Optimizing Real-Time Data Processing in Smart Cities Using Internet of Things (IoT) for Scalable, Efficient, and Sustainable Urban Service Delivery

Nik Mohd Noor Faizul Md Saad[1], Chen Kim Lim[2]

[1]Pusat Penyelidikan Langkawi (PPL), Pusat Pengurusan Makmal Alami dan Fizikal (ALAF), 07000, Langkawi, Kedah, Malaysia. E-mail: nikfaizul@ukm.edu.my
[2]Institute for Environment and Development (LESTARI), Universiti Kebangsaan Malaysia (UKM), Bangi 43600, Selangor, Malaysia. E-mail: kim@ukm.edu.my

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ABSTRACT

With the rapid increase of city population growth on a global scale, effective, scalable and sustainable systems to manage urban environments have become a high priority for cities. Smart cities utilize the Internet of Things (IoT) to gather information about their environment (real-time data) and make decisions based on that information. The information generated by IoT is then analyzed and presented back to decision-makers for use in managing the city. However, the amount, speed and diversity of data created by IoT present challenges. The biggest challenges are (1) how to process such a large volume of information in real-time, and (2) how to analyze such diverse sources of data to generate accurate and useful insights. In this study, we present an approach to improving urban service delivery through improved Real-Time Data Processing for Smart Cities using IoT technologies. Through a combination of edge computing, cloud architecture, and effective techniques for data stream processing, the researchers aim to reduce delays in the delivery of these services and improve the overall responsiveness of systems. With the implementation of edge devices, the processing of data will occur as near the data generating source as possible. Therefore, there will be minimal congestion within the network and decision-making will happen more quickly. Additionally, the system utilizes intelligent filtering, prioritization, and other data handling techniques for processing large amounts of data efficiently, thereby enabling better scalability to handle increasing demands for data within smart city systems, without degradation in performance Optimizing IoT-based data processing can enhance resource utilization and support sustainable urban development through real-time monitoring and adaptive control of urban services. This study shows that IoT-enabled solutions can lead to improved urban management, which results in smarter, more responsive, and more environmentally friendly cities.

Corresponding Author:

Nik Mohd Noor Faizul Md Saad,
Pusat Penyelidikan Langkawi (PPL),
Pusat Pengurusan Makmal Alami dan Fizikal (ALAF), Kedah, Malaysia.

1. INTRODUCTION

The integration of the Internet of Things (IoT) into the urban fabric signifies a fundamental shift in the conception, management, and design of cities. The challenges that urban regions face—from pollution and traffic to public safety and energy consumption—become increasingly tough as they continue to grow [1]. The IoT represents the cutting edge of creativity in the current urban environment, providing the opportunity to alter patterns of urban life as well as address numerous challenges associated with the 21st Century. IoT devices, such as intelligent devices and sensors, can be integrated throughout a city to allow it to be more attuned to the needs of its people by enabling real-time modifications of resources, services, and the overall quality of life. By linking innovative urban design, technological advancements, and data collection to ultimately create smart cities through IoT, we can establish communities where data and technology drive sustainable economic growth and improved quality of life. Cities suffer a variety of issues, such as environmental degradation and transportation congestion. in a time of unparalleled global urbanization.

As a result, the idea of "smart cities," which promises to use technological advancements to build more sustainable, effective, and livable urban settings, has become a ray of hope. At the heart of this shift lies the IoT, a network of interconnected devices and sensors that collect and exchange data to enable improved decision-making and automate operations. As the size and complexity of cities continue to grow, IoT Integration has become increasingly important to satisfy the critical needs of city residents as well as promote a city's future economic success [3]. The possibilities of IoT's revolutionary capabilities to transform rural areas are endless, and offer many different types of possibilities. Intelligent traffic management systems are another example of how IoT technologies can improve car, greenhouse gas emissions, and the daily commute for the modern day transportations systems [4].

IoT-powered smart grids transform energy management, maximize consumption, include renewable energy sources, and guarantee sustainability and dependability. In the meantime, IoT applications in public services, such as water distribution and trash management, improve responsiveness and efficiency, resulting in cleaner, healthier urban areas. These uses not only show how IoT may improve urban operations [5], but they also emphasize how it can help make cities more sustainable and livable. Data from networked devices can help cities to better understand the balance between economic, social and environmental considerations in their decision-making processes. This will ultimately lead to a future where resilience and sustainability are synonymous with urban living. Rapid urbanization in many areas has resulted in problems like traffic congestion, pollution, inadequate infrastructure and depletion of natural resources. In response to these challenges, the concept of "smart cities" has emerged - using advanced technology to develop urban environments that are more efficient, sustainable and livable. The IoT, which permits the integration of numerous physical devices and systems to gather and analyze data, optimize operations, and enhance people' quality of life, is essential to the development of Smart Cities [6]. The introduction of IoT has completely changed how cities function, providing a wide range of uses in numerous industries.

Urban environments have been transformed by the advent of IoT-enabled solutions, allowing cities to be more efficient and to enhance the lives of their residents through improved infrastructure, public services, transportation, and energy management. Through smart energy management systems that track energy usage patterns to promote energy efficiency and to help facilitate the adoption of renewable energy, and smart transportation systems using IoT technology to optimize traffic flows, reduce congestion, and improve the mobility of individuals, we are starting to see the disruptive effect of IoT in overcoming long-standing challenges in cities and creating more resilient and sustainable urban environments [7]. However, there are still a number of challenges that must be addressed to enable IoT to achieve its full potential in Smart Cities. Ensuring that the massive amounts of data created by IoT devices are properly managed and protected poses a significant threat to the privacy and security of individuals, so these considerations must be prioritized. It is also complicated to deploy IoT solutions seamlessly due to the technical challenges of ensuring interoperability across multiple devices and systems.

A cooperative strategy is necessary to get beyond these challenges [8]. To create strong privacy safeguards, interoperability standards, and an environment that promotes innovation while maintaining security and trust, policymakers, technology companies, and city officials must collaborate. The emphasis must continue to be on using IoT to improve urban living as Smart Cities develop, making sure that technology developments support the more general objectives of sustainability, efficiency, and inclusivity [9]. Notwithstanding the indisputable advantages of IoT in Smart Cities, there are still a number of important issues to take into account.

The main ones are interoperability, security, and privacy issues. IoT device growth raises valid concerns about cybersecurity and data privacy, requiring strong safeguards to protect sensitive data and reduce the danger of cyberattacks. Furthermore, interoperability issues are brought on by the diversity of IoT ecosystems, making it difficult for separate systems to integrate and exchange data [10]. To ensure that the promise of IoT in Smart Cities is realized while reducing possible hazards, addressing these difficulties calls for a multidimensional approach that includes technology advancements, regulatory frameworks, and stakeholder participation.

2. RELATED WORKS

[11] Offers a cutting-edge UAV-based traffic monitoring system that combines Internet-of-things (IoT)-enabled data transfer and real-time image processing for improved mobility evaluation. When fitted with IoT Compatible Communication (IoT) modules, as well as an onboard high-performance neural network accelerator designed specifically for capturing and processing images, unmanned aerial vehicles (UAVs) become autonomous, intelligent and highly efficient traffic analysis tools. The UAV has an 88% real-time detection success rate for vehicles based on the YOLOv8n Object Detection Algorithm, allowing for spatial mobility mapping of vehicles based on predetermined flight systems. The YOLOv8n detection system's accuracy and efficiency (ability to operate in real time) make it the most effective option for providing data for UAV Mobility Tracking when compared to current versions of YOLO (YOLOv9t, YOLOv10n, and YOLOv11n). The immediate transfer of data between relevant members of regulatory authorities and IoT networks allows for quick responses when managing traffic and making decisions differently than traditional methods of managing traffic which use batch processing. Furthermore, this study shows that there is a way to support the widespread use of UAVs in smart cities through real-time mobility studies of traffic using these new platforms to support real-time mobile computing/software communication systems. In contrast to traditional systems, this technology allows real-time transmission of data to legally authorized entities or sensors connected to IoT (Internet of Things) networks so that traffic can be dynamically managed and decisions made about supporting approvals. The report also supports the potential of UAV (unmanned aerial vehicles) to implement solutions for studying real-time movement of vehicles within smart city infrastructure due to their unique capabilities as a new mobile computing platform and communication technology.

[12] Analyze the cloud computing (CC) and Internet of Things (IoT)-based smart city data technology. Our first step is to gather IoT (Internet of Things) data related to smart cities. We then normalize that data before using machine learning technology (ML) to create a method for connecting machines together without involving a person in the process of connecting those machines. The Adaptive Random Forest (ARF) ML method allows us to do this. This study also proposes a resource allocation method (called Adaptive Cloud Computing Virtual Machine Resource Allocation (ACC-VMRA)) for use in multi-criteria optimization. To demonstrate how effective the proposed resource allocation is, we model and evaluate the application of CC and IoT technologies in smart cities. Experimental results show that the proposed resource allocation method outperformed previously existing resource allocations.

3. METHODOLOGY

In this section, we look into the implementation of IoT-based smart cities that use optimization technology. The approach overview is shown in Figure 1. In order to improve networking and information exchange, this study will examine how IoT and CC are being used in the deployment of smart cities [13].

3.1. Data Preprocessing Model

The Z range of features in the incoming data and the fact that each quality has a distinct set of numeric integers complicate processing. To equalize the data Z in the range of 0–1 and minimize computational effort, a normalization process is employed [14]. There are several methods for normalizing data. The suggested approach uses a suitable min-max normalization algorithm. Using equation (1), this approach displays a quantitative score from the given dataset into Znor with a range $[0, 1]$.

$$Z_{nor} = \frac{Z^{Z} - Z_{\min}}{Z_{\max} - Z_{\min}} \times [new\_ \max - new\_ \min] + new\_ \min \qquad (1)$$

In this case, $new_{m\sigma x} = 1$ and $new_{m\dot{m}} = 0$ are used. This method assigns values to each attribute that fall between 0 and 1.

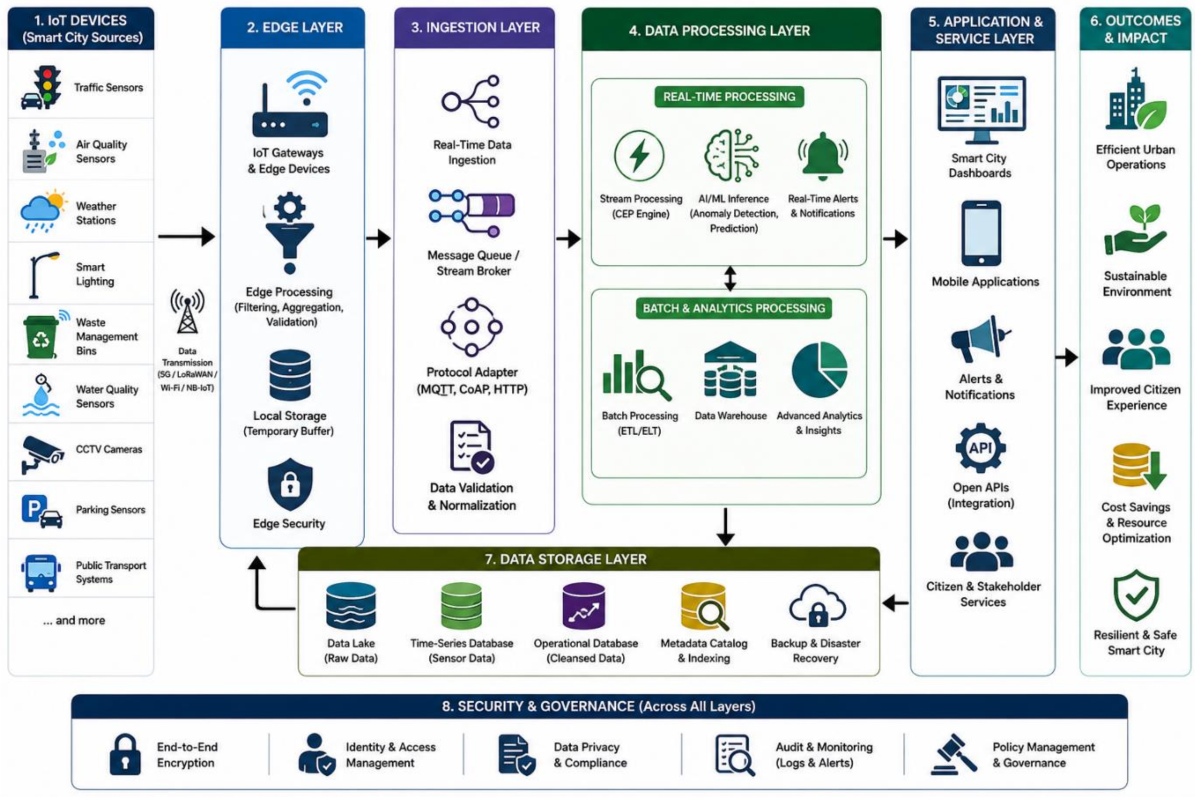

Figure 1. Overall Architecture Diagram for the Proposed Model

3.2. Machine Learning Approach

Machine learning is used in the IoT to enable machine communication without human intervention. This paper makes use of machine learning. In terms of precision, this approach usually performs better than the single tree classifier. It provides a way to categorize groups of dispersed data. However, arbitrarily selecting attributes, making it possible to select traits that are superfluous or distracting. This makes it very easy to choose the wrong characteristics. As a result [15], the classification results might not be very good. The data matrix that is applied for type categorization is lacking a substantial number of characteristics. It needs to be modified in order to use the basic ML in the classification of search forms. The training data set contains a significant number of unaccounted-for values because to the narrow feature space. Because there is a large amount of missing data, the attributes are not significant.

$$y^2 = \sum_{j=1}^{n} \sum_{k-1}^{2} \frac{(P_{jk} - f_{jk})^2}{f_{jk}} \tag{2}$$

In this case, n=$feamres.$ P_{jk} is defined as a measurable value that indicates the number of joint incidents.

$$P_{jk} = count\left(B = b_j \cap D = d_k\right) \tag{3}$$

Likewise,

$$\text{expected value} = f_{jk} = \frac{count(B=b_j) \times count(D=d_j)}{N} \tag{4}$$

Eq. (2) determines the weight of each character in the feature space. However, as the decision tree is being constructed, only those characteristics with large weights are considered. We began by building several decision trees, and then we combined each class's output using a probability estimation technique. The final results of the classification are then obtained by adding the values of the probabilities, as shown in equation

$$Q(J(y) = d_j) = \frac{1}{l}\sum_{k=1}^{l} Q\,(J(y) = d_j|i_k) \quad (5)$$

The Y input vector is regarded as being a component of $d_j$if and only if d_j has the highest probability. The training set would consist of [.1] features if there are n features, where f is the frequency of feature selection and 1 is the number of features. The given training data is used to learn many classes. The bootstrapping method is employed to choose training data. Equation and the addition of the trained decision tree to the forest $M^{\star}$ is employed to determine the unlabeled cases at the end of each cycle.

3.3. Optimization Algorithm

Unified physical resource management during smart city development is difficult because of hardware variances and incompatibilities in urban data centers. The cloud data center's virtualization technology makes sure that all of these resources—computer, storage, and networking—are integrated into a single, uniform virtual unit [16]. Virtual resource management technology enables users to access resources on demand, as well as automatic work plans and allocation, dynamic growth, and rapid deployment of CC resources. This makes it possible to develop a practical and scientific strategy for coordinated resource management. The suggested model is an algorithm for multi-criteria optimization that emerges in the context of developing smart cities. Every available resource on each physical node is represented by an n-dimensional vector, where the n dimensions represent each individual resource. Each VM resource is represented by a d-dimensional vector. The objective of this process is to minimize both the total number of physical nodes and the amount of variability of load across all of those nodes by aggregating a large number of virtual machine (VM) resources on to a few physical nodes. The following is a description of the multi-criteria optimization algorithm.

$$e_{OM} = \min \sum_e D_e \quad (6)$$
$$\sum C\,\varepsilon_j\, e_{KA} = \min \frac{n}{c} \quad (7)$$

The number of active physical nodes and the balanced load variance of the server cluster are denoted by the words e_{OM} and e_{KA}, respectively. The D_e value is given as follows:

$$D_e = \begin{cases} 1, Physical\ nodeiin\ use \\ 0\ Else \end{cases} \quad (8)$$

CThe j-dimensional variance in Eq. is denoted by $C\varepsilon_j$, which stands for total dimensionality is expressed:.369

$$\sum (\,O_{ji} - \overline{o})^2 C\varepsilon_j = \frac{n}{n} \quad (9)$$
$$\sum_j S_j^{epu} * w_{j\to i} \leq O_j^{equ} \quad (10)$$

$\hat{O}$ is the mean value along the $j - rh$ dimension for all nodes, and m is the total number of physical nodes in the previously given formula. As previously mentioned, the performance characteristics are normalized values that correspond to the percentage of the $j - rh$ dimension resources that are still assigned to the physical nodes I. O_{i^i} represents performance attributes in dimension j for i, the underlying physical node.

The mean value for all Nodes by the $j - rh$ dimensions ($\hat{O}$) is divided by 'm' which is the total physical nodes in the previous formula. The performance characteristics are the percentages of j-rh dimension resources still assigned to the physical nodes I. O_{i^i} based on the performance of the node I in dimension j.

$$\sum_j S_j^{mem} * w_j \leq O_i^{mem} \quad (11)$$
$$\sum_j S_j^{J/P} * w_j \leq O_i^{J/P} \quad (12)$$

$$\sum_{DN} S_{jp} \geq SLA_O \quad (13)$$

Equation (13) is used in the "dynamic resource scheduling" of several application areas in smart cities. Performance is the primary objective of resource monitoring software. When the load becomes too heavy, other virtual computers are launched to distribute it. When network bandwidth drops, the number of virtual machines (VMs) can be reduced if Eq. (13) is satisfied. In order to address the problem of virtual machine overload, or their underutilization, we have developed a method for dynamically scheduling virtual machines based on their application service performance. Pseudo code is provided below for a specific implementation of this dynamic scheduling technique that has low demand for the virtual resources associated with a particular virtual machine.

4. EXPERIMENTAL OUTCOMES

In this section, we assess the effectiveness of both suggested and existing approaches in this section. Latency, energy usage, throughput, and network longevity are the parameters. The existing approaches are LEACH, PEGASIS, and HEED.

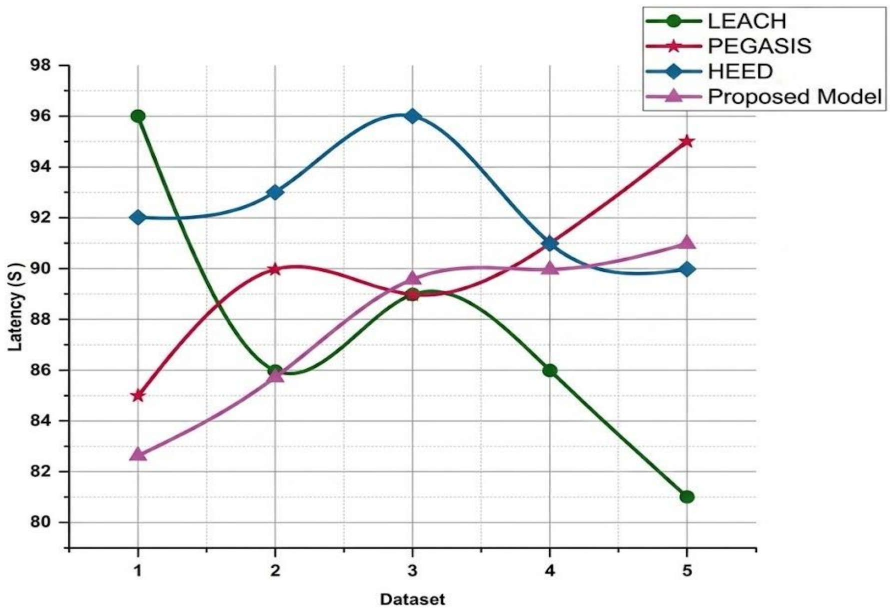

Figure 2. Comparative Analysis of Latency in the Proposed Model

The amount of time that elapses between a user's request and the server's response is known as latency. The latency comparison between the conventional and recommended methods is shown in Figure 2. The proposed approach takes less time than current techniques like LEACH, PEGASIS, and HEED. It demonstrates that our recommended optimization, when combined with the implementation of smart cities, is more effective than the other optimization techniques now in use.

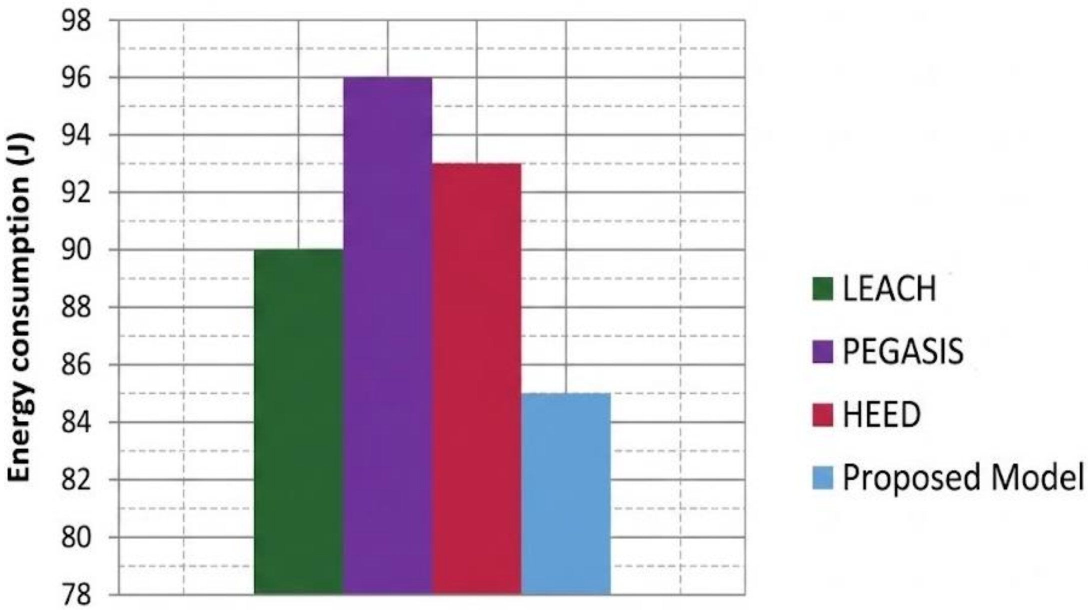

Figure 3. Comparative Analysis of Energy Consumption in the Proposed Model.

One important consideration when scheduling tasks is energy consumption. It is defined as the amount of energy consumed by each node when transmitting packets, and it computes the total energy used by the entire network. The unit of measurement is Joule (J). There is a large amount of task scheduling and an increase in energy utilization. The comparison of energy consumption using the conventional and recommended methods is shown in Figure 3. The suggested method uses less energy than existing methods like LEACH, PEGASIS, and HEED. Consequently, the proposed approach has a high task scheduling and performs better than earlier methods such as LEACH, PEGASIS, and HEED.

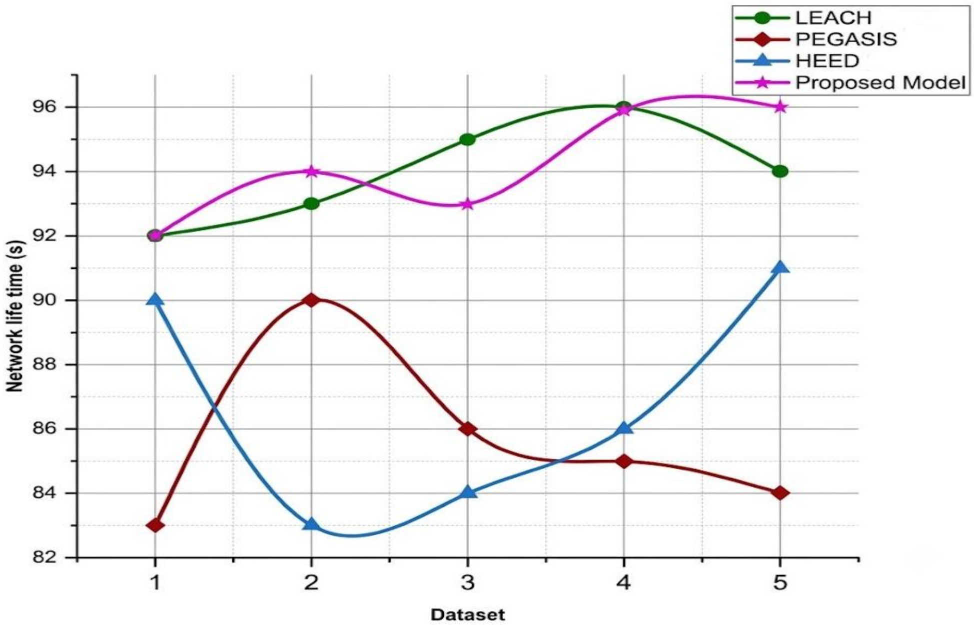

Figure 4. Comparative analysis of Network Lifetime in the Proposed Model

The amount of time before the network's initial node runs out of energy is known as the network lifetime. The throughput comparison between the conventional and recommended methods is shown in Figure 4. The recommended method has a longer network life time than the existing methods, such as LEACH, PEGASIS, and HEED.

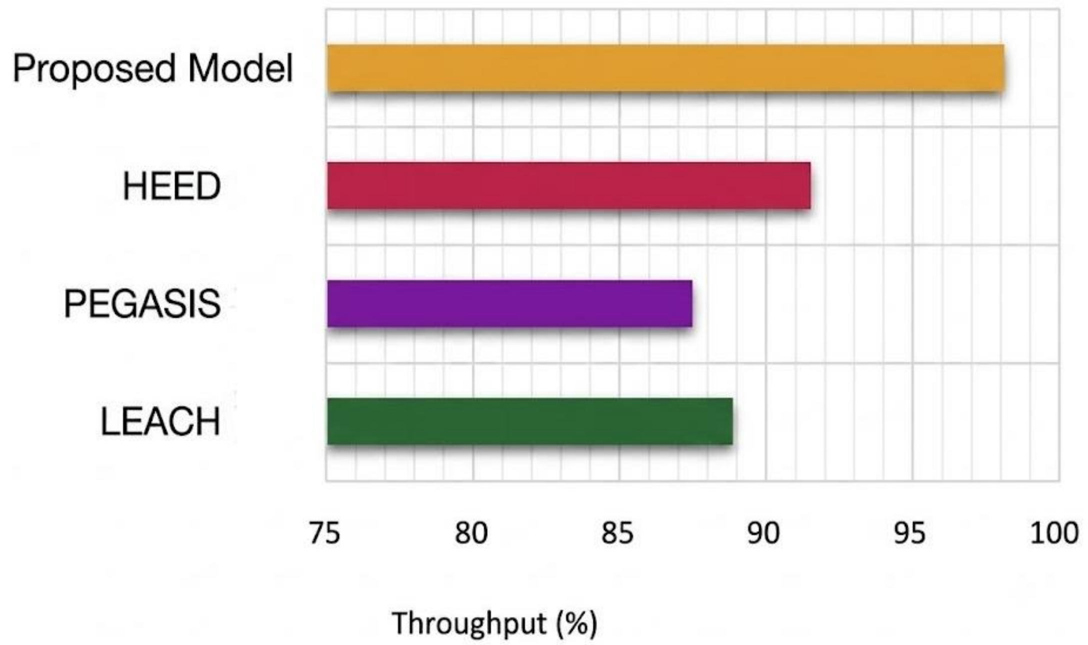

Figure 5. Comparative Analysis of Throughput in the Proposed Model

Throughput is the quantity of data that a system processes or transmits in a specific length of time. The throughput comparison between the conventional and recommended methods is shown in Figure 5. When it comes to information processing or transmission, the proposed method is far more efficient than the current approaches.

5. CONCLUSION

In this study, we present an approach to improving urban service delivery through improved Real-Time Data Processing for Smart Cities using IoT technologies. Through a combination of edge computing, cloud architecture, and effective techniques for data stream processing, the researchers aim to reduce delays in the delivery of these services and improve the overall responsiveness of systems. With the implementation of edge devices, the processing of data will occur as near the data generating source as possible. Therefore, there will be minimal congestion within the network and decision-making will happen more quickly. Additionally, the system utilizes intelligent filtering, prioritization, and other data handling techniques for processing large amounts of data efficiently, thereby enabling better scalability to handle increasing demands for data within smart city systems, without degradation in performance Optimizing IoT-based data processing can enhance resource utilization and support sustainable urban development through real-time monitoring and adaptive control of urban services. This study shows that IoT-enabled solutions can lead to improved urban management, which results in smarter, more responsive, and more environmentally friendly cities.

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