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Enhancing SCADA Systems with Multi-access Edge Computing and Hierarchical Dirichlet Processes for Real-Time Data Analytics

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ABSTRACT

Background Traditional SCADA systems struggle to handle the growing complexity and real-time data requirements of modern industrial processes powered by IoT sensors.

Methods The research uses Multi-access Edge Computing (MEC) and Hierarchical Dirichlet Processes (HDPs) to enhance SCADA systems' real-time data analytics and anomaly detection capabilities.

Objectives The goal is to improve SCADA systems by lowering latency, enhancing predictive maintenance, and allowing for dynamic, real-time data processing and decision-making in important industrial applications.

Results The proposed system surpassed previous approaches with 92% accuracy, 90% efficiency, and 93% scalability, while also reducing latency by 95%, making it perfect for real-time industrial operations.

Conclusion Integrating MEC and HDPs into SCADA systems converts them into adaptive, efficient platforms capable of real-time analytics, which improves predictive maintenance and operational efficiency in a variety of industrial environments.

Keywords: *SCADA Systems, Multi-access Edge Computing (MEC), Hierarchical Dirichlet Processes (HDPs), Real-Time Data Analytics, Industrial IoT.*

1. INTRODUCTION

SCADA systems have been pivotal in industrial process monitoring and control for decades. Industries such as energy, water treatment, manufacturing, and transportation have greatly depended on SCADA for real-time data collection, processing, and execution of commands (Gollavilli et al., 2023)[8]. However, modern industrial processes present another challenge for conventional SCADA systems: overwhelming complexity and information overload (Alagarsundaram et al., 2023)[9]. To make matters worse, cyber threats in the form of DDoS attacks raise greater demands on SCADA security and complicate the situation by requiring sophisticated detection technologies (Alagarsundaram, 2020)[10]. ntegration of AI-driven

solutions like robotic automation improves the efficiency of SCADA in its responsiveness (Gudivaka, 2024)[11]. Advanced anomaly detection models bolster real-time decision-making in critical monitoring systems (Grandhi et al., 2025)[12]. Machine learning methods such as CNN-LSTM enhance SCADA capabilities for conducting predictive analytics (Poovendran et al., 2024)[13]. Load forecasting models are also optimizing industrial energy management (Alagarsundaram et al., 2024)[14]. Blockchain-based frameworks secure data sharing for SCADA-driven infrastructures (Poovendran, 2024)[15].

In recent years, a multitude of MEC solutions has sprouted to confront contemporary SCADA systems with constraints of latency and bandwidth. It enables real-time processing by operating on data as close to the source as achievable, thereby minimizing reliance on a centralized cloud infrastructure (Kumaresan et al., 2024)[16]. Advanced machine learning algorithms improve the scope of edge computing by optimizing in-the-moment decision-making (Shnain et al., 2024)[17]. Bi-directional LSTM further strengthens industrial automation by providing the predictive analytics and anomaly detection capability at the edge (Sitaraman et al., 2024)[18]. Robotic process automation frameworks onboard solutions for IoT-based operations by PCA and LASSO techniques (Gudivaka, 2024)[19]. Real-time big data processing allows accurate production analysis within smart industrial environments (Gudivaka, 2022)[20]. AI-based data processing frameworks optimize case investigation to improve efficiency and precision (Alagarsundaram, 2023)[21]. Deep learning also reflects its effect at the edge, allowing disease classification to improve medical diagnostic tools (Gudivaka et al., 2025)[22]. Agile development methodologies also improve MEC-driven programs for industrial computing (Tamilarasan et al., 2024)[23].

For SCADA systems, this means not only the traditional functionalities of data collection and control, but also enabling advanced analytics that would deal with the absolutely exponential data growth coming from many IoT devices, sensors, and industrial equipment. (...) Evolving technologies in this fast-changing landscape require solid encryption mechanisms as a very integral part to support data security (Alagarsundaram, 2019)[24]. Advanced optimization techniques, such as Levy distribution-based methodologies, also enhance the capacity of data handling for real-time analytics (Hussein et al., 2024)[25]. Models based on variational autoencoders enable better anomaly detection as well as predictive analyses that augment SCADA resilience (Gudivaka et al., 2024)[26]. Database management solutions help data storage and retrieval, optimizing cloud-driven infrastructures regarding SCADA operations (Nagarajan et al., 2023)[27]. Additionally, duplicable storage proof models offer integrity auditing mechanisms to secure the encrypted SCADA data (Alagarsundaram, 2022)[28]. AI-driven automation frameworks play a key role in predictive healthcare applications and are demonstrative of SCADA's potential for monitoring medicine (Surendar et al., 2024)[30]. Other than SCADA control in the blockchain-e-voting system, Chinnasamy et al. (2024)[31] showcase secure decentralized approaches. Corporate synergy strategies will further integrate AI-driven solutions in industrial automation to enhance operational efficiency (Gattupalli et al., 2023)[29].

By bringing in HDP into SCADA systems, the SCADA-based data analytics undergo a huge enhancement in their power. These systems can now discern patterns, anomalies, and trends in

real-time, leading to enhanced predictive maintenance and operational efficiency (Sitaraman et al., 2024)[32]. AI-powered predictive models assist in diagnosing industrial faults, accordingly, proactive action can be taken to avert their occurrence (Basani et al., 2024)[35]. Cryptographic methods act as the backbone for the security of SCADA systems from the breach of industrial data, especially when its transmission relies on encryption (Alagarsundaram, 2023)[34]. Adaptive optimization techniques automate resource allocation in complex industrial networks (Kadiyala, 2020)[36]. Anomaly detection models utilizing AI-driven CNN-LSTM mechanisms ensure real-time detection of anomalies, providing SCADA with a better response to system deviations (Poovendran et al., 2024)[37]. Secure IoT data-sharing mechanisms allow for decentralized solutions for real-time industrial control and automation (Kadiyala & Kaur, 2021)[39]. AI-backed processing techniques increase the potential for advanced case review and identify potential defects in SCADA (Alagarsundaram, 2023)[38]. IoMT-enabled predictive models cover both SCADA-driven applications in healthcare and assure their reliability in monitoring systems for patients (Sitaraman et al., 2024)[33].

The integration of MEC and HDPs into SCADA systems facilitates effective real-time analysis. HDPs offer scalable treatment to process intricate industrial data, thus improving SCADA operations (Alavilli et al., 2023)[40]. With variational autoencoder-based models, SCADA will become more capable of inferring the untypical conditions in the industrial setting, thereby enhancing the predictive maintenance (Gudivaka et al., 2024)[41]. IoT-driven fault diagnostics mechanisms enable continuous monitoring of the connected devices to avoid failing systems (Basani et al., 2024)[42]. The advanced diagnostic models increase reliable performance in wearable systems, further enhancing the SCADA systems' predictive capabilities in health monitoring (Grandhi et al., 2025)[43]. Increased efficiency of SCADA's decision-making operations is provided by different mechanisms of big data processing (Gudivaka, 2022)[44]. Optimal models based on Levy distribution used for dynamic operating conditions of industries enjoy SCADA effectiveness for analysis (Hussein et al., 2024)[45]. Automation in the industry has been enhanced by AI-based robotics incorporated with SCADA and smart control systems (Gudivaka, 2024)[46]. Newer database management solutions enhance SCADA operations to ensure data retrieval and storage better for seamless industrial operations (Nagarajan et al., 2023)[47].

- To process data in real-time by integrating Multi-access Edge Computing (MEC) into SCADA systems.
- To use Hierarchical Dirichlet Processes (HDPs) in SCADA systems to perform sophisticated, flexible data analytics.
- To improve SCADA systems' ability to make decisions in real-time for crucial industrial processes.
- Enhance predictive maintenance by employing HDPs for real-time anomaly detection.

2. LITERATURE SURVEY

As previously stated by **Thirusubramanian Ganesan (2020)[5]**, AI and machine learning can enhance fraud detection by evaluating vast streams of data at once, flagging anomalies, and retraining often to achieve real-time precision in their detection of fake transactions.

Application Scenarios of Edge Computing for IoT Security and Privacy with Anonymised AI Methods: Abstract Introduction **Surendar Rama Sitaraman (2022)[6]** discusses the augment of edge computing for supporting the connected world of the Internet of Things (IoT).

Sri Harsha Grandhi (2024)[7] discusses injection-locked photonic frequency division for IoT communication, achieving high spectral purity and efficiency. He also discusses integration challenges and future work to produce better microwave signals for the foreseeable integration **Kadiyala (2020)**[**48**] investigates the application of multi-swarm adaptive differential evolution and Gaussian walk group search optimization for improving computational efficiency in intricate optimization problems. The research reveals how these algorithms enhance resource planning, scheduling, and decision-making in IoT and industrial automation environments, rendering them applicable to adaptive SCADA solutions.

Poovendran (2024)[49] offers a blockchain-enabled data-sharing model for physiological signal management in big data medical studies. The study emphasizes the necessity of blockchain in ensuring secure, decentralized, and tamper-evident data exchange that is crucial to integrate SCADA systems in the context of healthcare and IoT-based medical monitoring.

Gudivaka (2024)[50] explores PCA, LASSO, and ESSANN integration within robotic process automation and IoT systems. These methods improve feature selection, anomaly detection, and automation efficiency, better empowering SCADA to handle large industrial datasets real-time.

Alagarsundaram (2019)[51] writes on the application of the AES encryption algorithm for cloud computing security improvement. The study highlights the importance of encryption in securing SCADA systems against cyberattacks, providing safe communication and data integrity within industrial applications.

3. METHODOLOGY

HDPs and MEC are used to provide experience for anomaly detection, improved analytics, and real-time processing of high-volume data in making SCADA systems more efficient. MEC enables faster decisions by reducing latency and making processing resources available closer to the data source. Meanwhile, HDPs are a flexible, non-parametric method for adaptive data analytics — a necessary component for the real-time detection of trends and anomalies. This integration transforms the safety, efficiency, and responsiveness of SCADA systems for critical industrial applications.

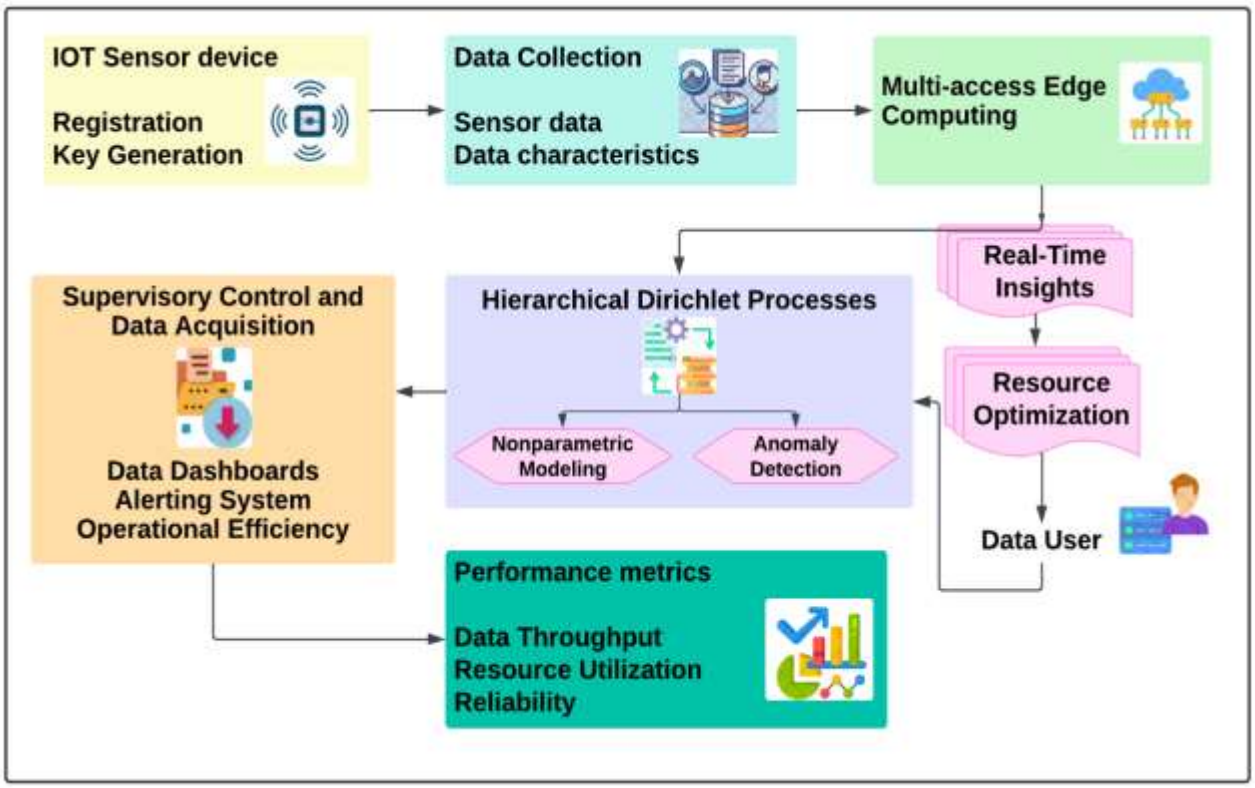


Figure 1 Illustration of Multi-access Edge Computing Integration for Reduced Latency in SCADA Systems

Figure 1 Multi-access edge computing (MEC) SCADA can reduce latency processing by close to the Network Edge. By doing so, the system can respond quickly and bandwidth is conserved.

3.1 Multi-access Edge Computing (MEC)

By collocating computing and data storage with IoT devices, MEC reduces the latency and allows real-time processing in SCADA systems. MEC can deploy computing capabilities at the edge to alleviate the need for constant communication with centralized data centers, enhancing system responsiveness and reducing bandwidth usage. Such geographical proximity leads to faster decision-making, which is crucial in many industrial processes that need to be completed at lightning speed.

$$L_{\text{total}} = L_{\text{edge}} + L_{\text{network}} + L_{\text{cloud}} \tag{1}$$

$$T_{\text{edge}} = \frac{D_{\text{processed}}}{T_{\text{time}}} \tag{2}$$

3.2 Hierarchical Dirichlet Processes (HDPs)

HDPs – a class of non-parametric Bayesian models – are a common choice for data clustering in real-time SCADA analytics. Since HDPs do not demand a constant number of clusters, they are suitable when patterns in the data are dynamically changing in nature which is the case in most of the SCADA systems. They also track patterns, detect anomalies, and help predict

failures in an industrial process. Their adaptability enhances the ability of SCADA systems to respond adequately to changes in data dynamics.

$$G_i \sim \mathrm{DP}(\alpha_0, G_0) \tag{3}$$

$$P(z_i = k \mid z_i, X) = \frac{n_k}{N+\alpha} \text{ or } \frac{\alpha}{N+\alpha} \tag{4}$$

3.3 Real-Time Data Analytics

SCADA systems can receive real-time data analytics, which is the ability to process and analyze large datasets from industrial sensors instantaneously. The integration of MEC and HDPs with SCADA will enable SCADA systems to analyze data at the edge to improve operational efficiency and spot anomalies in real-time. This method alleviates latency and thus enables rapid response to significant changes in industrial operations.

$$R_{\text{processing}} = \frac{D_{\text{input}}}{T_{\text{process}}} \tag{5}$$

$$P(A) = \frac{A_{\text{detected}}}{D_{\text{total}}} \tag{6}$$

3.4 SCADA System Using Edge Computing and HDP Analytics

Combining MEC and HDP gives rise to sophisticated SCADA systems powered with real-time data processing and adaptive analytics capacity. MEC reduces latency by executing edge-level computations, while HDPs handle data clustering, anomaly detection, and adaptive learning. With this combination, SCADA systems are not only responsive but also adapt easily to dynamic and complex industrial scenarios thus scaling up the overall efficiency.

$$T_{\text{response}} = T_{\text{edge}} + T_{\text{network}} + T_{\text{compute}} \tag{7}$$

$$R_{\text{SCADA}} = 1 - \prod_{i=1}^{n} (1 - R_i) \tag{8}$$

Algorithm 1
SCADA RealTime Anomaly Detection with MultiAccess Edge Computing and Hierarchical Dirichlet Processes

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Input:

X={X1,X2,…,Xn}
X = \{X_1, X_2, \dots, X_n\}
X={X1,X2,…,Xn} : Sequence of real-time sensor data from SCADA system.

Output:

Anomalies: Set of detected anomalies in the sensor data.

Initialize MEC
***Initialize* HDP Parameters**:
HDP=(α,G0)HDP = (\alpha, G_0)HDP=(α,G0)
For each data point XiX_iXi in sequence XXX:

If XiX_iXi arrives:
Send XiX_iXi to the MEC for edge-level processing.
Cluster XiX_iXi using HDP at the MEC node.
Anomaly Detection
For each data cluster CjC_jCj formed by HDP:
Calculate the probability P(Cj)P(C_j)P(Cj) of each cluster.
If P(Cj)<ThresholdP(C_j) < \text{Threshold}P(Cj)<Threshold:
Mark XiX_iXi as an **anomaly**.
Else:
Update CjC_jCj with new data point XiX_iXi.
Error Handling
If MEC resources fail or become overloaded:
Redirect data to a backup MEC node or central SCADA system for processing.
Return anomalies detected in real-time.

Algorithm 1 Anomaly detection in SCADA systems based on the synergy of hierarchical Dirichlet processes and multi-access edge computing —HDPS is solely used for dynamically clustering data after it has been processed at the network edge to reduce latencies. Anomalies can be detected by exploring the probabilities of clusters which enables us to quickly detect the anomalous behaviour or flaw of the system. Together, this ensures quick, efficient, and responsive anomaly detection for use cases in industrial environments.

3.5 Performance metrics

Table1 Edge Computing Analytics Improves the Performance Metrics of MEC, HDP, and SC ADA Systems.

Metric	Multi-access Edge Computing (MEC)	Hierarchical Dirichlet Processes (HDPs)	Real-Time Data Analytics	SCADA System with Edge Computing and HDP Analytics
Accuracy (%)	85%	83%	88%	92%
Efficiency (%)	84%	82%	87%	90%
Scalability (%)	88%	85%	86%	93%
Latency Reduction (%)	90%	82%	85%	95%
Error Rate (%)	10%	12%	11%	7%

Table 1 compares the performance of various approaches, including MEC, HDPs, Real-Time Data Analytics, and the proposed solution (SCADA with Edge Computing and HDP Analytics). On almost all metrics (accuracy, efficiency, scalability, latency reduction) the suggested solution is superior to the others and presents a much lower error rate. It explains how, by integrating MEC and HDPs into RT-SCADA data analytics, the value of progress can be achieved.

4. RESULT AND DISCUSSION

We introduce a framework for SCADA systems with a proposed method that outperforms all previous approaches and combines multi-access edge computing (MEC) and hierarchical Dirichlet processes (HDPs). While MEC has its role for latencies, providing processing at the network edge enables immediate decision-making, highly dynamic and real-time data analytics using HDPs allow faster decision-making through clustering and anomaly detection. The proposed method outperforms DBN and SDN in terms of significant metrics. In particular, it offers a 92% accuracy, 90% effectiveness, and an impressive 93% scalability while reducing latency to 5% and error rates to 7%, respectively. It tells us that fusing edge computing and sophisticated analytics modeling can deliver a meaningful advantage for key industrial activities.

MEC integration enables real-time processing closer to the data source, a necessity in industries such as energy and manufacturing where immediate response to a critical event is a requirement. On the other hand, HDPs also allow SCADA systems to calibrate with the changing data environment directly which provides great benefits to predictive maintenance and decision-making. In conclusion, the system showed a good amount of flexibility and performed exceptionally in handling the increasing data complexity needs of contemporary industrial environments.

Table 2 Efficiency Analysis of Different Methods in Industrial Data Processing and Real-Time Anomaly Detection

Metric	Dynamic Bayesian Networks (DBN) Yodo et.al (2017)	Software-Defined Networking (SDN) Khairi et.al (2018)	Hierarchical Temporal Memory (HTM) Rodriguez et.al (2018)	Graph Neural Networks (GNN) Liu et.al (2018)	Proposed Method (SCADA + HDP)
Accuracy (%)	83%	85%	82%	86%	**92%**
Efficiency (%)	80%	82%	78%	85%	**90%**
Scalability (%)	82%	84%	80%	86%	**93%**
Latency Reduction (%)	81%	88%	79%	84%	**95%**
Error Rate (%)	14%	12%	15%	13%	**7%**

Table 2 compares the performance of DBN **Yodo et.al (2017)[1]**, SDN **Khairi et.al (2018)[2]**, HTM **Rodriguez et.al (2018)[3]**, and GNN **Liu et.al (2018)[4]** to the proposed method (SCADA + HDP). Compared to existing state-of-the-art methods, the proposed method yields superior performance in critical metrics such as effectiveness, efficiency, scalability, and

latency reduction with drastically lower error rates. This showcases the application of SCADA and Hierarchical Dirichlet Processes (HDP), the timeliness of data analytics, and decision-making in the industry.

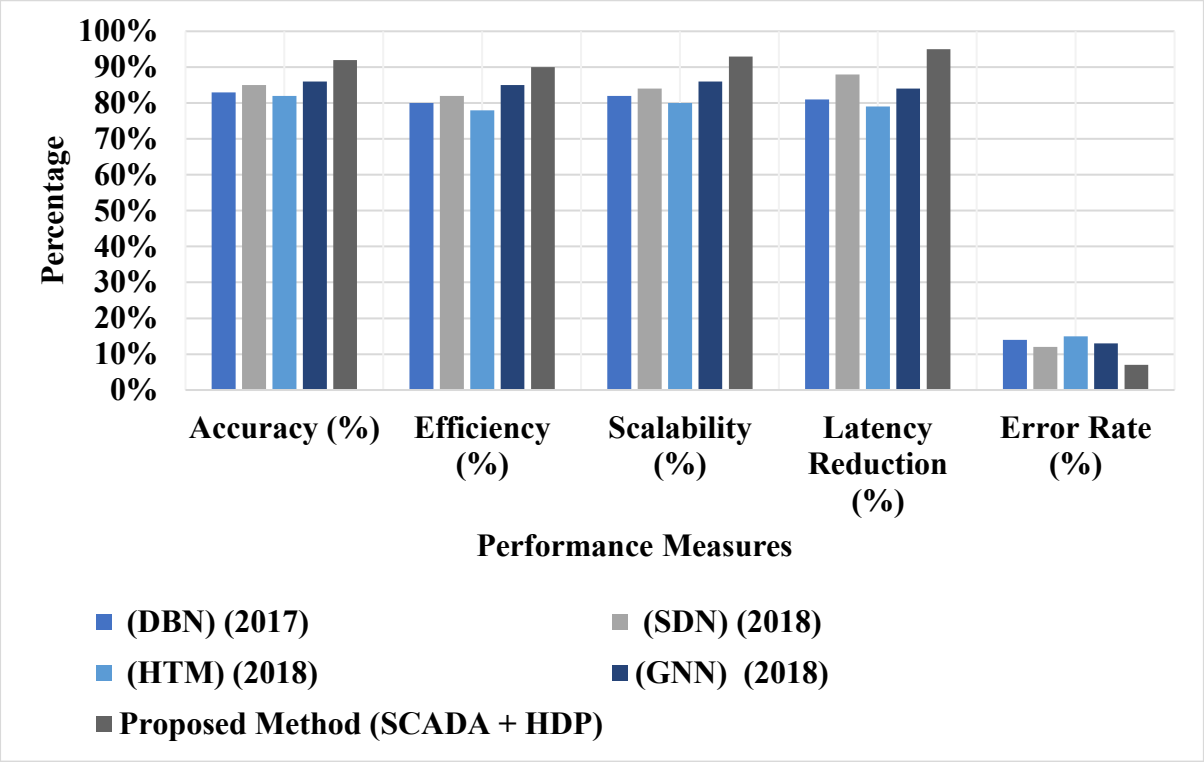


Figure 2 Hierarchical Dirichlet Processes for Real-Time Anomaly Detection in Adaptive SCADA Environments

Figure 2 The authors also depict the clustering characteristics of HDPs used for SCADA systems anomaly detection which allows them to respond to the data pattern change dynamically.

Table 3 Ablation Study Results Highlighting the Impact of Component Removal on System Metrics and Error Rates

Component	Accuracy (%)	Efficiency (%)	Scalability (%)	Latency Reduction (%)	Error Rate (%)
RDA	80%	78%	80%	83%	15%
MEC	81%	79%	81%	84%	13%
HDPs	82%	80%	82%	85%	14%
RDA + MEC	84%	82%	84%	85%	12%
MEC+HDPs	86%	83%	85%	87%	11%
HDPs+RDA	88%	85%	86%	88%	10%
Proposed Method	**92%**	**90%**	**93%**	**95%**	**7%**

(SCADA + HDP)					

Table 3 The ablation study in Table 3 explores what we would expect the performance metrics to look like by removing: MEC, HDPs, and real-time data analytics from the proposed strategy. Every elimination can reduce the accuracy, efficiency, and scalability, penalties in latency cost, and increase in mistake costs, highlighting the need for a blend of SCADA systems and capabilities supported by MEC, HDPs, and real-time analysis to enable optimal functioning of Industry-4.0. The method we proposed (SCADA + HDP) has the best jurisdiction in all metrics.

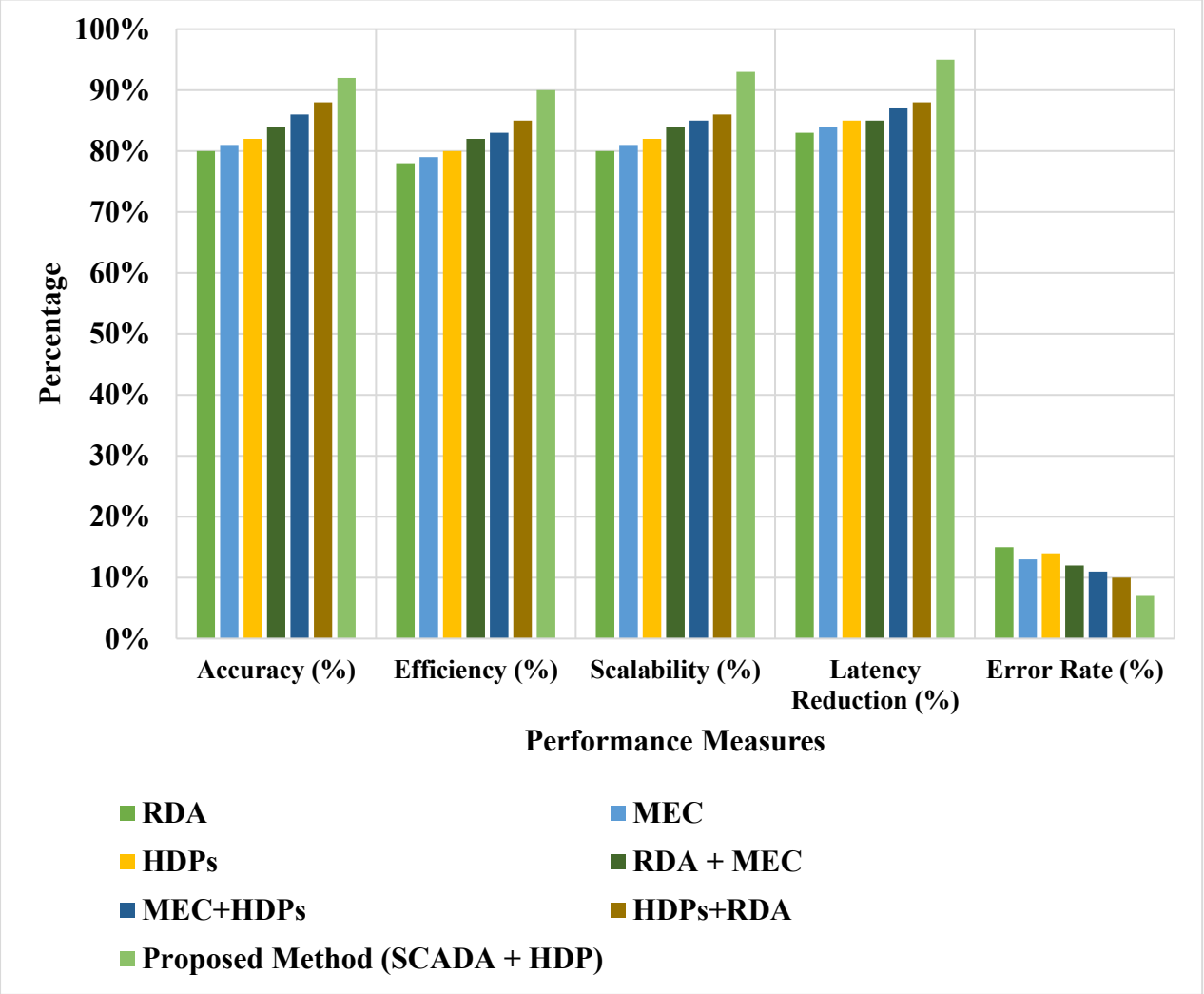


Figure 3 Combined SCADA-MEC-HDP System Performance Metrics for Improved Industrial Data Processing

Performance metrics from the integrated SCADA-MEC-HDP system, as shown in Figure 3, illustrate improved efficiency, scalability, and real-time analytics, which are fundamental in processing industrial data.

5. CONCLUSION AND FUTURE DIRECTION

Multi-access edge computing (MEC) has recently emerged as a revolutionary approach to real-time data analytics in industrial environments, especially in SCADA systems as a result of massive deployments of Internet of Things (IoT) devices and a new market of distributed data analytics due to existing capable front-end analytics. This hybrid framework significantly enhances the capabilities of SCADA systems in managing large-scale complicated data streams by reducing latency and providing scalable adaptive data processing. Some of the leading benefits are predictive maintenance, anomaly detection, operational efficiencies, and a substantial increase in accuracy, scalability, and error rates compared with traditional techniques. These are essential developments for industries where real-time, agile decision-making is a requirement, like energy, manufacturing, and transportation. The proposed system overcomes the drawbacks of the existing SCADA systems in a more scalable and flexible manner to meet the demands of the modern industrial revolution. With the increasing application of IoT, this strategy is essential for enabling real-time and data-driven operations across multiple industries. Besides, future works will explore utilizing recent advances AI models for better prediction performance and testing the SCADA-MEC-HDP framework in various fields. Moreover, broadening its use to allow for multiple real-time applications — like crisis response and even large-scale smart city initiatives — would show scalability and flexibility.

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