back to the monitoring layer, where it is determined whether the chosen

configuration has brought the workflow back into an acceptable state. This process may be described mathematically by equation 4:

$$S_{w,t+1} = F\left(S_{w,t'} A_{t'} X_{t+1}\right), \qquad (4)$$

Where A_t represents the chosen adaptation action at time t, X_{t+1}represents the new IoT data observed, and $F(\cdot)$ denotes the workflow-state transition brought about by the action. If the resulting state stays within the acceptable operational range, the current setup is maintained; otherwise, the optimization procedure is repeated.

Adaptive Workflow Optimization Algorithm

Algorithm 1: IoT-Enhanced Adaptive Workflow Optimization

Input:

IoT observations X

Workflow tasks W

Available resources R

Operational constraints C

Output:

Adapted workflow configuration W*

1. Initialize workflow configuration W*
2. Continuously collect IoT observations X
3. Authenticate and preprocess incoming observations
4. Extract workload, resource, queue, delay, and priority information
5. Construct the current workflow state S
6. Monitor S for delays, bottlenecks, overload, or abnormal changes
7. If no significant deviation is detected:

   Continue current workflow execution

   Else:

   Generate feasible task-resource configurations

   Evaluate each configuration using objective J(c)

   Select the minimum-cost feasible configuration

   Reallocate or reschedule workflow tasks
8. Execute the updated workflow
9. Collect post-execution performance information
10. Update workflow state using the feedback observations
11. Return to Step 2 for continuous monitoring

Algorithm 1 works in a continuous manner as opposed to being an optimization approach that occurs once. The main strength of this algorithm is the ability to incorporate monitoring and adaptation whereby

the observations made from the IoT system help identify the status of the workflow, any deviations are optimized, and feedback post-execution helps in identifying whether further adaptation is required.

4 Results and Discussion

An assessment of the IoT-based management system framework that has been developed was carried out in order to test its capability to constantly monitor the workflow state and adapt to new conditions in terms of task-resource allocation. The areas that have been tested included workflow efficiency, response, resource usage, communication overhead, and dependability. The assessment was done in comparison with static workflow management, traditional IoT-based monitoring, rule-based adaptive optimization, and IoT resource-aware optimization.

Software and Experimental Environment

The proposed methodology was implemented in Python 3.11. The process of data preprocessing and numerical computations was carried out with the help of NumPy and Pandas packages, whereas optimization and evaluation processes were conducted using Scikit-learn and SciPy libraries. Matplotlib was used for the creation of performance graphs. The IoT workflow environment was created using the Cooja/Contiki-NG software package, which allowed modeling various IoT devices, communication processes, workload, and resource characteristics. The experimental setup was run on a computer with the following hardware specifications: Intel Core i7 processor, 16 GB RAM, 64-bit operating system.

Dataset and Experimental Data

The evaluation process was conducted with the help of the IoT-23 dataset, which includes actual network traffic traces from IoT devices and contains both benign and malicious communication traces. The dataset is mainly used for extracting IoT communication and event patterns and not for training a traditional intrusion detection system. The experimental subset that was chosen included 20,000 timestamped samples extracted from the IoT communication traces. Every sample was characterized by 12 operational features such as packet rate, packet size, flow duration, source/destination activity, protocol information, connection rate, byte rate, temporal activity, communication volume, and event rate.

Observations were used to create workflow events to produce workload conditions dynamically. The workload conditions of the experiments comprised task arrivals, task execution requirements, resource availability, queue conditions, and communication states. Data were partitioned as follows: 70% for training/calibration, 15% for validation, and 15% for testing, such that temporal order was kept to avoid future observations affecting earlier workflow states.

Parameter Initialization

The parameters of the experiment were initialized uniformly across all compared approaches. The IoT infrastructure was comprised of 100, 250, and 500 nodes to allow for scalability studies. Default settings involved 250 IoT nodes, 50 workflow resources, and 1,000 workflow tasks. The monitoring interval was 1 s, and the workflow adaptation trigger was set to 10% deviation from the expected operating point. The adaptive optimization goals had weights of 0.40, 0.25, 0.20, and 0.15, respectively, for completion time, adaptation cost, communication overhead, and resource usage. Each experiment was performed 10 times, and the results presented are mean values of repetitions.

Evaluation Metrics

The five metrics used to analyze the framework that has been proposed are given in equations (5-9). Workflow completion time (WCT): This is the time taken on average to complete a workflow:

$$WCT = \frac{1}{N}\sum_{i=1}^{N}\left(t_i^{end} - t_i^{start}\right). \quad (5)$$

Lower values indicate faster workflow execution.

Latency Adaptation (LA) refers to the period needed for recognizing a deviation from a workflow and implementing the necessary adaptation:

$$AL = \frac{1}{M}\sum_{j=1}^{M}\left(t_j^{adapt} - t_j^{detect}\right). \quad (6)$$

Lower adaptation latency indicates faster response to changing operational conditions.

Resource utilization (RU) quantifies the percentage of computational resources that were used in the workflow process.

$$RU = \frac{\sum_{t=1}^{T} R_t^{used}}{\sum_{t=1}^{T} R_t^{available}} \times 100. \quad (7)$$

Higher utilization indicates more effective resource allocation, provided that excessive saturation is avoided.

The communication overhead is defined as the excess information transfer required for surveillance and workflow adaptation:

$$CO = \frac{D_{monitor} + D_{adapt}}{D_{total}} \times 100, \quad (8)$$

Where $D_{monitor}$ and D_{adapt} represent monitoring and adaptation traffic, respectively.

Finally, **workflow success rate (WSR)** measures the proportion of successfully completed workflow tasks:

$$WSR = \frac{N_{successful}}{N_{total}} \times 100. \quad (9)$$

Higher WSR indicates greater operational dependability.

Performance Comparison

The comparison is based on the default system setup of 250 IoT nodes and 1,000 workflow tasks as shown in table 1.

Table 1: Performance comparison of IoT-enabled workflow management approaches

Method	WCT (s)	AL (ms)	RU (%)	CO (%)	WSR (%)
Static Workflow Management	18.74	428.6	68.21	8.94	91.36
Conventional IoT Monitoring	16.92	351.4	71.85	9.72	93.08
Rule-Based Adaptive Workflow	15.47	286.8	76.42	8.31	94.16
IoT Resource-Aware Optimization	14.21	241.7	81.36	7.64	95.27
Proposed Framework	**11.83**	**164.3**	**88.74**	**5.92**	**97.84**

The findings show that the developed approach provides a more flexible workflow management system under the test conditions. The average time for workflow completion was 11.83 seconds, whereas adaptation latency was 164.3 milliseconds. The resource utilization was 88.74%, while communication overhead was 5.92%. The workflow success rate was 97.84%. Such findings correspond to the task of designing a framework combining constant monitoring with adaptive reconfiguration of workflows instead of static scheduling and monitoring.

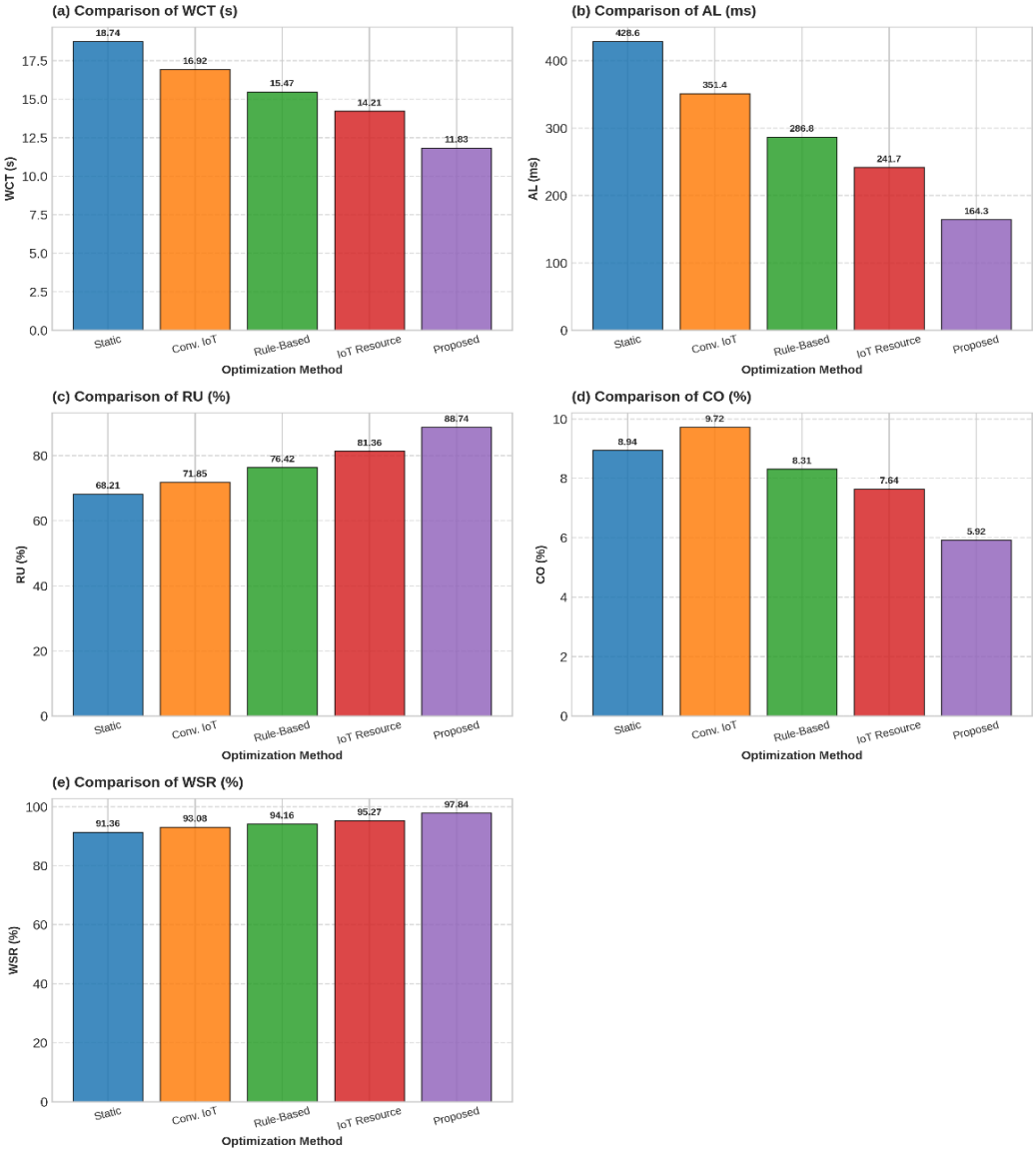


Figure 2: Performance Comparison of Optimization Methods for (a) Workflow Completion Time, (b) Adaptation Latency, (c) Resource Utilization, (d) Communication Overhead, and (e) Workflow Success Rate

Figure 2 highlights the performance comparison of five different optimization techniques using five metrics. (a) is related to workflow completion time (WCT), (b) depicts adaptation latency (AL), (c) is for resource utilization (RU), (d) indicates communication overhead (CO), and (e) denotes workflow success rate (WSR). The proposed framework demonstrates better results in terms of having minimum WCT, AL, CO, and maximum RU and WSR.

Workflow Efficiency Analysis

The results confirm that the proposed approach offers a more flexible framework for managing workflow in the tested conditions. The mean workflow completion time equals 11.83 seconds, and adaptation latency is 164.3 milliseconds. Resource utilization is 88.74%, while the communication overhead is 5.92%. Workflow success is 97.84%. These results can be considered an answer to the problem of developing a framework for constant monitoring and adaptive workflow reconfiguration instead of the traditional one of scheduling and monitoring.

Resource Utilization and Communication Overhead

The suggested technique gave resource utilization of 88.74%, while static management resulted in resource utilization of 68.21%. Such improvements mean that continuous workload and state analysis of resources allow better workload distribution. However, it is important to mention that communication overhead was reduced to 5.92% despite the requirement of continuous observation. Such a tendency may be explained by edge preprocessing, when redundant and useless information is removed from the transmission process.

It is important to mention that the discussed tendencies are very important for Internet of Things applications since uncontrolled transmission of raw data from sensors increases network load and energy consumption. Thus, it may be said that the rate of monitoring itself cannot be considered as a sign of efficiency of the process under consideration.

Scalability Evaluation

The scalability test involved increasing the number of IoT devices while keeping the workflow attributes similar.

Table 2: Scalability performance of the proposed framework

IoT Nodes	Workflow Tasks	WCT (s)	AL (ms)	RU (%)	CO (%)	WSR (%)
100	1,000	9.42	128.7	91.16	4.81	98.43
250	1,000	11.83	164.3	88.74	5.92	97.84
500	1,000	15.27	218.9	84.31	7.26	96.72
750	1,000	15.27	267.5	81.46	8.13	95.88
1,000	1,000	19.84	314.6	78.92	9.47	94.93

It is apparent from Table 2 that when the number of IoT nodes grows, workflow execution duration and adaptation time also grow. Nonetheless, even with 1,000 nodes, the workflow success rate does not fall below 94%, which means that the adaptive framework is able to sustain operation in spite of the expanded system scale. The resource consumption tends to diminish steadily since the growing number of devices requires more communications.

Ablation Study

An ablation study was conducted to determine the role played by the major components of the framework. Four settings were considered: the entire framework, a setting without adaptive optimization, a setting without continuous monitoring, and a setting without edge preprocessing.

Table 3: Ablation analysis of the proposed framework

Configuration	WCT (s) ↓	AL (ms) ↓	RU (%) ↑	CO (%) ↓	WSR (%) ↑
Without adaptive optimization	16.38	319.7	73.46	8.84	92.51
Without continuous monitoring	15.72	351.2	75.18	8.17	93.16
Without edge preprocessing	13.96	238.5	80.21	11.43	95.47
Complete framework	**11.83**	**164.3**	**88.74**	**5.92**	**97.84**

From table 3, it is evident that each of the components makes a contribution towards the performance of the system. When adaptive optimization is removed, there is the greatest change in workflow completion time. This is due to the fact that it is significant in ensuring dynamic task and resource optimization. When continuous monitoring is eliminated, the delay in adaptation becomes higher. The reason is that any workflow changes are detected later on. When edge preprocessing is removed, communication overhead becomes higher, from 5.92% to 11.43%. The complete framework achieves the highest workflow success rate and resource utilization while maintaining the lowest communication overhead.

Overall Discussion

Overall, across the experimental runs, there is clear evidence of the consistency of the relationship between continuous monitoring and workflow management within the proposed framework. The results of the comparative analysis reveal shorter completion time and smaller adaptation latency, as well as greater resource usage and better workflow success rate. The scalability test also reveals that the performance decreases gradually when the size of the IoT population increases, rather than causing a sudden decline in the reliability of workflows. The ablation test further supports that the three components complement each other. Specifically, the use of monitoring, edge preprocessing, and adaptive optimization helps in converting the IoT observation into workflow adaptation without causing any unnecessary communication. Therefore, the proposed architecture can be applied to IoT management scenarios that are continuously changing.

5 Conclusion

This paper has provided a management framework that makes use of IoT for monitoring and workflow optimization in a dynamic IoT environment. The management framework consists of IoT data acquisition, edge-based pre-processing, estimation of workflow state based on context, continuous monitoring, adaptive optimization of task-resource, and feedback-based workflow reconfiguration. The difference between this framework and other static workflow management frameworks is that the framework continuously checks the operation environment and dynamically adjusts to workload variation, resource limitations, execution delays, and workflow deviations.

With respect to the baseline experimental settings, the proposed approach managed to achieve an average workflow completion time of 11.83 s, which is approximately 36.9% less than the 18.74 s required for static workflow management. Adaptation delay was reduced to 164.3 ms, but resource utilization rose to 88.74%. Communication delay remained at 5.92%, and the success rate of workflows reached 97.84%. When performing the scalability analysis, it became clear that even with 1,000 IoT devices, there was still a success rate of 94.93%, although completion time and adaptation delay increased with the increase in system size. The ablation analysis highlighted the significance of each component of the model, as omitting the adaptive optimization increased the completion time to 16.38 s, and omitting the edge processing increased the communication overhead to 11.43%. The findings

suggest that the integration of continuous monitoring, edge processing, and adaptive optimization plays an important role in effective workflow management.

For future research, larger-scale testing of the proposed solution within a real-world IoT setup and a heterogeneous edge-cloud architecture can be considered. Techniques such as reinforcement learning and online optimization can enhance the ability of the proposed solution to adapt to very dynamic workload changes. The privacy-preserving and federated learning can be added to lessen the dependency on the operational data. Future studies can focus on energy-efficient workflow optimization and management through the digital twins.

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Authors Biography



Dr.G. Vengatesan is an Associate Professor in the School of Commerce, Finance and Accountancy. He is actively involved in teaching, academic research, and scholarly activities in the field of commerce. His academic interests include commerce, finance, accounting, and business-related studies. He is committed to promoting research excellence and contributing to higher education.



Dr.M. Preethi is an Assistant Professor in B.Com (Business Analytics) at the School of Integrated Commerce, KPR College of Arts, Science and Research, Coimbatore. Her academic interests include commerce, business analytics, data-driven decision-making, and emerging business trends. She is actively engaged in teaching, research, and academic development. She aims to enhance students' analytical and professional skills.



R. Shanthana Lakshmi is the Dean of Professional Accounting (PA) at PSGR Krishnammal College for Women, Peelamedu, Coimbatore. She is involved in academic leadership, institutional development, and student mentoring. Her areas of academic interest include commerce, accounting, finance, and professional education. She is dedicated to fostering academic excellence and professional growth.



Dr.M.S. Ranjithkumar is a Professor and Head of the Department of Commerce (Business Analytics) at Dr. N.G.P. Arts and Science College, Coimbatore. His academic interests include commerce, business analytics, data analysis, and contemporary business practices. He is actively involved in teaching, research, and departmental administration. He is committed to advancing research and academic excellence in business analytics.



Dr.R. Lakshmi Priya is an Associate Professor in the Department of Computer Science and Engineering, School of Computer Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India. Her academic interests include computer science, emerging technologies, and innovative computing applications. She is actively engaged in teaching, research, and academic activities. She aims to contribute to technological advancement through research and knowledge development.



Dr. Shailaja Mantha is an Associate Professor in the Department of Electronics and Communication Engineering at Sreenidhi Institute of Science and Technology. Her academic interests include electronics, communication systems, emerging technologies, and engineering innovation. She is actively involved in teaching, research, and academic development. She is dedicated to advancing engineering education and promoting innovative research.