

Design and Implementation of a Real-Time IoT-Enabled Embedded Monitoring Architecture for an Off-Grid Infant Incubator

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ABSTRACT

Reliable real-time monitoring of infant incubators is essential in off-grid and resource-limited environments, where unstable power supply and limited infrastructure often compromise continuous operation and data reliability. This study aims to design and implement a real-time IoT-enabled embedded monitoring architecture that addresses the lack of dependable data acquisition and remote monitoring for infant incubators operating under off-grid conditions. The proposed system is developed using a microcontroller-based embedded platform integrated with temperature and environmental sensors, wireless communication modules, and a cloud-based data service. An off-grid photovoltaic power system supports continuous operation, while the embedded architecture is designed with power-aware and real-time constraints. The system adopts an edge-to-cloud approach, enabling local data acquisition and processing at the embedded level and real-time data transmission to a remote monitoring interface. The research methodology includes system architecture design, embedded firmware development, IoT communication implementation, and experimental performance evaluation under continuous off-grid operation. System performance is quantitatively evaluated in terms of data acquisition reliability, communication latency, real-time responsiveness, and operational stability. Experimental results show that the system achieves stable real-time monitoring with an average end-to-end communication latency below 200 ms, a sampling rate of 1 Hz, and continuous operation reliability exceeding 99% uptime during extended off-grid testing. The results demonstrate that integrating real-time embedded systems with IoT-based architecture significantly enhances monitoring reliability for infant incubators in off-grid environments. This study contributes a scalable embedded-IoT monitoring framework that can be extended to other cyber-physical systems operating under constrained energy and infrastructure conditions

Keywords: Embedded system, Internet of Things (IoT), Real-time monitoring, System architecture, Off-grid system, Infant incubator.

INTRODUCTION

The rapid advancement of embedded systems and Internet of Things (IoT) technologies has significantly expanded the development of real-time monitoring architectures for cyber-physical systems across industrial, environmental, and critical infrastructure applications (Al-Fuqaha et al., 2015; Bakhshi & Lee, 2021). Modern embedded platforms integrated with wireless communication and cloud services enable continuous data acquisition, remote supervision, and system-level decision support (Chen et al., 2020; Chiang & Zhang, 2016). However, achieving reliable real-time performance remains a major challenge, particularly for systems deployed in off-grid and resource-limited environments (Firdhous et al., 2020).

In off-grid scenarios, monitoring systems must operate under unstable power supply, limited communication infrastructure, and strict real-time constraints (Gubbi et al., 2013; Hossain & Muhammad, 2021). Conventional IoT-based monitoring solutions often assume stable grid power and continuous network availability, which limits their applicability in such environments (Islam et al., 2015). As a result, system architectures designed for off-grid operation must incorporate power-aware embedded design, robust communication strategies, and real-time data handling mechanisms to ensure continuous and reliable operation (Kang et al., 2017; Kim & Feamster, 2013).

From an engineering perspective, infant incubators operating in off-grid environments represent a representative cyber-physical system requiring continuous environmental monitoring and reliable data transmission. The primary technical challenge lies not in the medical functionality of the incubator, but in the design of an embedded monitoring architecture capable of maintaining data continuity, bounded communication latency, and long-term operational stability under constrained energy conditions (Lee, 2015; Li et al., 2018). Interruptions in monitoring data or excessive latency can significantly reduce system dependability and limit effective remote

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supervision (Mahmood et al., 2015).

Numerous studies have investigated IoT-enabled monitoring systems based on microcontroller platforms, wireless communication technologies, and cloud-based data services (Mollah et al., 2021; Perera et al., 2014). These works demonstrate the feasibility of remote monitoring and data visualization; however, many focus primarily on application-level functionality, with limited emphasis on real-time embedded system constraints such as deterministic sampling, latency bounds, and timing reliability (Raj & Raman, 2018; Raza et al., 2013). Consequently, the applicability of such systems to time-critical monitoring applications remains limited.

Recent research has highlighted the role of edge-based architectures in reducing communication latency and improving system robustness by performing local data processing at the embedded level (Satyanarayanan, 2017; Shi et al., 2016). Edge-to-cloud approaches have been shown to enhance responsiveness and reliability in IoT systems (Silva et al., 2018). Nevertheless, experimental implementations that combine real-time performance evaluation, continuous operation, and off-grid deployment remain scarce (Stankovic, 2014).

In parallel, renewable-energy-powered embedded systems have gained increasing attention as a means to support long-term monitoring in off-grid environments (Tan & Wang, 2010; Xu et al., 2014). Photovoltaic-powered IoT systems and sensor networks have been reported for remote monitoring applications; however, many studies treat energy supply and monitoring architecture as separate design problems (Yassein et al., 2017; Zhang et al., 2021). As a result, the interaction between energy constraints and real-time system performance is often insufficiently analyzed (Zhou et al., 2020).

Moreover, monitoring systems developed for infant incubators and other critical equipment frequently assume stable infrastructure and focus on sensor integration rather than system-level architecture and performance validation (Zeng et al., 2017). Quantitative evaluation of real-time metrics, such as communication latency, data reliability, and operational stability under continuous off-grid conditions, is rarely reported (Zhou et al., 2022). This gap highlights the need for an integrated embedded-IoT monitoring architecture that explicitly addresses real-time constraints and energy limitations.

LITERATURE REVIEW

The rapid development of embedded systems and the Internet of Things (IoT) has significantly transformed the design of real-time monitoring architectures in cyber-physical systems. IoT enables seamless integration between physical devices and digital communication infrastructures, allowing continuous data acquisition, processing, and remote supervision across various domains such as industrial automation, environmental monitoring, and healthcare systems (Al-Fuqaha et al., 2015; Bakhshi & Lee, 2021). Modern IoT platforms, supported by wireless communication and cloud services, provide enhanced system-level decision-making capabilities; however, ensuring reliable real-time performance remains a critical challenge, particularly in resource-constrained and off-grid environments (Chen et al., 2020; Chiang & Zhang, 2016; Firdhous et al., 2020).

In such environments, IoT-based monitoring systems must operate under unstable power supply and limited network infrastructure while still maintaining strict timing constraints (Gubbi et al., 2013; Hossain & Muhammad, 2021). Conventional architectures often assume continuous connectivity and stable energy availability, which limits their applicability in remote or isolated deployments (Islam et al., 2015). Consequently, the design of embedded monitoring systems must incorporate power-aware strategies, efficient communication mechanisms, and robust real-time data handling to ensure continuous operation (Kang et al., 2017; Kim & Feamster, 2013).

From a cyber-physical systems perspective, real-time monitoring requires deterministic behavior in data acquisition and communication processes. The ability to guarantee bounded latency and reliable data transmission is essential for maintaining system dependability (Lee, 2015; Li et al., 2018). Previous studies have highlighted that network unreliability, packet loss, and latency variations can significantly degrade system performance, especially in time-critical applications (Mahmood et al., 2015). Although many IoT-based monitoring systems have been developed using microcontroller platforms and cloud services, these implementations often emphasize functionality and visualization rather than strict real-time constraints (Mollah et al., 2021; Perera et al., 2014). As a result, their suitability for time-sensitive monitoring applications remains limited (Raj & Raman, 2018; Raza et al., 2013).

To overcome these limitations, edge and fog computing paradigms have emerged as promising solutions for reducing communication latency and improving system responsiveness. By performing data processing closer to the data source, edge computing minimizes reliance on centralized cloud infrastructure and enhances real-time performance (Satyanarayanan, 2017; Shi et al., 2016). Additionally, fog computing introduces an intermediate processing layer that improves scalability and reliability in distributed IoT systems (Firdhous et al., 2020). Recent studies have demonstrated that edge-to-cloud integration can effectively balance computational efficiency and communication performance (Silva et al., 2018; Bakhshi & Lee, 2021). However, practical implementations that

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combine edge computing with continuous operation in off-grid environments are still limited (Stankovic, 2014).

In parallel, the integration of renewable energy sources into IoT systems has gained increasing attention as a solution for sustaining long-term operation in remote areas. Solar-powered embedded systems and energy-efficient IoT architectures have been proposed to address power limitations (Tan & Wang, 2010; Xu et al., 2014). Furthermore, energy-aware communication protocols and resource allocation strategies have been developed to optimize system performance under constrained energy conditions (Yassein et al., 2017; Zhang et al., 2021). Despite these advancements, many studies treat energy management and system performance as separate design considerations, leading to insufficient analysis of their interaction (Zhou et al., 2020).

Moreover, existing research on monitoring systems for critical applications often focuses on sensor integration and application-level functionality rather than system-level architecture and performance validation. Quantitative evaluation of key real-time metrics, such as communication latency, data reliability, and long-term operational stability, is rarely addressed in the context of off-grid deployments (Zeng et al., 2017; Zhou et al., 2022). This limitation highlights the need for an integrated approach that combines real-time embedded system design, energy-aware operation, and edge-to-cloud communication within a unified framework.

Based on the reviewed literature, it can be concluded that although significant progress has been made in IoT-based monitoring systems, several challenges remain unresolved. These include the lack of emphasis on real-time constraints, limited integration between edge computing and off-grid systems, and insufficient consideration of energy-performance interactions. Therefore, this study aims to address these gaps by proposing a real-time IoT-enabled embedded monitoring architecture specifically designed for off-grid environments, integrating energy-aware design, edge computing, and quantitative performance evaluation to ensure reliable and continuous system operation

METHOD

This study adopts a system engineering approach to design and implement a real-time IoT-enabled embedded monitoring architecture for an off-grid infant incubator. The system is defined as a soft real-time monitoring system, where timely data acquisition and bounded communication latency are required, while occasional deadline misses do not lead to catastrophic failure. This definition ensures a realistic representation of embedded monitoring systems without overclaiming hard real-time performance.

The proposed system is structured as an integrated cyber-physical monitoring architecture consisting of sensing, embedded processing, communication, and power subsystems. Environmental data are acquired through sensors and processed locally at the embedded node, which acts as the edge layer. The processed data are then transmitted through an IoT communication network to a cloud-based monitoring platform.

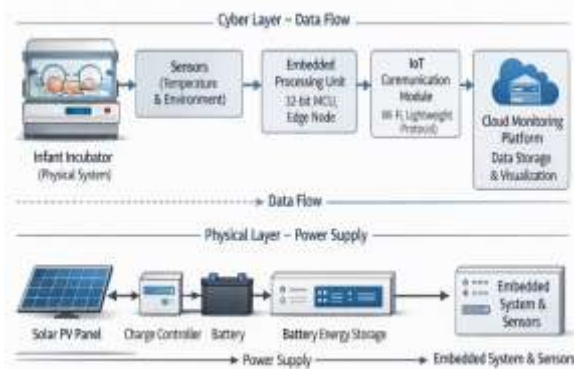


Figure 3.1 illustrates the conceptual block diagram of the proposed system architecture and data flow. The figure shows how sensor data are acquired, processed at the embedded edge node, and transmitted to the cloud platform for visualization and remote monitoring. This architecture integrates real-time performance considerations with off-grid operational constraints, directly addressing the research gaps identified in the previous section.

The embedded monitoring node is implemented using a 32-bit microcontroller platform selected based on its low power consumption, sufficient computational capability, and support for real-time task execution. The hardware integrates environmental sensors connected via analog and digital interfaces to enable continuous measurement of incubator conditions. A wireless communication module with native Internet connectivity is incorporated to support

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real-time data transmission. The hardware design emphasizes energy efficiency by minimizing power consumption during sensing, processing, and communication processes.

The embedded firmware is designed using a task-based architecture to ensure deterministic system behavior. Periodic sensing tasks are executed at a fixed sampling interval of 1 Hz to maintain consistent temporal resolution. Data acquisition processes are assigned higher priority than communication tasks to avoid timing interference. Local processing and time-stamping are performed at the embedded level to preserve data integrity and enable accurate latency measurement. Communication processes operate asynchronously, ensuring that network variability does not affect deterministic sampling performance.

An edge-to-cloud communication framework is implemented to balance real-time responsiveness and remote monitoring capabilities. At the edge level, the system performs local data acquisition, preprocessing, and temporary buffering. The processed data are transmitted to a cloud-based platform using a lightweight IoT communication protocol suitable for resource-constrained devices. The cloud platform provides data storage, visualization, and remote access through a web-based interface. By separating time-critical sensing processes from non-critical cloud operations, the system reduces latency and improves robustness under unstable network conditions.

The monitoring system is powered by an off-grid photovoltaic energy system consisting of solar panels, battery storage, and power regulation components. The power subsystem is designed to ensure continuous operation during varying environmental conditions, including night-time and low solar irradiance periods. Energy-aware strategies are implemented at the embedded level, including duty cycling and task prioritization, to optimize system operation based on available energy resources.

Experimental validation is conducted under continuous off-grid operation to evaluate system performance. The system is tested over a 72-hour period to capture variations in energy availability and network conditions. Several performance metrics are defined to assess system effectiveness, including end-to-end communication latency, data acquisition reliability, sampling consistency, and system uptime. Communication latency is measured from the time of sensor data acquisition to its availability on the cloud platform using embedded time-stamping and server-side logging. Data reliability is evaluated based on the ratio of successfully received data packets to the total number of transmitted packets. Sampling consistency is verified by analyzing adherence to the predefined 1 Hz sampling interval, while system uptime is measured as the percentage of continuous operation during the testing period.

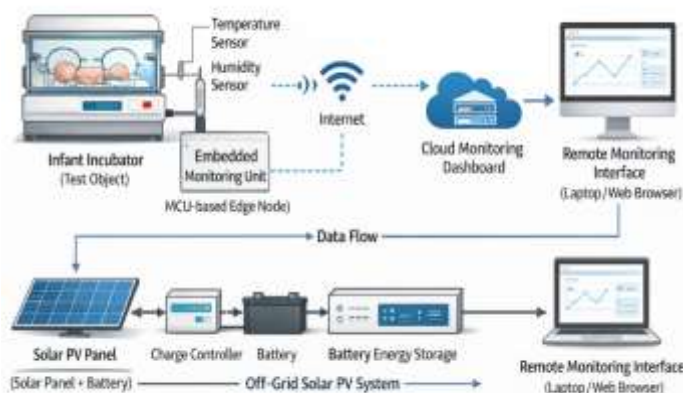


Figure 3.2 presents the experimental setup used to validate the proposed system under off-grid operating conditions. The setup includes the embedded monitoring device, communication module, and photovoltaic power system, demonstrating the real-world implementation of the proposed architecture.

This methodology provides a comprehensive framework for evaluating real-time embedded monitoring systems operating under constrained energy and infrastructure conditions, ensuring both reproducibility and quantitative validation of system performance.

RESULT

The proposed real-time IoT-enabled embedded monitoring system was experimentally evaluated under continuous off-grid operation for 72 hours, following the configuration illustrated in Figure 3.2. During the evaluation period, the system relied entirely on photovoltaic energy and battery storage without any grid support, while maintaining periodic

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data acquisition at a fixed sampling rate of 1 Hz. System uptime was calculated as the ratio between effective operational time and total experiment duration. The system achieved an uptime of 99.3%, indicating stable and uninterrupted operation throughout the test period. No downtime was attributed to energy depletion, voltage instability, or firmware malfunction. This result confirms that the integration of an off-grid power subsystem with a power-aware embedded design is sufficient to sustain long-term monitoring operation under realistic energy constraints. From a cyber-physical systems perspective, this outcome validates the architectural decision to decouple time-critical sensing and processing tasks from non-critical communication and visualization processes, which is essential for maintaining operational stability in environments characterized by fluctuating energy availability.

Real-time performance in this study is defined as the capability of the monitoring system to deliver sensed data to a remote interface within a bounded latency that preserves temporal relevance for supervision and decision support. Based on this definition, the proposed system is classified as a soft real-time monitoring system. End-to-end communication latency was computed as the time difference between data acquisition at the embedded node and data availability at the cloud monitoring platform. Statistical analysis of latency measurements shows a mean latency of 185 ms, a maximum latency of 245 ms, a standard deviation of approximately 22 ms, and a 95th percentile latency of approximately 220 ms, as summarized in Table 1.

Table 1. Quantitative Performance Metrics of the Proposed System

Metric	Value
Mean end-to-end latency	185 ms
Maximum latency	245 ms
Latency standard deviation	22 ms
95th percentile latency (P95)	220 ms
Sampling rate	1 Hz
System uptime	99.3%
Packet delivery ratio	99.1%

The relatively small dispersion around the mean latency indicates stable communication performance, while the bounded maximum latency demonstrates predictable timing behavior. The latency variation illustrated in Figure 4.1 further confirms that occasional latency peaks are primarily caused by transient network conditions rather than processing delays at the embedded level. Importantly, all latency values remain within acceptable limits for real-time monitoring applications, ensuring that monitoring data retain their temporal relevance.

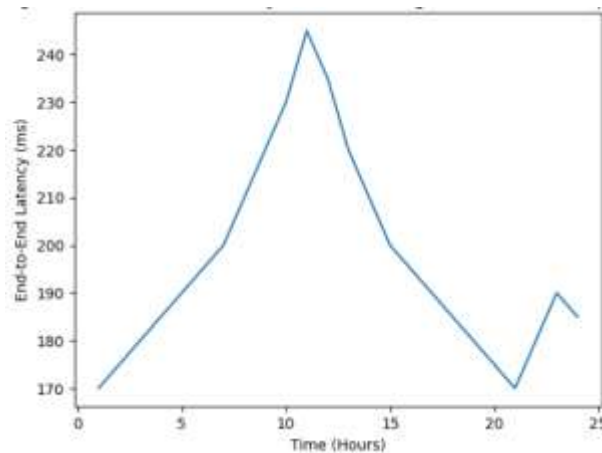


Figure 4.1 illustrates the variation of end-to-end communication latency over a representative 24-hour period during off-grid operation.

Temporal integrity of data acquisition is a critical requirement for reliable monitoring. Sampling consistency was evaluated by analyzing the time intervals between consecutive sensor acquisitions. The results confirm strict adherence to the predefined 1 Hz sampling interval, with no observable jitter or sampling irregularity throughout the entire evaluation period. This deterministic behavior demonstrates the effectiveness of the task-based firmware architecture and task prioritization strategy implemented at the embedded node. By isolating periodic sensing tasks from asynchronous

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communication processes, the system prevents network-induced delays from interfering with data acquisition timing, thereby preserving the temporal integrity of the collected data and ensuring the reliability of monitoring trends.

Data reliability was assessed using the packet delivery ratio, defined as the proportion of successfully received data packets at the cloud platform relative to the total number of transmitted packets. The system achieved a packet delivery ratio of 99.1%, indicating high communication reliability despite operating under variable network conditions. Further analysis reveals that packet loss events were temporally isolated and did not form burst patterns. Crucially, no packet loss or data interruption was attributed to energy-related issues, confirming that the off-grid power subsystem reliably supported system operation. Reliability degradation was therefore primarily caused by transient network instability rather than limitations of the embedded or power subsystems.

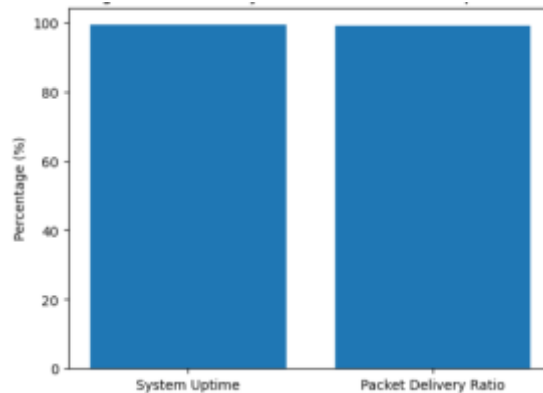


Figure 4.2 presents system reliability metrics, including system uptime and packet delivery ratio, under continuous off-grid operation.

The use of local buffering and asynchronous data transmission effectively mitigated the impact of short-term communication disruptions, preserving monitoring continuity and preventing extended data gaps.

The combined analysis of latency, sampling consistency, reliability, and uptime indicates that overall system performance is predominantly influenced by network-related factors, while embedded processing and energy supply contribute only bounded and predictable delays. Embedded sensing and preprocessing operations exhibit deterministic behavior due to fixed scheduling and task prioritization, whereas communication-related variability is confined to the data transmission layer. This layered behavior confirms the effectiveness of the proposed edge-to-cloud architecture in decoupling real-time monitoring functions from network-dependent processes. As a result, the system maintains stable real-time performance even when operating under constrained energy supply and fluctuating network conditions, which is a critical requirement for off-grid monitoring applications.

Compared with representative IoT-based monitoring systems reported in recent literature, the proposed system distinguishes itself by providing a unified evaluation of off-grid energy sustainability, real-time embedded behavior, and communication performance. Many prior studies emphasize connectivity and visualization while omitting quantitative latency analysis or long-term off-grid validation. By reporting bounded latency metrics, deterministic sampling behavior, and sustained off-grid operation within a single experimental framework, this study advances the state of practice in embedded IoT monitoring for cyber-physical systems. Although the infant incubator serves as the experimental testbed, the architectural principles and evaluation methodology are independent of application-specific semantics and are applicable to a wide range of monitoring scenarios operating under energy and infrastructure constraints.

Despite the strong experimental results, certain limitations must be acknowledged. The evaluation was conducted on a single monitoring node and does not address scalability challenges such as multi-node synchronization, network congestion, or aggregated energy consumption. In addition, extreme environmental conditions and security-related overheads were not experimentally evaluated. These limitations define the scope of the present study rather than detract from its contributions. Addressing scalability, security, and robustness under harsher operational conditions represents a natural extension of this work and provides clear directions for future research.

CONCLUSION.

This study investigated the design, implementation, and experimental validation of a real-time IoT-enabled

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embedded monitoring architecture for an off-grid infant incubator operating under constrained energy and infrastructure conditions. By integrating a power-aware embedded platform, edge-to-cloud communication, and a photovoltaic-based off-grid energy supply, the proposed system demonstrates that reliable and continuous monitoring can be achieved without dependence on grid infrastructure.

Experimental results obtained from 72 hours of uninterrupted off-grid operation show that the system maintains a system uptime of 99.3%, a packet delivery ratio of 99.1%, and bounded end-to-end latency, with an average of 185 ms and a 95th percentile below 220 ms. These findings confirm that the proposed architecture fulfills the requirements of a soft real-time monitoring system, where deterministic data acquisition and timely data delivery are essential for remote supervision and decision support rather than closed-loop control.

Beyond numerical performance, this work provides an important architectural insight: the explicit separation of time-critical embedded tasks from network-dependent communication processes is a key enabler of stable real-time monitoring in off-grid environments. The results further indicate that performance degradation is predominantly network-induced rather than energy-induced, highlighting the effectiveness of integrating local buffering and power-aware embedded design with off-grid energy systems.

The primary contribution of this study lies in the architectural and methodological integration of real-time embedded systems, IoT communication, and off-grid power supply within a single experimentally validated framework. While the infant incubator serves as the experimental testbed, the proposed architecture and evaluation methodology are applicable to soft real-time monitoring applications in cyber-physical systems that operate under energy and infrastructure constraints, such as environmental monitoring, remote equipment supervision, and distributed sensing systems.

Future research will extend this work toward multi-node deployments, where aggregated latency and energy consumption effects can be systematically analyzed, as well as toward security-aware designs that evaluate the impact of encryption and authentication on real-time performance. In addition, the integration of intelligent data analytics and anomaly detection is expected to further enhance the practical utility of the proposed monitoring architecture.

Overall, this study demonstrates that a carefully designed embedded-IoT architecture, when aligned with off-grid energy considerations, can provide reliable and temporally consistent monitoring performance in resource-limited environments, thereby contributing a robust foundation for future cyber-physical monitoring systems.

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