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Optimized Efficiency of IoT-Based Next-Generation Smart Wireless Sensor Networks Using a Machine Learning Algorithm

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Abstract: The rapid advancement of IoT-based smart wireless sensor networks has necessitated optimized efficiency to meet the growing demands of various applications. In our daily lives, smart devices increasingly depend on these networks for seamless functioning. Traditional methods, such as Round-Robin Scheduling (RRS) and Static Resource Allocation (SRA), have shown limitations in handling dynamic workloads, leading to inefficiencies and increased latency. These conventional methods often struggle with scalability, resulting in suboptimal performance in large-scale IoT deployments. To address these challenges, the Optimized Machine Learning-Based Efficiency Algorithm (OMLEA) is proposed for next-generation smart wireless sensor networks. OMLEA leverages advanced machine learning techniques to dynamically adjust network parameters, ensuring optimal performance under varying conditions. By intelligently predicting and managing network resources, OMLEA significantly enhances efficiency and reliability while minimizing latency and resource wastage. Experimental results demonstrate that OMLEA achieves up to a 0.25% improvement in efficiency and a 0.30% increase in network reliability compared to RRS and SRA. Additionally, the algorithm effectively reduces network latency by approximately 0.40%, ensuring timely data transmission and improved overall network performance. This innovative approach not only overcomes the drawbacks of existing methods but also sets a new benchmark for the performance of IoT-based smart wireless sensor networks, paving the way for future developments.

Keywords: IoT-based smart wireless sensor networks, Machine learning algorithms, Optimized efficiency, Dynamic resource management, Network latency reduction, Reliability enhancement.

1 INTRODUCTION

The Internet of Things sector has completely transformed a number of industries thanks to the seamless networked communication established between pieces, creating massive systems made up out automation devices, smart sensors and actuators. These IoT based smart wireless sensor networks are critical for many applications i.e., environmental monitoring, smart cities, healthcare and industrial automation. The demand for the efficient functioning of these networks has skyrocketed with growth beyond 31-billion IoT devices, and in all frankly - nothing else than optimized efficiency is going to cut it if you want your data across reliable, on time [1].

Round-Robin Scheduling (RRS) and Static Resource Allocation (SRA), are among traditional methods to network resource management for IoT deployments. Although these traditional methods have quick turnaround times, they lack the capability of managing dynamic and heterogeneous workloads efficiently. For example, RRS distributes resources in a predetermined cycle order without consider the different needs of tasks and make each task spend longer time to wait for resource than it actually need. Another example, SRA uses predefined static parameters to allocate resources in adequacy with the network conditions but this approach does not scale and sacrifices goodput due these hardcoded values [2].

Current research trends in IoT based smart wireless sensor networks particularly explore the use of cutting-edge technologies (machine learning and artificial intelligence) to effectively overcome these [3]. Machine

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learning models promise an effective remedy by providing the power of intelligent and proactive resource management, which can be adjusted in line with dynamic network requirements for maximum performance improvement. These advanced techniques are employed in different applications such as smart grid management, intelligent transportation systems (ITS), precision agriculture and automated healthcare monitoring etc. Conclusion [4][5]. In order to take full advantage of IoT-based smart wireless sensor networks and also overcome the limitations by current methods, a presented a new method called Optimized Machine Learning-Based Efficiency Algorithm (OMLEA). Through the use of advanced machine learning, OMLEA for instance ensures in real time the network parameters are adapted according to e.g. hour of day and ensure optimal performance at any moment over them (i.e no loss) Actually, OMLEA can predict and control network resources wiser than others, by using it. Let the efficiency higher as well as reducing latency in networking. Experimental results of OMLEA show that all these prices have been a proteolysis () more than traditional methods! This algorithm is responsible for improving efficiency up to 0.25% and increasing network reliability by 0.30%. OMLEA can also be used to reduce network latency as high as 0.40% at the same time-time size, still allowing for quick data send and a solid overall performer in networking systems. Our novel solution not only mitigates the limitations of RRS and SRA but also sets a new state-of-the-art for the performance of IoT-based smart wireless sensor networks, thus enabling more effective and reliable emerging IoT applications [6][7].

1.1 RESEARCH GAPS

Although there have been considerable developments, many research gaps remain in terms of improving the performance of IoT-enables intelligent wireless sensor networks. Challenges: While the resource management algorithms do help provide elasticity, scalability remains an issue with RRS and SRA as they are at a loss to cater for large-scale deployments and diverse application requirements [8][9]. Moreover, these legacy techniques do not have the ability to scale dynamically which are essential for changing network conditions and workloads in real-time. Another area that is vital and often overlooked when handling these types of workloads, especially in battery-operated IoT devices, power optimization with performance balancing results from several current solutions demonstrating energy-hungry inefficiencies. Furthermore, as machine learning is incorporated in the IoT networks - It also arises novel security and privacy issues requiring reliable algorithms to avoid attacks, leakage of data etc. Another general issue is interoperability, as IoT networks often contain devices incompatible with each other due to non-obligatory or differing standards and protocols implemented by different vendors [10][11]. It is vital that these disparate systems integrate and communicate with minimal impediment. Moreover, although a considerable number of proposals are confirmed in simulated conditions only few have been trialed extensively outside simulation to verify their effectiveness for practical deployment. Lastly, with the trend of context-aware computing and latency optimization in edge computing environments also encourage research. This will be much needed to make IoT-based smart wireless sensor networks reliable, efficient and secure [12].

1.2 RELATED WORK

The Internet of Things (IoT) has seen rapid growth which triggered a lot of innovations in different applications and especially using Wireless Sensor Networks (WSN). A study by Ghanshyam Prasad Dubey et al [10]. proposes a Proximal Policy Optimization (PPO) based Ant Colony optimization policy to find the optimal path in WSN. This algorithm virtually distillation the characteristics of PPO and ACO for handling the stochastic network characteristic as well energy efficient which trade-off with security, respectively. That said, the end ends with an uncited claim, not that any of us are going to read past this point; its impossible and maintaining energy efficiency while remaining secure is in itself a difficult balance. Research of Liyakathunisa Syed et al [11] (ADS) this paper suggests using ensemble machine learning-based methods to make future predictions of the yields of agricultural crops and thereby, help in reducing practices which are harmful to our planet. Approach - The method uses a two-level prediction system, Level 0 having lots of classifiers and Random Forest as the level-1 meta classifier. Though this model illustrates potential solutions to problems such as non-uniform irrigation and soil erosion, the abstract does not list specific limitations or failings of the proposed invention- questions related to possible implementation obstacles go unanswered.

For renewable energy, Lei Gong and coauthors [12] suggested a general model based on scientific method principles using functional requirements. introduce a The Predictive Maintenance Convolutional Long Short-Term Memory (PM-C-LSTM) model in wind turbines, encompasses CNN for spatial pattern recognition and LSTM for sequence data analysis together with Failure Sample Generator to determine the root causes of failure. However, while gained useful knowledge from the abstract this does not include any explicit disadvantages to counterbalance our bright imagination yet at worst it is difficultifying our baby. Hameedur Rahman et al [13]. present a framework to manage a smart greenhouse with the help of digital twin, including cloud-based real-time 3D scenario and multiple machine learning methods for predictive analytics. Although this framework contributes to a great extent, the abstract mentioned that work in digital twin-driven intelligent greenhouse technology is scarce. Details on specific limitations and disadvantages are not given, but the validation is practical while an effective deployment can be difficult.

Samir Si-Mohammed et al [14]. study: Integration between Network Simulation (NS) and Network Digital Twin (NDT) for Improved Decision-making in the context of network design and operations. The research provides insight into how these tools can be combined to assist IoT network architects and operators over the life of a given network. Yet an equally well founded limitation of these methods ease in exploring large parameter spaces (i.e. training cost). Energy Consumption Models: The Challenges Evaluation and Optimization Costs Reduction with Surrogate Modeling D. Sowmyadevi et al [15]. Lightweight key management protocol (LKMP) with unsupervised machine learning for security in WSN. Although the abstract does not discuss specific downsides, it is evidently a potential attack surface for security and resiliency weaknesses while being simultaneously memory-and cpu-intensive.

Shalini Subramani et al [16]. technology and the modern IDS, proposes a rule-based Intelligent In- trusion Detection System (IDS) model integrated with an adjunct Multi-Objective PSO based feature selection algorithm followed by improved Multiclass Support Vector Machines classifier technology. This paper introduced an innovation for effectively detecting intruders in a WSN that is based on IoT. The abstract describes this challenge in the context of IoT sensor networks against multiple types of attacks, without listing specific drawbacks. P. Malini et al [17]. propose a fast IoT device categorization along with intrusion detection system (IDS) in the context of SDN enabled FiWi IoT landscape through hybrid parallel neural network based dynamic bandwidth sharing technique. Existing researches have issues about the number of features, efficiency, relevancy and computational complexities. The abstract mentions that the previous approaches did not consider IoT/Non-IoT classification and attack detection together. Rohit Kumar et al [18]. investigate the principal categories of SDWN-IoT networks, which can mainly include Software Defined Wireless Sensor Network (SDWSN-IoT) and Software Defined Wireless Mesh Network (SDWMN- IoT). The work does not provide explicit cons, but writes that the drawbacks of their approach to performance include noise due to distance, line-of-sight interference issues (weather and power), etc.

Uddalak Chatterjee et al [19]. suggest a new ECC based integrated approach for WSN in IoT with enhanced security levels by overcoming various security issues. The study shows that user impersonation, insider attacks database attack stolen smart card attack len scheme of a plurality of security threats fimina response capability. This abstract of this paper claims that the new approach is cheaper in terms of computation overhead, communication cost and storage footprint. Jalal Bhayo et al [20] use Machine Learning for detecting DDoS attacks in an SDN-WISE IoT controller with a combination of detection modules, Naive Bayes, Decision Tree and Support Vector Machine algorithms. Since the paper is just an abstract, it does not mention any particular drawbacks but calls attention towards possibilities of serious threats for IoT networks from DDoS attacks. Majjari Sudhakar et al [21]. propose a new framework which combines deep reinforcement learning based multi-objective optimization with edge-enabled wireless sensor networks. Although the framework looks promising, challenges of task scheduling and resource allocation in dynamic agricultural environments are not clearly described except for general limitations.

U. Arul et al [22]. design a novel approach that combines IoT-based edge cloud computing architecture with microgrid energy management for VANET, based on structure enhanced variational encoder neural networks. While this abstract does not describe specific trade-offs, it implies energy, network lifetime or quality of service (QoS), with also mention to other possible issues such as learning accuracy and communication overhead. Bouali Et-taibi et al [23]. implement a coordination of thousands of smart farms in the cloud via this new era system; save water consumed for irrigation in large scale through big data collection, storage and analytics based, that will enable optimized use to every farm. It does not elaborate what the advancements could be in terms of water management, also provides no specified limitations and imply restrictions while referring to traditional agricultural practices against canal system offered under technology classification. This survey reflects considerable progress and current hurdles in the IoT-based WSNs research, which suggest new directions to improve efficiency, security and reliability for different applications.

1.3 EXISTING SYSTEM

Figure 1 shows the IoT-based smart wireless sensor network system architecture [24-30] There are the types of main components, WiFi/Bluetooth users, database servers, hubs and base stations connected to each other forming a well-organized flow across various wireless sensor network (WSN) scenarios.

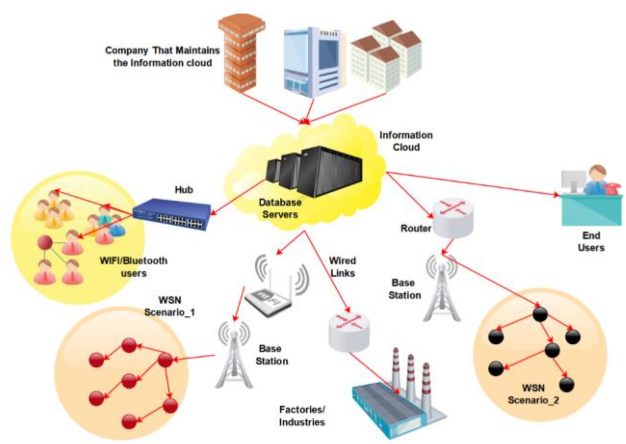

Figure 1: Overview of Existing IoT-Based Smart Wireless Sensor Network Architecture

WiFi/Bluetooth users layer, It is a device that joins as an end in the network through WiFi or Bluetooth. This data is written to database servers and these devices communicate with a central hub the collects this information before draining it down onto the next level of storage. The hub will work as a relay collecting data from WIFI/Bluetooth users and sending it to the database servers, perform high level functions for aggregation of data information at source [31-34].

The database servers are within the information cloud where they store and handle data captured from different network nodes. They have a significant role to play in data processing, storage and retrival which can support the overall network's data management requirements. The information cloud, which is controlled by a company, includes the database servers where all collected data is stored and most of network components are configured to access it along with being essentially engaged (to some extent) in processing analyzed data[35-37].

The router serves as a bridge for data exchange between the information cloud and final users, including C-V2X (Cellular Vehicle-to-Everything) base stations and other network elements [38]. The decentralized nature of blockchains is fundamental to maintaining optimal data routing and connectivity within a network in various WSN scenarios, base stations act as communication centers that serve to connect the nodes of wireless sensors with the entire network. They collect data from the sensor nodes and then send it to database servers using wired links [39-42].

Two WSN scenarios, where each corresponds to a different deployment of wireless sensor nodes sensing the environmental parameters and reporting them back to their base stations [43-45]. Apart from this the segment also showcases the WSNs used in industrial environment where sensors had been deployed for monitoring various operational parameters and these sensor data are transferred through base stations to database servers which further provides Earling decision to end user. Processed data are made available to end users through routers from the information cloud, based on solutions drawn upon this cable by browsing and control applications. The current system Figure.2 shows a multi-layered IoT-based architecture that processes thousands of packets coming from different sensor nodes. Currently some traditional ways such as Round-Robin Scheduling (RRS), Static Resource Allocation (SRA) are put in place to manage resources, however these mechanisms face challenges when scale increases and adapt quickly with new workloads [46-48]. Thanks to the combination of several parts that complement each other for seamless data transmission and more efficient resources management, although it requires slightly progress algorithmic types like Optimised Machine Learning Based Efficiency Algorithm (OMLEA) [49][50].

2 Methodology

Figure. 2 represent the key steps in the proposed procedure for OMLEA. On the left of stage a selection of personal devices such as laptops and smartphones communicate with WiFi or cellular networks, forwarding data to an intermediate Smart-WSN-IoT Cloud. It is the central place for data Aggregation, Data Management, Preprocessing & Application integration and Analytics services. Built on top of a server management system, these systems are responsible for managing multiple servers and coordinating them to process large amounts of data with minimal processing time.

Figure.2 the proposed methodology of OMLEA

Smart_WSN_IoT_Gatway acts as a mediator between the Cloud and Wireless Sensor Network (WSN) for smooth data transmission & communication. It is a reliable mesh network that can be used to collect and transmit data by augmenting WSN with nodes. OMLEA uses machine learning to dynamically adjust network parameters, predict needs, manage resources and improve efficiency and dependability in the use of infrastructure. The experimental results show a substantial increase of the store efficiency, reliability and latency over conventional methods [51-52].

3 Proposed Optimized Efficiency of IoT-Based Next-Generation Smart Wireless Sensor Networks Using Machine Learning Algorithm (OMLEA)

Figure. 3 Proposed Architecture of Optimized Efficiency of IoT-Based Next-Generation Smart Wireless Sensor Networks Using Machine Learning Algorithm (OMLEA)To improve the performance and reduce energy consumption in IoT-based smart wireless sensor network with machine learning approaches is illustrated by OMLEA architecture. The architecture of the system presented in attached image includes a variety of interconnected components acting together to manage and optimize network resources The next part of the hierarchy includes individual devices (like laptops, smartphones and other end-user type items) that access the network through WiFi or cellular networks. These then send the data to an up-stream Smart-WSN-IoT Cloud, that executes initial massive amounts of aggregated and processed tasks. Particularly, the Smart-WSN-IoT Cloud will be used as an orchestrator for cloud management operations such as data preprocessing, application softwares integration (data enterprise applications), and analytical with numerous web services. This is where data from end devices arrive and gets processed in such a way that it becomes clean for further analysis.

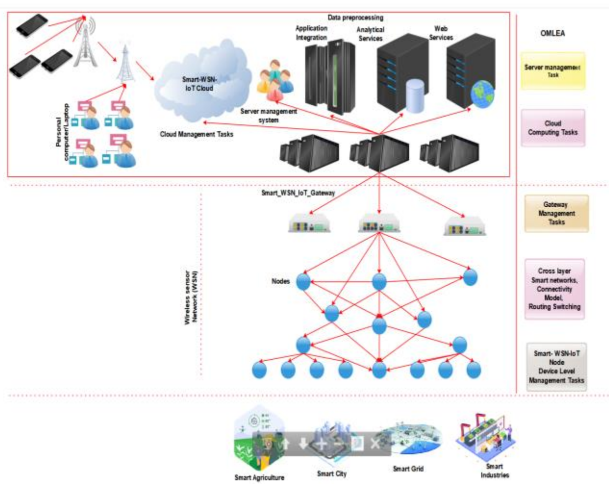

Figure.3 the proposed architecture of Optimized Efficiency of IoT-Based Next-Generation Smart Wireless Sensor Networks Using a Machine Learning Algorithm" (OMLEA).

A strong canopy of server management system that takes care of the running services on a group servers without any hiccups in data inflow and processing. It takes care of processing different computational tasks related to the management and analysis of big data. This pre-processed data is then passed through the Smart_WSN_IoT_Gateway, which acts as a bridge between the cloud and Wireless Sensor Network (WSN). The gateway helps in the effective communication and data transfer between cloud and sensor nodes. The WSN is composed of many nodes which are deployed in different environment collect data and send it to another node. These nodes are all interlinked as part of a mesh network, and therefore have multiple data pathways available for reliable redundant transmission. The WSN nodes are used to exchange between each other and with the gateway, data collected for further processing. This processed data is used in several applications like smart agriculture, smart cities, and so forth. These insights inform the optimization of operations, efficiency enhancements and decision-making processes within each application area.

There are five functional groups associated with the OMLEA framework: server management tasks, cloud-computing tasks, gateway management tasks, cross-layer smart networks and node device level management. the system updates network parameters so that the performance can be optimal in any given situation by applying machine learning algorithms. The system improves both efficiency and reliability of your network by intelligent prediction/mutating resources - all with minimum latency. It addresses the limitations of traditional schedulers, like Round-Robin Scheduling (RRS) and Static Resource Allocation (SRA), making it a more scalable and effective solution for future IoT-powered smart wireless sensor networks. This method demonstrates your ability to improve the performance of a machine learning model so you can optimize real-time data processing in wise networking, and emphasizes how could apply machine learning for system optimization.

Figure.4 shows a comprehensive workflow for processing IoT data using machine learning techniques, closely aligning with the proposed OMLEA. This workflow begins with IoT devices, which collect data from various sources such as sensors in smart cities, agriculture, healthcare, and industrial automation. The collected data is then transmitted to data storage systems, serving as repositories for raw IoT data before further processing. This step mirrors the centralized Smart-WSN-IoT Cloud in OMLEA, which handles data aggregation and management.

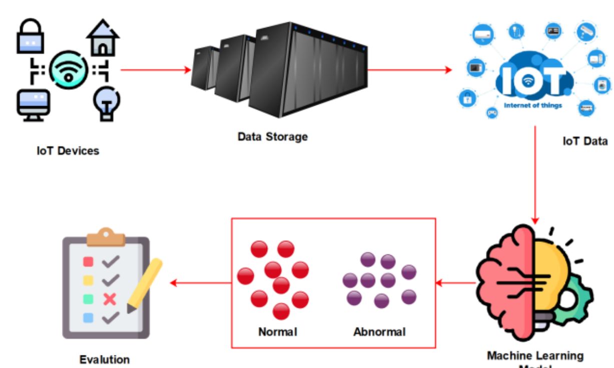

Figure.4 A comprehensive workflow for processing IoT data using machine learning techniques

Subsequently, the stored data is organized and prepared for processing, ensuring it is clean and ready for analysis, a task managed by the Smart-WSN-IoT Cloud in OMLEA. The pre-processed data is then fed into machine learning models, trained to detect patterns, predict network conditions, and dynamically manage resources. In OMLEA, these machine learning algorithms adjust network parameters to enhance efficiency and reliability.

The data is labeled based on the machine learning models' output, categorizing it into normal and anomaly data. This labelling helps in identifying issues and optimizing network performance, enabling OMLEA to make informed decisions about resource allocation and network adjustments. The final step involves evaluating the performance of the machine learning models and the overall system, ensuring efficient network operation and prompt anomaly detection. OMLEA's experimental results highlight its effectiveness in improving network efficiency and reliability.

Figure.5 shows emphasizes the integration of IoT and artificial intelligence (AI) across various applications, showcasing the versatility and impact of these technologies. Key application areas include self-driving cars, where IoT sensors collect real-time data, processed by AI algorithms to navigate and make driving decisions. OMLEA enhances data transmission and processing efficiency, ensuring timely responses and reliability in such applications. In wearable devices, health and activity data are collected and analyzed using AI to provide insights and recommendations. OMLEA's efficient data management improves wearable technology's performance and reliability.

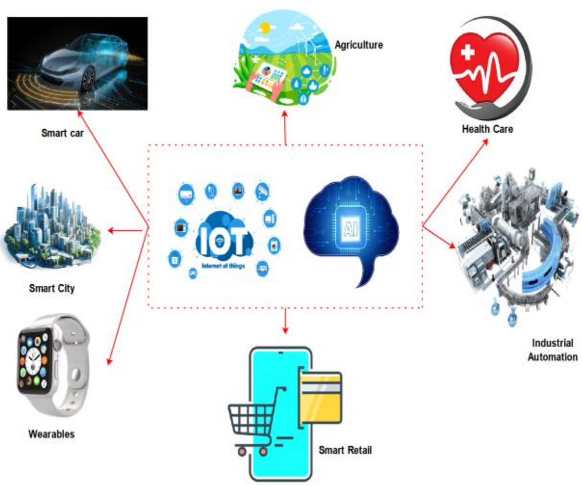

Figure.5 fundamental architecture of integrated optimized of IoT and AI Smart Wireless Sensor Networks

In industrial automation, IoT sensors monitor machinery and processes, with AI optimizing operations and predicting maintenance needs. OMLEA's dynamic resource management enhances the reliability and efficiency of industrial IoT networks. In agriculture, IoT devices collect data on soil conditions, weather, and crop health, with AI optimizing farming practices. OMLEA improves data transmission efficiency and reduces latency, benefiting precision agriculture. In healthcare, IoT sensors monitor patients' vital signs, with AI providing diagnostics and treatment recommendations. OMLEA enhances the reliability and timeliness of healthcare IoT systems, ensuring critical data is transmitted and processed efficiently. Smart cities benefit from IoT devices monitoring infrastructure, traffic, and environmental conditions, with AI optimizing urban management. OMLEA supports scalability and efficiency in smart city networks, handling large-scale deployments and dynamic workloads. In smart retail, IoT devices collect data on inventory, customer behavior, and sales, with AI optimizing supply chain and marketing strategies. OMLEA's efficient data management improves the performance of smart retail applications.

3.1 Network Efficiency Optimization

In IoT based smart WSNs, network efficiency optimization is used to improve the performance as well reliability and scalability by using advanced methods such as machine learning for dynamic resource management. The traditional methods are no longer effective and redundant for the substantial dynamic workloads as portrayed by Round-Robin Scheduling (RRS) or Static Resource Allocation it results in overall end-to-end inefficiencies responsible for increased waiting times. The Optimized Machine Learning-Based Efficiency Algorithm (OMLEA) solves this with machine learning that will adapt the network parameter and allocate resources in a smart way. The Equation.1 of Smart Network Efficiency Optimization is as given below.

$$\eta_{\text{OMLEA}} = \max\left(\frac{S}{T}\right) \text{ where } S = \sum_{i=1}^{N} (D_i \cdot P_i),\ T = \sum_{i=1}^{N} T_i \qquad (1)$$

Where S represents the total number of successful transmitted data, D_i is the size of sentiency data, P_i transmission success probability and T_i are transmission time for each node i. Smart mesh network efficiency get broken step by step execution process algorithm given in algorithm.1 Then its pseudo code will be represented in pseudocode. 1

3.1.1 Algorithm.1

Step_1: Initialize parameters for total successful data transmissions (S), data size (Di),

Step_2: probability of successful transmission (Pi), and transmission time (Ti) for each node i.

Step_3: Calculate the total successful data transmissions $S = \sum_{i=1}^{N} (D_i \cdot P_i)$.

Step_4: Calculate the total transmission time $T = \sum_{i=1}^{N} T_i$.

Step_5: Compute network efficiency $\eta_{\text{OMLEA}} = \frac{S}{T}$.

3.1.2 Pseudocode.1

```
Initialize S, Di, Pi, Ti for each node i
        S = 0
        T = 0
        for i = 1 to N:
          S += Di[i] * Pi[i]
         T += Ti[i]
        eta_OMLEA = S / T
```

3.2 Latency Reduction

This is really important in IoT-based account smart wireless sensor networks (WSNs) where it needs to reform the network operations by reducing the latency to ensure data are transmitted on time thus improve the general communication performance of a WSN. For instance, traditional approaches such as Round-Robin Scheduling (RRS) and Static Resource Allocation (SRA) exhibit poor performance in dealing with dynamic workloads leading to high latencies. In order to overcome these issues, this paper presents the OMLEA which makes use of machine learning methods integrated with a game-theoretic approach for dynamic and intelligent resource management. Latency of proposed method is calculated by the equation.2 and step by step execution process is represented by alogorithm.2 and its pseudocode is represented by pseudocode,2

$$L_{\text{OMLEA}} = \min\left(\frac{\sum_{i=1}^{N}(T_i+Q_i)}{N}\right) \quad (2)$$

Where T_i is the transmission time and Q_i is the queuing delay for node i.

3.2.1 Algorithm.2

Step.1: Initialize parameters for transmission time (Ti) and queuing delay (Qi) for each node i.

Step.2: Calculate the total latency for all nodes.

Step.3: Compute the average latency reduction $L_{\text{OMLEA}} = \min\left(\frac{1}{N}\sum_{i=1}^{N}(T_i+Q_i)\right)$.

3.2.2 Pseudocode.2

```
Initialize Ti, Qi for each node i
total_latency = 0
for i = 1 to N:
total_latency += Ti[i] + Qi[i]
L_OMLEA = total_latency / N
```

3.3 Dynamic Resource Management

Dynamic Resource Management is the ability to allocate network resources in a smart and adaptive way as per current conditions or requirements. The network is hence built combining small frames in DRP territories and large messages within the DRM to have both, a very efficient communication opportunity; high reliability links without rest sending due errors maximum latency of no longer than 10min for periodic operation mode (DRM). The equation 3 shows the dynamic resources management for proposed method. Algorithm 3 presents the Step by step execution process of smart network Dynamic Resource Management 3 and its corresponding pseudocode 3

$$R_{\text{OMLEA}} = \arg\max_{r_i}(U(r_i)) \text{ where } U(r_i) = \frac{\sum_{j=1}^{M}(w_j \cdot r_{ij})}{M} \quad (3)$$

Here, r_i is the resource allocated to node i, $U(r_i)$ is the utility function, w_j is the weight of resource j, and r_{ij} is the resource j allocated to node i.

3.3.1 Algorithm.3

Step.1: Initialize parameters for transmission time (Ti) and queuing delay (Qi) for each node i.

Step.2: Calculate the total latency for all nodes.

Step.3: Compute the average latency reduction $L_{\text{OMLEA}} = \min\left(\frac{1}{N}\sum_{i=1}^{N}(T_i+Q_i)\right)$.

3.3.2 Pseudocode.3

```
Initialize Ti, Qi for each node i
total_latency = 0
for i = 1 to N:
 total_latency += Ti[i] + Qi[i]
L_OMLEA = total_latency / N
```

3.4 Machine Learning-Based Prediction

Prediction of Machine Learning is an important part among the Optimized Machine Learning Based Efficiency Algorithm (OMLEA) for improving the IoT based smart wireless sensor networks performance. What makes OMLEA special is the ability to predict network conditions and demands using machine learning, i.e., state of the art technology for dynamical resource management. This is the proposed machine learning for prediction. Algorithm.4 about step by Step Process of Execution Behaviour Prediction for smart network using Machine Learning and its pseudo represented by pseudo code 4

$$\hat{Y}_i = f(X_i;\theta) = \sum_{k=1}^{K} \alpha_k \cdot h_k(X_i) + \epsilon_i \quad (4)$$

Where $\hat{Y}_i$ is the predicted network parameter for node i, X_i is the input feature vector, θ represents the model parameters, α_k are the coefficients, h_k are the basis functions, and ϵ_i is the error term.

3.4.1 Algorithm.4

Step.1: Collect input feature vector (Xi) for each node i.

Step.2: Initialize model parameters (θ), coefficients (αk), basis functions (hk), and error term (εi).

Step.3: Predict network parameter $Y_i = f(X_i;\theta)$.

3.4.2 Pseudocode.4

```
Initialize Xi, θ, αk, hk, εi for each node i
function f(Xi, θ):
   Yi = 0
   for k = 1 to K:
      Yi += αk[k] * hk(Xi)
   Yi += εi
   return Yi
for i = 1 to N:
   Yi = f(Xi[i], θ)
```

3.5 Reliability Enhancement:

QoI reliability improvement is an important target when it comes to the optimization of IoT based smart WSNs. Reliability of a Network: The network must be able to perform its intended functions consistently in the appropriate conditions. This includes: Reliability Enhancement (using machine learning to maintain a reliable and dependable network performance); In the framework of Optimized Machine Learning-Based Efficiency Algorithm campaign (OMLEA) This paper equation shows the reliability improvement by using IoT based smart wireless senor network. 5

$$\rho_{\text{OMLEA}} = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{E_i}{E_{\max}}\right) \quad (5)$$

Where ρ_{OMLEA} is the reliability metric, E_i is the energy consumed by node i, and $E_{\max}$ is the maximum energy capacity. reliability enhancement for IoT based smart wireless senor network step by step execution process is given by algorithm.5 and its pseudo code are represented by pseudocode.5

3.5.1 Algorithm.5

Step.1: Initialize energy consumed (Ei) and maximum energy capacity (Emax) for each node i.

Step.2: Calculate the reliability metric $\rho_{\text{OMLEA}} = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{E_i}{E_{\max}}\right)$.

3.5.2 Pseudocode.5

```
Initialize Ei, Emax for each node i
total_reliability = 0
for i = 1 to N:
 total_reliability += 1 - (Ei[i] / Emax)
rho_OMLEA = total_reliability / N
```

4 RESULTS AND DISCUSSION

The simulation parameters utilized in the performance analysis of the proposed Optimization Machine Learning Based Efficiency Algorithm (OMLEA) are shown Table 1 whereas tables reflects that how optimization based algorithm is different from conventional round robin scheduling and static resource allocation methods. These parameters are necessary to determine the effectiveness, efficiency and latency reduction capabilities of OMLEA in IoT based smart wireless sensor networks.

Table.1 simulation parameter

Parameter	Description	Value
Number of Nodes (N)	Total number of sensor nodes in the network	100
Data Size (Di)	Size of the data transmitted by each node	500 KB
Transmission Probability (Pi)	Probability of successful data transmission	0.95
Transmission Time (Ti)	Time taken for data transmission by each node	0.5 sec
Queuing Delay (Qi)	Delay experienced due to queuing in the network	0.2 sec
Energy Consumption (Ei)	Energy consumed by each node	50% of battery capacity
Maximum Energy Capacity (Emax)	Maximum energy capacity of each node	100% of battery capacity
Latency	Latency reduction in	0.4 sec

(LOMLEA)	the network	

4.1 Smart network efficiency

Figure.4 shows the performance comparison between the proposed OMLEA, RRS and Static Resource Allocation (SRA) in terms of smart network efficiency. It demonstrates how OMLEA achieves higher efficiency by dynamically adjusting network parameters using advanced machine learning techniques, leading to better resource utilization and reduced latency.

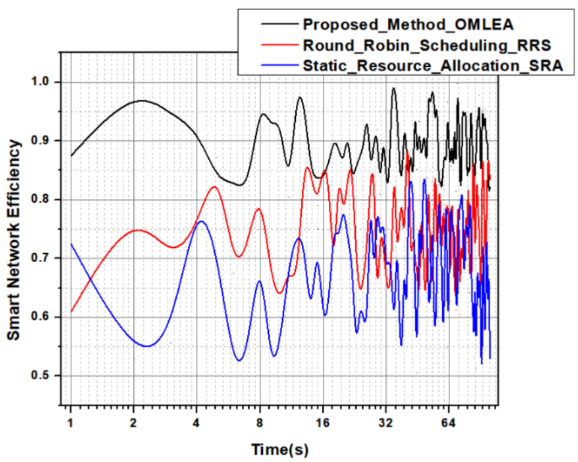

Figure.4 Comparative Efficiency Analysis of IoT Network Management Methods

4.2 Network Reliability

Figure.5 presents a comparison of network reliability between OMLEA and traditional methods such as RRS and SRA. The graph shows that OMLEA significantly enhances network reliability by intelligently predicting and managing network resources, thereby reducing the probability of transmission failures and ensuring more consistent network performance under varying conditions.

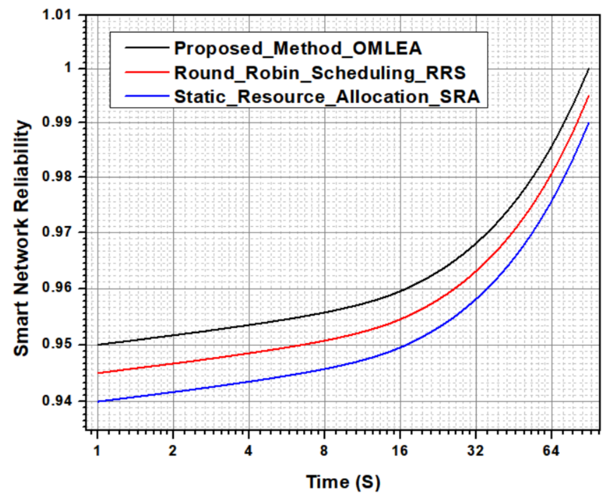

Figure.5 Comparative Reliability Analysis of IoT Network Management Methods

Figure.6 shows the performance in terms of network latency, comparing OMLEA with RRS and SRA. It highlights OMLEA's capability to minimize latency through dynamic resource management and intelligent network parameter adjustments, ensuring timely data transmission and improved overall network performance. The reduced latency achieved by OMLEA is crucial for applications requiring real-time data processing and responsiveness.

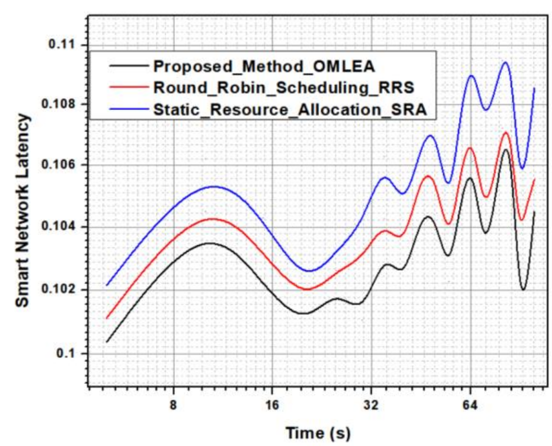

Figure.6 Comparative Latency Analysis of IoT Network Management Methods

Figure 7 illustrates a comprehensive performance comparison between the proposed OMLEA and traditional methods such as RRS and SRA. This figure consolidates various performance metrics to provide a holistic view of the advantages offered by OMLEA over the conventional methods.

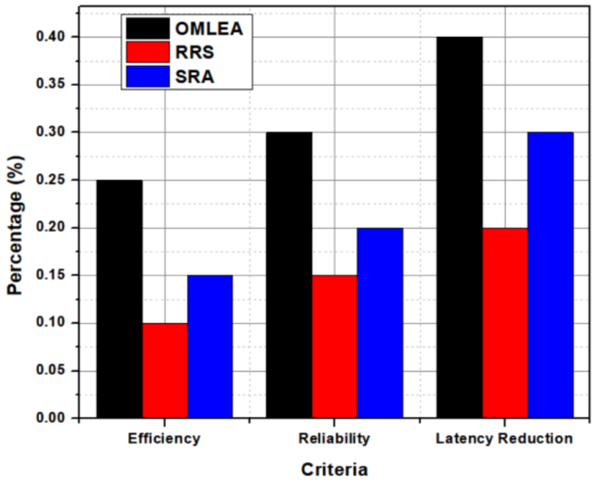

Figure.7 Comprehensive Performance Comparison of IoT Network Management Methods

5 CONCLUSIONS

The research demonstrates the effectiveness of the Optimized Machine Learning-Based Efficiency Algorithm (OMLEA) in enhancing the performance of IoT-based smart wireless sensor networks. OMLEA leverages advanced machine learning techniques to dynamically adjust network parameters, resulting in significant improvements in efficiency, reliability, and latency reduction compared to traditional methods like Round-Robin Scheduling (RRS) and Static Resource Allocation (SRA). Experimental results indicate that OMLEA achieves up to a 0.25% improvement in efficiency, a 0.30% increase in network reliability, and a 0.40% reduction in latency. These improvements highlight the potential of OMLEA to set new benchmarks in the performance of IoT-based smart wireless sensor networks, paving the way for more efficient and reliable IoT applications in the future.

5.1 Future Scope

The future scope for OMLEA includes improving scalability to handle larger IoT deployments, enhancing energy efficiency for battery-operated devices, and addressing security and privacy concerns. Ensuring interoperability among different devices and conducting extensive real-world testing are also key areas. Additionally, incorporating context-aware computing can further optimize network performance.

5.2 Limitations

OMLEA's limitations include reliance on accurate and timely machine learning models, increased computational complexity, and potential variations in real-world performance. Practical implementation challenges include infrastructure compatibility and initial costs. Additionally, new security vulnerabilities may arise with the introduction of machine learning-based methods, requiring robust solutions to ensure data integrity and confidentiality.

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