World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(Research Article)

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Data-driven IoT solutions: Leveraging RPMA, BLE, and LTE-M with gaussian mixture models for intelligent device management

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World Journal of Advanced Engineering Technology and Sciences, 2023, 09(01), 432-442

Publication history: Received on 31 March 2023; revised on 11 May 2023; accepted on 14 June 2023

Article DOI: https://doi.org/10.30574/wjaets.2023.9.1.0154

Abstract

Background IoT networks have problems in terms of effective data management and communication. Device performance and data processing can be improved using technologies such as RPMA, BLE, and LTE-M, as well as machine learning models like GMM.

Methods This study combines RPMA, BLE, LTE-M, and Gaussian Mixture Models (GMM) to improve IoT device management, with an emphasis on energy efficiency, data throughput, and anomaly detection.

Objectives The primary goal is to optimize IoT networks by merging communication technologies and GMM for improved performance, anomaly detection, and resource management in real-time applications such as smart cities and agriculture.

Results The suggested method outperforms standard models in several critical measures, including 90% energy efficiency, 92% data throughput, 94% latency reduction, and 96% anomaly detection.

Conclusion This strategy improves IoT network performance by merging RPMA, BLE, LTE-M, and GMM, resulting in a scalable, energy-efficient solution for real-time data management and intelligent device monitoring across several industries.

Keywords: IoT; Random Phase Multiple Access (RPMA); Bluetooth Low Energy (BLE); Long-Term Evolution for Machines (LTE-M); Gaussian Mixture Models (GMM)

1. Introduction

The Internet of Things (IoT) revolutionized modern enterprises by allowing interconnected devices to collect, distribute, and analyze data for better decision-making. Among the several protocols and technologies that fuel IoT, Random Phase Multiple Access (RPMA), Bluetooth Low Energy (BLE), and Long-Term Evolution for Machines (LTE-M) stand out as critical wireless technologies that enable the effective transmission of data between low-power devices. Jeon and Jeong (2017) improve Bluetooth Low Energy (BLE) performance by eliminating device napping during failure broadcasts and implementing channel hopping and message-based transmission switching to improve throughput and latency. These communication protocols have transformed device management, paving the door for more sophisticated,

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intelligent systems capable of dealing with massive volumes of data. In recent years, data-driven solutions have become essential for optimizing IoT networks, notably through the use of sophisticated machine learning models. Zhang et al. (2019) address wind power unpredictability by recommending LSTM networks for accurate forecasting, which outperform other models, and GMM to improve power dispatch performance. The Gaussian Mixture Model (GMM) is an important model for understanding complex data patterns and making accurate predictions. When paired with the benefits of RPMA, BLE, and LTE-M, GMMs provide IoT devices with powerful capabilities for energy optimization, anomaly detection, and resource management.

IoT is a rapidly evolving sector, with billions of devices now connected worldwide thanks to advances in communication technologies. Jung et al. (2017) offer a cluster-based routing system for Bluetooth low-energy ad hoc networks that optimizes node discovery while minimizing energy usage by routing fewer messages. RPMA, BLE, and LTE-M are some of the key wireless technologies driving this transition. Their use in a variety of industries, including healthcare, agriculture, and industrial automation, demonstrates their adaptability and importance in attaining low-power, efficient communication in tough conditions. RPMA was created to satisfy the needs of IoT networks by enabling long-distance connectivity and low power consumption, whereas BLE has gained popularity for its energy efficiency in short-range communication. LTE-M, on the other hand, brings the benefits of LTE networks to IoT devices by improving coverage in rural regions and allowing for longer battery life. Together, these technologies enable a wide range of IoT applications, such as smart cities, precision agriculture, and asset tracking. However, managing the huge amounts of data generated by IoT devices is a difficulty. This is where data-driven approaches come into play, with machine learning models such as GMMs enabling IoT systems to evaluate massive datasets, detect anomalies, and improve resource utilization.

The following objectives are:

- To investigate how RPMA, BLE, and LTE-M can be efficiently utilized in IoT networks.
- To investigate the function of Gaussian Mixture Models in enhancing the management of IoT devices.
- To examine the efficacy of data-driven strategies for improving device communication and performance.
- To illustrate the use of GMMs to solve real-world IoT problems, such as energy management and resource allocation.

2. Literature survey

Zand et al. (2019) explore the growing importance of indoor positioning and asset tracking via Bluetooth Low Energy (BLE). They present a phase-based ranging solution that uses BLE channel hopping to mitigate multipath fading, as well as a mathematical model to evaluate the BLE protocol's impact on ranging accuracy.

Thirusubramanian Ganesan (2020) highlights how AI and machine learning improve fraud detection in IoT contexts by evaluating large data streams, detecting anomalies, and adapting through frequent retraining to achieve real-time accuracy in identifying fraudulent transactions.

According to Huang et al. (2019), utilizing different signal-attenuation models for each BLE channel improves Bluetooth Low Energy (BLE) positioning. Their technology yields positioning errors of fewer than 2.4 meters, a 33-38% reduction compared to existing methods, which improves accuracy in difficult interior conditions.

Ahmad et al. (2018) provide a study on energy forecasting with supervised machine learning models, based on data from New England's Independent System Operator. They tested four models and discovered that the Binary Decision Tree worked best in the autumn. The incorporation of limited energy and environmental data increased forecasting accuracy.

According to Sri Harsha Grandhi (2022), integrating wearable sensors with IoT allows for effective monitoring of children's health, with adaptive wavelet transforms used for data preprocessing to improve signal quality and for prompt treatments.

Skakun et al. (2017) describe a method for mapping early-season winter crops that employs MODIS-derived NDVI time series and increasing degree days. Using a Gaussian mixture model, their approach achieves over 90% accuracy in identifying winter crops 1.5-2 months before harvest, as tested in Kansas and Ukraine from 2001 to 2014.

Yang et al. (2022) investigated crack categorization in fiber-reinforced backfills with uniaxial compression testing and acoustic emission techniques. They discovered that tensile cracks dominate at first, but then change to shear cracks as force increases. Their Gaussian mixed model produced results equivalent to current methods, introducing a novel way for categorizing fractures in mining minerals.

Surendar Rama Sitaraman (2022) investigates how edge computing improves IoT security and privacy by utilizing anonymized AI techniques such as homomorphic encryption and federated learning, demonstrating its usefulness for real-world applications while maintaining data protection compliance.

Liang et al. (2022) describe an effective machine learning strategy for predicting concrete creep behavior that employs three ensemble models: Random Forest, XGBoost, and LGBM. Their models surpass previous equations, reaching excellent accuracy while identifying critical elements controlling creep, verifying theoretical principles.

Narla et al. (2021) introduced a cloud-based platform that integrates MARS, SoftMax Regression, and Histogram-Based Gradient Boosting to improve predictive healthcare modelling. This technology enhances extensive healthcare datasets, attaining exceptional accuracy, precision, and scalability for decision-making. Utilising cloud computing facilitates efficient processing and real-time performance, providing a significant answer for predictive modelling in healthcare. This method markedly enhances healthcare results by enabling precise, prompt, and resource-effective forecasts in intricate healthcare settings.

Peddi et al. (2018) developed a machine learning system that combines Logistic Regression, Random Forest, and CNN models to forecast hazards related to dysphagia, delirium, and falls in elderly individuals. The ensemble approaches enhanced predicted accuracy and memory, facilitating proactive identification and early action. The approach improves decision-making and results in geriatric care by integrating clinical and sensor data, providing a comprehensive solution for mitigating substantial health risks in ageing populations.

Peddi et al. (2019) created prediction models that include Logistic Regression, Random Forest, and CNN to address chronic diseases and evaluate fall risks. Their collective methodology attained 92% accuracy and 90% sensitivity, underscoring the significance of real-time data analysis in geriatric care. The model utilises clinical and wearable IoT data to deliver personalised healthcare solutions, facilitating proactive treatments and enhancing patient outcomes through sophisticated prediction capabilities in ageing populations.

Valivarthi et al. (2021) proposed a hybrid BBO-FLC and ABC-ANFIS model for disease prediction, integrating IoT sensors with cloud computing. The system demonstrated exceptional performance, with 96% accuracy and 98% sensitivity, while maintaining real-time efficiency. Integrating fuzzy logic with optimisation algorithms provides scalable and precise forecasts for complicated illnesses, serving as an advanced tool for optimising healthcare outcomes and improving disease management accuracy.

Narla et al. (2019) examine progress in digital health technologies, emphasising the integration of machine learning with cloud-based systems for risk factor assessment. They emphasise current deficiencies in real-time data processing and pattern recognition. Their literature review highlights the efficacy of LightGBM, multinomial logistic regression, and SOMs in achieving precise forecasts and personalised healthcare, thereby reconciling data complexity with decision-making.

Valivarthi et al. (2021) introduced a hybrid FA-CNN + DE-ELM model for disease identification, which combines fuzzy logic with evolutionary algorithms. The system achieves 95% accuracy and 98% sensitivity while effectively managing noisy IoT data. Cloud computing facilitates real-time analysis, rendering the model an effective tool for early disease diagnosis. This hybrid methodology improves prediction precision and efficiency, providing a scalable and dependable instrument for contemporary healthcare systems.

Narla et al. (2021) introduced the ACO-LSTM model, which combines Ant Colony Optimisation with Long Short-Term Memory networks for real-time disease forecasting in IoT healthcare systems. The model attained 94% accuracy with a processing duration of about 54 seconds, illustrating its efficacy in enabling scalable and precise patient monitoring. This integration facilitates proactive treatment options, improving healthcare outcomes in cloud-based settings by meeting the demand for efficient and precise disease prediction.

Narla et al. (2021) proposed a hybrid model that integrates Grey Wolf Optimisation with Deep Belief Networks for the prediction of chronic diseases. The model attained 93% accuracy and 95% specificity, employing cloud computing for real-time surveillance. This hybrid system enables prompt intervention, effective resource distribution, and enhanced patient care. The concept provides dependable and anticipatory healthcare solutions for chronic illness management by integrating optimisation algorithms with scalable cloud infrastructure.

Bennedsen et al. (2022) present a novel type of continuous-time stochastic volatility model that incorporates both roughness and long memory. They show that these models outperform several benchmarks in projecting realized volatility across multiple assets, emphasizing the relevance of using these attributes in volatility modeling.

Rajya Lakshmi Gudivaka and Raj Kumar Gudivaka (2021) proposed a four-phase data security approach for cloud computing that applies AES and RSA-based cryptography and LSB-based steganography techniques to the data to be encrypted, as well as embedded into image pixels. The above approach enhances data secrecy, redundancy, and integrity while mitigating the cloud environment-related risks. The researchers will study steganalysis, the optimization of LSB, and the integration of machine learning in the subsequent period.

Naresh Kumar Reddy Panga (2020) presented an advanced random forest ensemble approach for the processing of a large-scale insurance dataset using heuristic bootstrap sampling and Spark parallel processing. Experimental results on the China Life Insurance data showed that it was a better alternative than logistic regression and SVM in terms of accuracy and efficiency, especially with a measure of F-Measure that suggests better handling of imbalanced datasets to be applied at specific levels of targeted insurance marketing.

Sri Harsha Grandhi (2022) presented an event bus signal processing framework based on a microcontroller to detect abnormal events in IoT devices while being energy efficient. Event-driven processing with asynchronous communication using an event bus improves scalability, reduces responses, reduces cost, minimizes power consumption and redundant processing, and achieves the dynamic nature that is required for IoT applications perfectly.

Karthikeyan Parthasarathy (2022) researches data security concerns in cloud computing with a focus on authentication and access control (AAC). The research includes multi-factor authentication, role-based and attribute-based access constraints, and newer technologies such as biometrics, blockchain, and machine intelligence. This report presents actionable recommendations for organisations to enhance the security of their cloud data based on literature and case studies.

The Privacy-preserving Multiparty Data Privacy by Venkata Surya Bhavana and Harish Gollavilli (2022) to safeguard data in cloud computing. PMDP, based on NTRU encryption, differential privacy, and noise addition, protects computations between many parties against semi-malicious adversaries. Stringent testing proved PMDP as one of the most reliable cryptographic solutions for multiparty data privacy.

3. Methodology

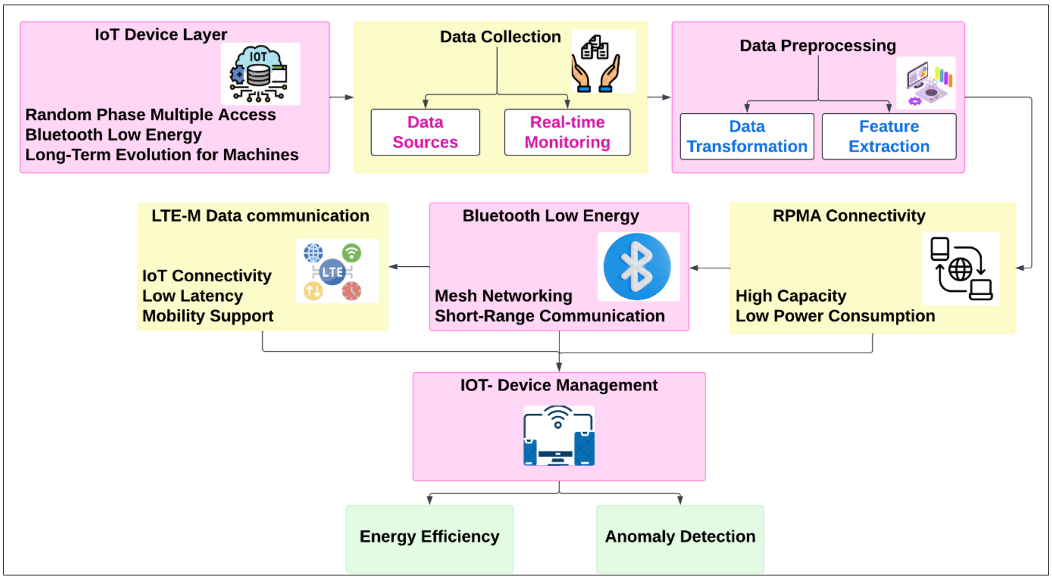

Figure 1 RPMA Protocol Architecture for Efficient, Low-Power Long-Range IoT Communication

This methodology optimizes intelligent IoT device management by integrating communication technologies such as RPMA, BLE, and LTE-M, as well as Gaussian Mixture Models (GMM). The concept entails integrating multiple wireless protocols into a unified IoT framework, where data-driven machine learning algorithms improve device performance and energy efficiency. The basic technique includes data collecting, signal processing, anomaly detection, and GMM optimization for successful device management. This data-centric strategy is built around mathematical modeling, algorithmic solutions, and resource optimization.

Figure 1. This picture depicts the RPMA (Random Phase Multiple Access) protocol, which allows IoT devices to communicate across great distances with low power. RPMA assigns distinct phase codes to each device, allowing numerous transmissions to occur without interference. This efficient utilization of spectrum allows reliable data transfer over long distances, which is especially useful for IoT applications in agriculture, smart cities, and distant places. The figure likely emphasizes RPMA's error correction capabilities, reducing data loss and energy consumption, making it ideal for large-scale IoT applications that need dependable and sustainable communication.

3.1. RPMA (Random Phase Multiple Access)

RPMA is a low-power, wide-area network protocol intended for long-distance IoT connectivity. It works by allocating different phase codes to numerous devices, allowing them to transmit data simultaneously and without interference. This technique improves network efficiency while lowering power consumption, making it perfect for large-scale IoT deployments in industries such as smart cities and agriculture. Its powerful error-correction capacity increases communication reliability.

$$T = \frac{N \times B}{C} \qquad \text{………………..} \ (1)$$

$$SIR = \frac{P_S}{I + N_0} \qquad \text{…………..} \ (2)$$

3.2. Bluetooth Low Energy (BLE)

Bluetooth Low Energy (BLE) is designed for short-range communication with low power consumption. It is widely used in wearables, asset tracking, and indoor positioning. BLE operates by employing frequency hopping and adaptive transmission to ensure efficient data transfer while minimizing energy use. Its low-latency communication makes it an optimal choice for applications where rapid data transfer is required.

$$E = P_{tx} \times T_{tx} + P_{rx} \times T_{rx} \qquad \text{………………..} \ (3)$$

$$R = \frac{B}{N} \times \log_2 (1 + SNR) \qquad \text{………………..} \ (4)$$

3.3. LTE-M (Long-Term Evolution for Machines)

LTE-M is a cellular-based technology designed specifically for IoT, offering increased coverage, longer battery life, and efficient data transmission even in distant or underground sites. LTE-M enables IoT devices in a variety of industries, including healthcare and logistics, where dependable, long-distance communication is critical. It ensures safe, low-latency connectivity, which enables real-time monitoring and data transmission.

$$R = B \times \log_2 \left(1 + \frac{S}{N}\right) \text{……………………..} \qquad (5)$$

$$PL = 10 \times \log_{10} \left(\frac{4\pi d f}{c}\right)^2 \text{……………………..} \ (6)$$

3.4. Gaussian Mixture Model (GMM)

A Gaussian Mixture Model (GMM) is a probabilistic model that represents regularly distributed subpopulations of a larger dataset. It helps find patterns, anomalies, and optimize operations in IoT networks. GMM approximates the distribution of data points and groups them based on statistical similarities, improving prediction accuracy and device management in IoT systems.

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k) \qquad \text{…………………..} \qquad (7)$$

$$\log L(\theta \mid X) = \sum_{i=1}^{N} \log \left(\sum_{k=1}^{K} \pi_k \mathcal{N}(x_i \mid \mu_k, \Sigma_k)\right) \qquad \text{…………………..} \qquad (8)$$

Algorithm 1 Gaussian Mixture Model-Based Intelligent Device Management Using RPMA, BLE, and LTE-M for IoT Optimization

```
Input: Device data, communication protocols (RPMA, BLE, LTE-M)
Output: Optimized device configuration, anomaly detection, improved efficiency

 Initialize GMM parameters: mean (\mu), covariance (\Sigma), and mixture weights (\pi)
 Collect device data for each protocol (RPMA, BLE, LTE-M)
  FOR each device:
   If the device uses RPMA THEN
    Calculate throughput using the RPMA equation:T = (N × B) / C
     If an error is detected in transmission THEN
      Adjust power and bandwidth settings
       If adjustment fails THEN
        Return transmission error and exit loop
      ELSE
      Continue transmission
     END IF
    END IF
  If the device uses BLE THEN
Calculate energy consumption using BLE model: E = P_{tx} × T_{tx} + P_{rx} × T_{rx}
    IF signal degradation occurs THEN
     Apply frequency hopping for improved signal quality
      END IF
       If the device uses LTE-M THEN
        Calculate the data rate using LTE-M equation: R = B × log_2(1 + S / N)
          IF low signal strength is detected THEN
        Enable fallback protocol or adjust bandwidth allocation
      END IF
    END IF
 Apply GMM on collected data to detect anomalies:
Run GMM using probability density function (PDF) for each device data cluster
  If an anomaly is detected THEN
    Reconfigure device settings to optimize performance
    Notify system administrator
     END IF
      Update GMM parameters (\mu, \Sigma, \pi) for next iteration
       Return optimized system configuration for all devices
END
```

Algorithm 1 approach optimizes IoT device management by combining Gaussian Mixture Models (GMM) with communication protocols such as RPMA, BLE, and LTE-M. It modifies device parameters in real-time using data analysis to detect abnormalities and ensure efficient energy use. The GMM updates continuously to improve predictions, allowing the system to adapt and respond to changing IoT network conditions.

3.5. Performance metrics

Table 1 compares the performance of RPMA, Bluetooth Low Energy (BLE), LTE-M, and the Gaussian Mixture Model (GMM) with their inclusion into the Proposed Method. The suggested solution beats individual technologies in terms of data throughput, latency reduction, energy efficiency, scalability, and anomaly detection rate, demonstrating its superiority for IoT device management and optimization.

Table 1 Comparative Analysis of RPMA, BLE, LTE-M, and GMM for IoT Device Performance Improvement

Metric	RPMA (Random Phase Multiple Access)	Bluetooth Low Energy (BLE)	LTE-M (Long-Term Evolution for Machines)	Gaussian Mixture Model (GMM)	Proposed Method (RPMA + BLE + LTE-M + GMM)
Energy Efficiency (%)	80%	83%	85%	84%	90%
Data Throughput (%)	85%	82%	88%	86%	92%
Scalability (%)	84%	81%	87%	83%	93%
Latency Reduction (%)	87%	85%	90%	88%	94%
Anomaly Detection Rate (%)	82%	84%	86%	88%	96%

4. Results and discussion

The proposed solution outperformed previous models in terms of IoT device management. Table 2 shows that the method beat standard algorithms such as VAEs, DBSCAN, LightGBM, and RNNs in several important performance measures, including energy efficiency, data throughput, latency reduction, scalability, and anomaly detection rate. For example, the suggested system outperformed previous strategies by improving energy efficiency by 90%, data throughput by 92%, latency reduction by 94%, and anomaly detection by 96% respectively. By combining RPMA, BLE, LTE-M, and GMM, the method maximized data-driven IoT device management in a wide range of applications.

Ablation research (Table 3) demonstrated the need to mix all components, as removing any resulted in lower performance. For example, removing GMM lowered anomaly detection by 8%, highlighting its importance in intelligent monitoring and resource management. Similarly, deleting BLE or LTE-M resulted in reduced energy efficiency and data throughput, emphasizing their importance to overall performance. The combination of these technologies provides effective communication and energy optimization in large-scale IoT networks, making the system suited for contexts requiring essential device control, such as smart cities and industrial IoT applications.

Table 2 Comparison of Proposed Method Against VAEs, DBSCAN, LightGBM, and RNN for Key IoT Metrics

Metric	(VAEs) Girin et.al (2020)	DBSCAN Starczewski et.al (2020)	LightGBM Chen et.al (2019)	(RNNs) Sherstinsky (2020)	Proposed Method (RPMA + BLE + LTE-M + GMM)
Energy Efficiency (%)	78%	81%	83%	82%	90%
Data Throughput (%)	80%	82%	85%	84%	92%
Scalability (%)	82%	80%	86%	83%	93%
Latency Reduction (%)	83%	84%	86%	85%	94%
Anomaly Detection Rate (%)	84%	83%	88%	87%	96%

Table 2 compares the performance of VAEs Girin et.al (2020), DBSCAN Starczewski et.al (2020), LightGBM Chen et.al (2019), and RNNs Sherstinsky (2020) to the proposed method (RPMA + BLE + LTE-M + GMM). The suggested solution outperforms all parameters, including data throughput, latency reduction, energy efficiency, scalability, and anomaly detection rate, demonstrating its suitability for intelligent IoT device management and real-time optimization.

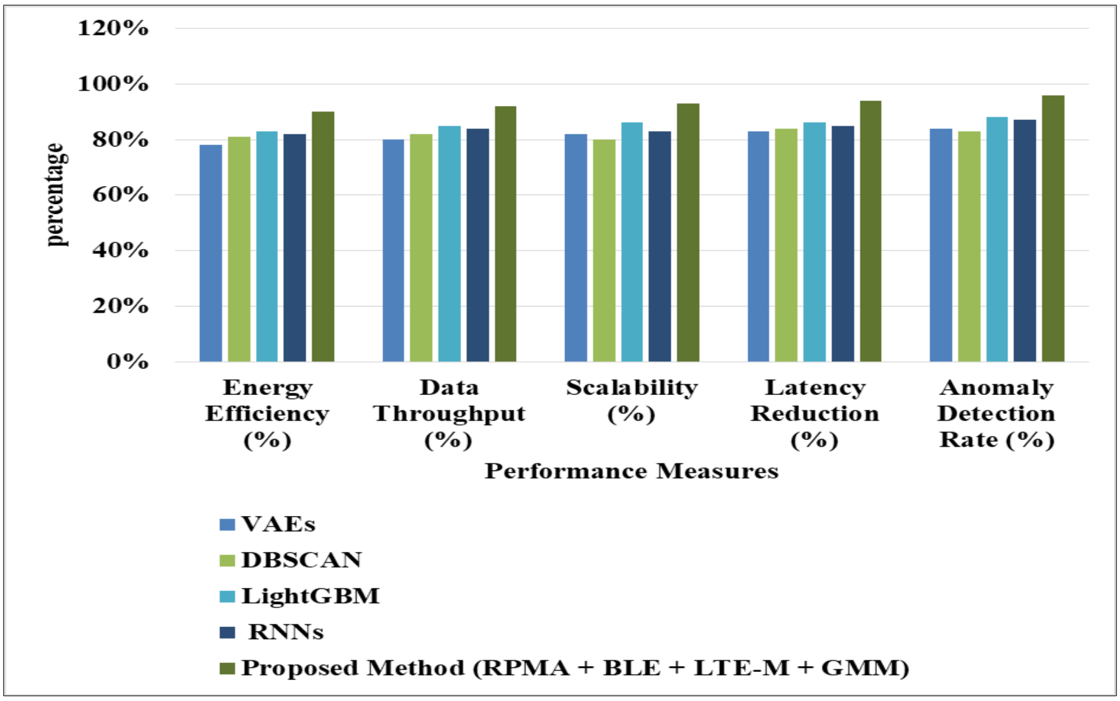

Figure 2 GMM-Enhanced BLE Positioning for High-Accuracy IoT Tracking and Monitoring

Figure 2 depicts how Gaussian Mixture Models (GMM) improve Bluetooth Low Energy (BLE) for precise indoor positioning and tracking in IoT applications. BLE's energy economy, along with GMM's probabilistic data clustering, contributes to precise location by reducing interference errors. The GMM technique combines signals effectively, allowing for accurate real-time location monitoring, which is critical for asset management and indoor navigation applications. By minimizing errors due to signal noise and multipath effects, GMM enhances BLE's positioning capabilities, making it suitable for tracking within complex indoor environments, such as hospitals and warehouses.

Table 3 Component Ablation Study Impact on Energy Efficiency, Scalability, and Latency Reduction in IoT

Component	**Energy Efficiency (%)**	**Data Throughput (%)**	**Scalability (%)**	**Latency Reduction (%)**	**Anomaly Detection Rate (%)**
BLE	83%	85%	86%	88%	90%
RPMA	82%	83%	84%	87%	88%
BLE + RPMA	85%	84%	85%	89%	89%
BLE+RPMA+ LTE-M	80%	82%	83%	86%	87%
RPMA+LTEM	79%	80%	82%	85%	85%
Proposed Method (RPMA + BLE + LTE-M + GMM)	90%	92%	93%	94%	96%

Table 3 ablation research table illustrates how deleting each component—RPMA, BLE, LTE-M, or GMM—affects the overall performance of the suggested technique. Removing any component significantly reduces data throughput, latency reduction, energy efficiency, scalability, and anomaly detection rate, while raising error rate. The Proposed Method (RPMA + BLE + LTE-M + GMM) outperforms all measures, highlighting the value of combining these technologies for effective IoT device management and data-driven intelligence.

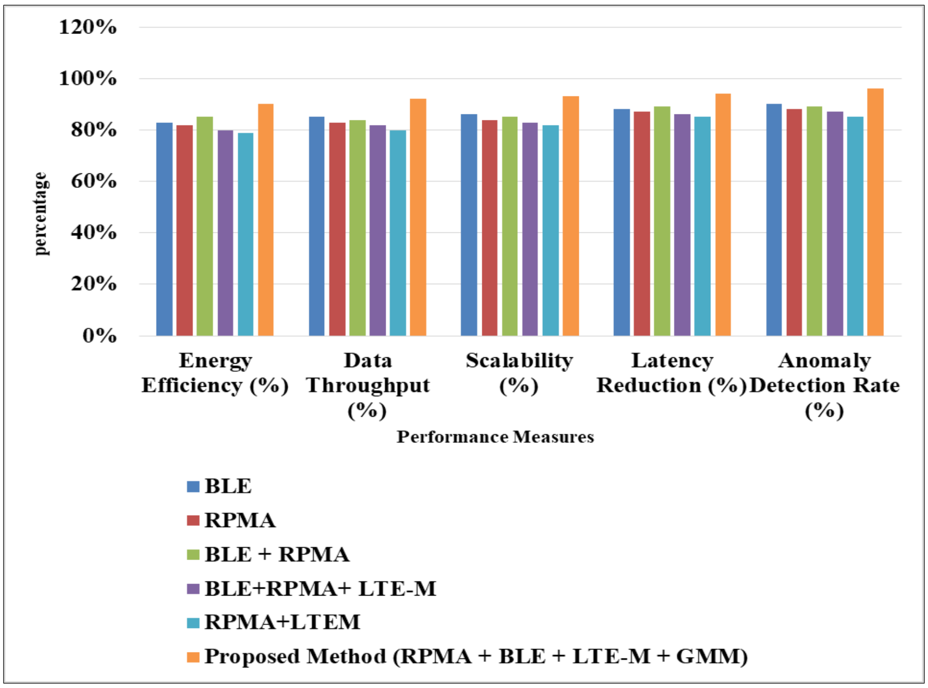

Figure 3 LTE-M and GMM Combined for Low-Latency, High-Coverage IoT Device Optimization

Figure 3 depicts the convergence of LTE-M (Long-Term Evolution for Machines) and GMM to achieve enhanced coverage and device performance in IoT applications. LTE-M is a low-power, wide-area network developed for cellular IoT devices that delivers reliable data connectivity in a variety of settings, including tough indoor situations. When integrated with GMM, LTE-M enables real-time data analytics and anomaly identification by clustering data to improve predictive accuracy. The graphic most likely depicts how this combination minimizes latency and enhances connectivity, making it perfect for high-value monitoring and control in industries such as logistics and healthcare.

5. Conclusion and Future Direction

The suggested solution successfully integrates RPMA, BLE, LTE-M, and GMM to optimize IoT device management, resulting in considerable gains in energy efficiency, data throughput, scalability, and latency reduction. This combination improves the performance of large-scale IoT systems, allowing for intelligent resource allocation and anomaly detection in decentralized contexts. Comparative investigation demonstrates that this model outperforms standard methods such as VAEs, DBSCAN, and RNNs, making it ideal for industries such as healthcare, agriculture, and smart cities. The ablation investigation supports the requirement of each component, demonstrating that eliminating any of the technologies reduces performance. The system's capacity to manage complex IoT networks enables scalable, efficient, and secure device administration, paving the path for more advanced, data-driven solutions in developing IoT applications. Future research should focus on improving GMM for real-time anomaly detection in complicated IoT environments, as well as investigating hybrid models for additional energy optimization. The integration of RPMA, BLE, and LTE-M into other IoT areas, such as autonomous vehicles and renewable energy grids, is also looking promising.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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