

USER REQUEST DRIVEN SMART DATA AGGREGATION IN IOT
(IOT'DE KULLANICI İSTEĞİNE DAYALI AKILLI VERİ TOPLAMA)

by

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Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

in

INTELLIGENT SYSTEMS ENGINEERING

in the

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

of

GALATASARAY UNIVERSITY

JANUARY 2025

Approval of the thesis:

USER REQUEST DRIVEN SMART DATA AGGREGATION IN IOT

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ACKNOWLEDGMENTS

I would like to express my sincere thanks to my supervisor Assist. Prof. Dr. Ozgun PINARER and Galatasaray University, Institute of Science, Department of Intelligent Systems Engineering, who increased my interest and motivation in smart systems and IoT with their knowledge and guidance. I would also like to thank my family, whose belief and love I have always felt, for their patience and support.

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ABSTRACT

Ensuring effective, efficient, and fast data communication in IoT networks is a critical challenge, given the resource limitations of nodes within these networks. Data aggregation emerges as a promising solution to address this challenge by consolidating data from multiple sources before transmission, thereby reducing memory consumption, enhancing energy efficiency, and improving transmission speed. This study proposes an approach to examine the impact of different data aggregation methods and transmission frequencies on memory usage in resource-limited sensor nodes, considering these client requests. Specifically, we will investigate how memory consumption changes when data is transmitted to the sink node at various frequencies using different aggregation techniques. Additionally, memory usage is measured when the aggregation method and transmission frequency are dynamically determined, and aggregated data is transmitted to the requested server or service. In the proposed system for user-request driven smart data aggregation in IoT networks, the data flow follows a structured process to efficiently handle client requests while optimizing resource usage. Based on these requests, sensors will aggregate the data and transmit it to the sink node, the client system, or the server at the specified frequency. By comparing the measured memory usage values, we aim to identify the aggregation method and transmission frequency that result in the least memory usage. These optimal values are expected to enhance energy efficiency and memory usage efficiency in the IoT network, consequently prolonging its lifespan. The proposed data flow ensures that client requests are efficiently handled while minimizing resource consumption in the IoT network. In summary, this study aims to contribute insights into optimizing memory usage in IoT networks through efficient data aggregation and transmission strategies, considering client requests.

Keywords : BIM-based environment management, Smart infrastructure, IoT integration, Sustainable building operations, Real-time monitoring

RÉSUMÉ

Assurer une communication efficace, efficiente et rapide des données dans les réseaux IoT constitue un défi critique, étant donné les limitations en ressources des nœuds au sein de ces réseaux. L'agrégation de données émerge comme une solution prometteuse pour relever ce défi en consolidant les données provenant de plusieurs sources avant leur transmission, réduisant ainsi la consommation de mémoire, améliorant l'efficacité énergétique et augmentant la vitesse de transmission. Cette étude propose une approche visant à examiner l'impact des différentes méthodes d'agrégation de données et des fréquences de transmission sur l'utilisation de la mémoire dans les nœuds capteurs à ressources limitées, en tenant compte de ces demandes des clients. Plus précisément, nous étudierons comment la consommation de mémoire évolue lorsque les données sont transmises au nœud puits à différentes fréquences à l'aide de différentes techniques d'agrégation. De plus, l'utilisation de la mémoire est mesurée lorsque la méthode d'agrégation et la fréquence de transmission sont déterminées de manière dynamique, et les données agrégées sont transmises au serveur ou service demandé. Dans le système proposé pour l'agrégation intelligente des données pilotée par les demandes des utilisateurs dans les réseaux IoT, le flux de données suit un processus structuré pour gérer efficacement les demandes des clients tout en optimisant l'utilisation des ressources. En comparant les valeurs de consommation de mémoire mesurées, nous visons à identifier la méthode d'agrégation et la fréquence de transmission qui entraînent la moindre utilisation de la mémoire. Le flux de données proposé garantit que les demandes des clients sont gérées efficacement tout en minimisant la consommation de ressources dans le réseau IoT. En résumé, cette étude vise à apporter des informations sur l'optimisation de l'utilisation de la mémoire dans les réseaux IoT grâce à des stratégies efficaces d'agrégation et de transmission de données, en tenant compte des demandes des clients.

Mots Clés : Gestion de l'environnement basée sur BIM, infrastructure intelligente, intégration IoT, opérations de construction durables, surveillance en temps réel

ÖZET

IoT ağlarında etkili, verimli ve hızlı veri iletişimi sağlamak, bu ağların düğümlerinin sınırlı kaynakları göz önüne alındığında kritik bir zorluktur. Veri birleştirme, verilerin iletim öncesinde birden fazla kaynaktan toplanmasıyla bu zorluğa çözüm olarak ortaya çıkar, bu da bellek tüketimini azaltır, enerji verimliliğini artırır ve iletim hızını iyileştirir. Bu çalışma, kaynak sınırlı sensör düğümlerinde farklı veri birleştirme yöntemlerinin ve iletim frekanslarının bellek kullanımına etkisini, müşteri isteklerini göz önünde bulundurarak incelemeyi önermektedir. Özellikle, verilerin farklı birleştirme teknikleri kullanılarak çeşitli frekanslarda sink düğümlüne iletilmesi durumunda bellek tüketiminin nasıl değiştiğini araştıracağız. Ayrıca, birleştirme yöntemi ve iletim frekansının dinamik olarak belirlendiği ve birleştirilmiş verilerin istenilen sunucuya veya servise iletilmesinin ölçüldüğü bellek kullanımı da değerlendirilecektir. IoT ağlarında kullanıcı isteğine bağlı akıllı veri birleştirme için önerilen sistemde, veri akışı, kaynak kullanımını optimize etmek için yapılandırılmış bir süreci izler. Bu isteklere dayanarak, sensörler veriyi birleştirecek ve belirtilen frekansta sink düğümlüne, müşteri sistemine veya sunucuya iletecektir. Ölçülen bellek kullanım değerlerini karşılaştırarak, en az bellek kullanımına neden olan birleştirme yöntemini ve iletim frekansını belirlemeyi amaçlıyoruz. Bu optimal değerlerin IoT ağında enerji verimliliğini ve bellek kullanımı verimliliğini artırması beklenmektedir. Çeşitli koşullar altında bellek kullanım değerlerini karşılaştırarak, sistem kaynak kullanımında en etkili yaklaşımı belirleyebilecektir. Özetle, bu çalışma, müşteri isteklerini dikkate alarak IoT ağlarında bellek kullanımını optimize etmeye yönelik etkili veri birleştirme ve iletim stratejileri konusunda içgörüler sağlamayı amaçlamaktadır.

Anahtar Kelimeler : Yeni Nesil Yaygın Çevre Yönetimi, Akıllı altyapı, IoT entegrasyonu, Sürdürülebilir bina işletmeleri, Gerçek zamanlı izleme

LIST OF ABBREVIATIONS

AAL	Ambient Assisted Living
BIM	Building Information Modeling
IOT	Internet of Things
PEMS	Pervasive Environment Management System
WSN	Wireless Sensor Networks



1 INTRODUCTION

In recent years, the integration of the Pervasive Environment Management System (PEMS) with Building Information Modeling (BIM) has emerged as a popular research area, promising significant advancements in environmental monitoring and management. This study seeks to explore the implications of this integration through the lens of energy efficiency and memory awareness within the Internet of Things (IoT). Our investigation begins with a contextual understanding of the challenges facing contemporary environmental management. The proliferation of urbanization, industrialization, and global population growth has intensified the need for sophisticated systems capable of comprehensively monitoring and managing environmental conditions. From air quality to water resources, the demands on environmental monitoring systems have grown exponentially, necessitating innovative solutions to navigate the intricacies of modern environmental management.

PEMS operates on the premise of pervasive computing, offering a dynamic and responsive system tailored to the challenges of environmental monitoring. Its integration with BIM, a structured approach to creating and managing digital representations of physical environments, establishes a synergistic relationship that provides a robust framework for pervasive environmental management. Leveraging the strengths of both systems, we anticipate a holistic approach that goes beyond mere data collection, providing a nuanced understanding of the built environment.

From the perspective of IoT, energy efficiency stands as a cornerstone for sustainable system operations. PEMS addresses this imperative by incorporating energy-aware algorithms, optimizing energy consumption while maintaining the integrity of environmental monitoring. Through strategic measures, PEMS navigates the delicate balance between comprehensive data collection and energy conservation, ensuring efficient operations across diverse environmental settings.

As we delve into the energy-aware IoT perspective within PEMS, attention is drawn to the adaptability of the system. PEMS intelligently adjusts its monitoring intensity based on contextual factors and user-defined parameters, ensuring judicious use of energy resources and practicality in diverse environmental settings. Whether in smart

buildings or industrial complexes, PEMS emerges as a versatile solution capable of meeting the unique demands of each environment while upholding principles of energy efficiency.

Memory constraints pose a significant challenge in the IoT landscape, where devices often grapple with limited resources. Drawing inspiration from BIM principles, PEMS adopts a strategic approach to memory awareness, involving intelligent data prioritization and compression strategies aimed at enhancing memory efficiency. By carefully managing data storage and retrieval, PEMS ensures critical environmental information is retained without overwhelming the memory resources inherent in many IoT devices.

The emphasis on memory efficiency aligns with the pragmatic realities of IoT applications. Rather than viewing memory constraints as obstacles, PEMS treats them as parameters necessitating thoughtful consideration in system design. The result is a system that effectively monitors environmental conditions while respecting the inherent limitations of IoT devices.

Synthesizing the energy-aware and memory-aware perspectives within the PEMS-BIM integration reveals overarching implications. PEMS, guided by BIM principles, offers a comprehensive and practical approach to pervasive environmental management. Its adaptability ensures it is not a one-size-fits-all solution but a dynamic system capable of addressing the unique challenges posed by different environments.

The implications extend beyond data collection and monitoring, contributing to the broader discourse on sustainable technology applications. By optimizing resource utilization, PEMS aligns with principles of responsible technology deployment, crucial considerations in the age of IoT.

Practically, the integration of PEMS with BIM holds promise for various sectors. In smart buildings, PEMS's adaptability ensures energy is not needlessly expended in areas with lower occupancy, contributing to cost savings and environmental sustainability. In industrial settings, PEMS's memory efficiency ensures critical data is retained without straining IoT device resources, fostering reliable and continuous monitoring.

In summary, the integration of PEMS with BIM principles provides a pathway toward sustainable and efficient pervasive environmental management. Its energy-aware and memory-efficient design reflects a nuanced understanding of contemporary environmental monitoring challenges, aiming to contribute accessible insights into the practical

implications and benefits of the integration, particularly in energy conservation and memory efficiency.

The remainder of the document is structured as follows : Literature review is given in Chapter 2. Chapter 3 presents our proposed approach. Chapter 4 introduces perfor-

med experiment scenarios and experiment results. Finally, conclusion and discussion are given in Chapter 5.



2 LITERATURE REVIEW

2.1 IoT Environment Management via Autodesk Revit Tool

In recent years, the Internet of Things (IoT) has emerged as a transformative technology, offering innovative solutions for various industries. One notable application is in the environment management, where IoT technologies play a crucial role in monitoring and controlling environmental conditions. This section focuses on the utilization of Autodesk Revit Tool as a practical means to implement IoT in environment management. Autodesk Revit, a widely used Building Information Modeling (BIM) software, presents an accessible platform for integrating IoT devices to enhance the monitoring and control of environmental factors. The papers cited in this section explore the potential of this combination, aiming to shed light on the practical implications and benefits of employing Autodesk Revit as a tool for IoT-based environment management.

In terms of energy efficiency, less than 10% of existing buildings in Europe are at the target level. In order to achieve the European Commission's targets in the 2050 road map, it is necessary to ensure energy efficiency in an estimated 97% of existing occupied buildings. It is necessary to have information about buildings in order to determine and plan the strategy to be created to strengthen, maintain and ensure energy efficiency in existing buildings and to accurately evaluate the interventions to be made. In (Desogus et al., 2021), a building model was created on BIM to reduce energy consumption in existing buildings and to plan reinforcement and maintenance works in buildings. Thanks to the IoT sensors placed in the building, the indoor environment temperature, brightness, etc. information has been collected. Data collected from IoT sensors is dynamically and automatically transmitted to the BIM model with the integration established between BIM and IoT sensors. The transmitted data and energy consumption parameters in the building can be monitored through BIM.

BIM is a common source of information that can be used to share and provide reliable information about a facility throughout the building's lifecycle, and can be used to store, transfer and reapply information at all stages of the traditional building lifecycle. BIM is actually used to refer to elements/objects that conform to specific information

standards (such as Industry Core Classes, IFCs). The IFC data model is universal, designed to support all modeling operations required by the construction industry and enables intuitive viewing of others' content in stereoscopic 3D. The use of the IFC standard can effectively reduce the occurrence of errors and defects and enable quick resolution of disputes and errors between professionals. BIM using the IFC standard can minimize or eliminate costs and lost time resulting from extensive rework. BIM models are also useful and effective in assessing energy efficiency. Currently, building management issues have been solved through the use of numerical calculations using data from sensors monitoring building spaces, but failure to integrate the data with the BIM model of the building will prevent the facility manager from being able to intuitively identify potential problems. (Chang et al., 2018) aims to provide a platform by integrating sensor data with BIM. This platform will have 3 goals. The first of these is the automatic collection of data from physical sensors and storage in the BIM system. Secondly, index value-based numerical calculations are automatically performed on the data and visualized with color charts. Third, it enables the user to switch between different contexts to different subsets of sensors installed in the space.

Proper management of the maintenance phase in building management is very important to reduce costs and energy consumption, preserve the value of the asset over time, and maintain the building performance level required by users. In order for the maintenance phase to be carried out faster, more efficiently, effectively and error-free, BIM can be integrated with IoT technology, which is a revolutionary technology, and visualization, analysis and management of the data can be done through real-time data. There are many building warning systems based on IoT and BIM. However, most of them enable capturing and monitoring environmental data with IoT sensors. They do not have any building maintenance services. Maintenance is generally classified as corrective, scheduled, preventive, predictive and proactive. (Villa et al., 2021) et al. study largely applied the preventive maintenance methodology. Preventive maintenance is about inspecting and checking the system at certain and fixed intervals to prevent unexpected failure of the system. The purpose of this study is to create an IoT network for facility maintenance, monitor the components of the HVAC system and identify errors in the system. In addition, it aims to offer a data management methodology integrated with fault detection, specially designed for facility management. In the study, a system that provides IoT and BIM integration with a cloud-based user interface was created. The fault detection methodology in the system sends an alert to the facility manager when it detects an anomaly. Facility managers/operators can easily

find the component causing the malfunction and its location through the 3D model. Thanks to the cloud-based user interface, facility managers can monitor the system remotely and take action when data arrives from the physical environment outside the specified intervals.

During the operation and maintenance stages throughout the building's life cycle, building condition data such as temperature, humidity, air quality, energy consumption need to be corrected to effectively manage the building. Because these data can help diagnose the condition of the building and be effective in decision-making by managers. (Kim et al., 2018) et al. propose a method to collect this data of the building in real time using IoT and BIM and to correct this data according to real data. In IoT systems, change management of wired sensors is very difficult and costly. In this study, wireless sensors were used to overcome these challenges. By providing IoT and BIM integration, real-time data is collected and transmitted to a cloud-based center. The end user can monitor the data coming from the IoT system using wireless sensors and mapped to BIM via a web-based interface.

The comfort level in the human body is difficult to evaluate generally and objectively. To increase the comfort level, building owners or managers adjust the physical properties of buildings such as temperature, humidity and air quality. In fact, the electricity consumption of buildings can be reduced by minimizing the unnecessary use of heating and cooling systems. (Wu and Liu, 2019) present a system that includes persuasive computing was created by integrating building information modeling (BIM), IoT and COZyBIM systems to ensure comfort and reduce energy consumption in smart and green buildings. The system to be created has 4 basic tasks to be achieved. The first of these is to provide visualization and smart suggestion functions to help building managers and users analyze and develop plans according to space usage and electrical equipment demands; second, using Internet of Things technology to minimize the difference between real situations and those simulated in building information modeling (BIM); third, accurately assessing indoor comfort levels and improving equipment operating efficiency based on quantified comfort levels; and fourth, to create a compelling workflow for creating energy-saving systems. In the designed system; With the IoT system, temperature, humidity and CO levels are measured and the measured data is transferred to the BIM system. In the COZyBIM system, measured data is pulled from BIM and checked and analyzed. When it exceeds certain values, an alarm is generated for the users or the relevant device in the building can be turned off and on by remote

control such as the heating/cooling system.

While the BIM approach is an approach that can be applied at all stages of the construction life cycle, it is generally used only at the design stage. However, one of the most complex and important stages of the life cycle of a construction is the monitoring phase, which is a key element for the maintenance and safe use of buildings. There are many techniques that can be applied during the monitoring phase. For example, providing BIM integration with SHM (Structural Health Monitoring), HSM, IoT sensors and developing a web-based user interface for monitoring. This research aims to explore the possibilities of low-cost sensor monitoring of structures by analyzing in real time the operating status of a bridge beam model connected to its digital twin using an IoT sensor system. In many studies carried out so far, BIM integration was only provided with IoT devices, and current real-time data from sensor data was not shared over a network. In the integration established in (Scianna et al., 2022), the data measured by the sensor is transmitted to the relational database management system and allows real-time connection between the BIM model and its digital twin.

Standards and certification systems such as LEED (Leadership in Energy and Environmental Design), Green Globe and WELL have inspired designers to introduce innovative solutions and the latest technologies into built spaces. With the green building standards framed by these certificates, it is expected to reduce energy consumption and greenhouse gas emissions while improving the quality of the built environment. Considering that people spend the majority of their time indoors, it is seen that Indoor Environmental Quality (IEQ) affects people's health, well-being and proactivity. Additionally, IEQ provides information about building performance in relation to people's comfort and satisfaction. Factors such as energy consumption, greenhouse gas emissions, IEQ and occupancy rate constitute the overall performance of the building. In parallel, GIS (Geographic Information Systems) has become powerful in analyzing and visualizing spatial-temporal information. By integrating BIM-IoT-GIS systems, a digital twin, which is a digital version of a physical structure, can be created by leveraging the power of these technologies. (Tripathi et al., 2023) examines the use of digital twin with BIM-IoT-GIS integration for POE.

In the management of a facility, physical and functional information about the facility is of great importance. At this point, Building Information Model helps present the data required for facility management within a standard framework. The method

by which the data provided by BIM will be fed into BIM is equally important. The simplest and most cost-effective way to feed data to BIM today is to use IoT sensors. By collecting, evaluating and visualizing real-time data about the building, it supports facility managers in making accurate and effective decisions on issues such as energy consumption, cost savings, facility operations and maintenance. By establishing integration between BIM and IoT sensors, real-time data can be transferred to BIM. In addition, errors that may occur in heating, air conditioning, ventilation system equipment and functions for facility management, It can be prevented or the source of the error can be easily detected by using IoT sensors such as temperature and humidity positioned in the systems. (Su and Kensek, 2021) et al. aim is to establish integration between BIM and IoT sensors and develop a data visualization prototype tool to warn if the required values in systems such as HVAC in the building exceed certain conditions or ranges and to detect the error. Here, the values expected to be measured in the future can be predicted by using past data before the required physical values go out of certain ranges.

BIM supports decision-making during the design and construction stages of building construction. It ensures that the scope and purpose are fully understood by all stakeholders in the project. It allows better visualization of alternative designs and thus better offers can be presented. It supports the provision of excellent, innovative and possible fast solutions. It is a 3D technology that allows project data to be transferred to other data management. In (Waas et al., 2022), the functions, features, potentials and limitations of Graphisoft Archicad and Autodesk Revit software, two popular BIM tools in the world, are examined and their advantages and disadvantages are shown. Appropriate BIM software can be selected according to these advantages and disadvantages in accordance with the scope and purpose of construction projects.

The high rate of urbanization and industrialization brought about by the spread of major innovative technologies in the past decades has had a huge impact on people's living standards. In addition, it caused increased environmental pollution and degradation. It is accepted that the use of digital innovative technologies will provide a smart, sustainable built environment for people and change and improve people's lives. Especially the built environment, high energy use, greenhouse gas emissions, etc. For these reasons, sustainable practices should be taken seriously and implemented. For this, the construction industry needs to make its own digital revolution. This digital revolution can be started with the BIM model, which provides the standard for building informa-

tion management, including the physical and functional characteristics of buildings. In order for the BIM model to be created here to be implemented effectively and easily, it will be of great benefit to integrate it with Internet of Things sensors. (Malagnino et al., 2021) et al. study conducted between 2015 and 2020 on BIM-IoT integration and interoperability, which has been the subject of separate research so far, were reviewed and reported. According to the research results, best solution practices using BIM-IoT integration have been suggested to provide resources for professionals and researchers.

In case of fire, there are conditions that pose a danger to firefighters and building occupants. These conditions can lead to lack of knowledge about the fire scene and spatial configuration, poor judgment in choosing the escape route, and uncertainty about changes to the fire scene, causing building occupants to spend a lot of time trying to escape. In order to eliminate this danger and manage fires with less damage and cost, an integrated framework with FDS and IoT is presented (Chen et al., 2018).

(Chen et al., 2018) et al. integrate Internet of Things (IoT) technology, which enables monitoring at the scene. In the event of the source of a fire being detected and also the environment reaching a certain temperature and CO concentration level, the BIM model will immediately display the situation and sound an alert that the building occupants should evacuate. Then the fire simulation results and the real-time situation can be used to control the escape pointers to guide evacuees along a safe escape route, increasing their chance of survival.

In order to manage a building in all its aspects, data is needed from different types of sources. For example; It is aimed to achieve holistic building management by obtaining data from sources such as Building Management System, Internet of Things sensor networks, Building Information models. Here, interoperability of data is important for effective use of masses of information from different sources. In addition, semantic web technologies such as BRICK schema can be used to standardize the semantic explanations of physical, logical and virtual entities in the building and their relationships with each other. (Vittori et al., 2023) et al. present a methodology to automatically collect data from different types of sources, combine them and integrate them into the building information model for knowledge graphs. In fact, a digital twin of the building is created by dynamically collecting information from different types of sources with IoT sensors, integrating it into the building model, and using this data in a semantically standard structure in the building management system. With the digital twin concept,

it is ensured that the building's activities such as maintenance, operation, reinforcement, and ensuring the comfort of the building occupants are effectively, easily and digitally monitored.

(Hou et al., 2021) et al. present a BIM-based framework supported by the LSTM deep learning method is presented to monitor building health during the construction and maintenance stages and to provide a visual warning (SHM) in case of danger. With the presented framework, the data from the sensors placed in the building are stored in the database and when a situation occurs outside the specified ranges (threshold) or a danger is predicted based on the data previously received by the LSTM method, the dangerous area can be displayed with visual warnings on the building. BIM is used as a model in this study. And BIM is integrated with data mining algorithm.

(Machete et al., 2023) et al. aim to determine the kinetic and mechanical properties of old masonry structures and new structures, to measure the data through sensors to ensure protection and preservation against possible disasters and extraordinary situations, and to store and manage the data by establishing a structural information system. WSN (Wireless Sensor-Network) was implemented with IoT systems to collect information about building features. In this way, it is aimed to obtain data quickly and at low cost. It is recommended to use prediction models with machine learning methods to make it easier and faster to process, analyze, interpret and use real-time big data coming from sensors and use it in decision making. H-BIM (Heritage Building Information Model) model will be established for this study.

Building information management (BIM) is a common source of information that can be used to share and provide information about a building throughout its life cycle, starting from the building's design. With BIM, it is possible to store, transfer and reapply information at all stages of the building life cycle. In BIM, objects are created, shared, stored and transferred in accordance with specific information standards (Industry Core Classes-IFC). IFC is a universal standard and supports all modeling processes needed by the construction industry. The use of IFC reduces the occurrence of errors and defects and helps to resolve errors quickly and effectively. In BIM, spatial, temporal and physical data about the building are kept and it is possible to intuitively view the model in stereoscopic 3D in BIM. By integrating and using the BIM model and IoT systems, many benefits are provided in people's daily lives. With sensors placed in the building environment, the building's physical, location and vibration information

can be transferred to BIM. With the integration to be established, these data can be transferred to the BIM system and monitored in real time. When the threshold values to be defined for these data are exceeded, a warning mechanism can be created and actions can be taken. Data from sensors placed in the environment, such as temperature, humidity, and air quality, are transferred to the BIM system and compared with real weather data, and the building's values such as temperature, humidity, and air quality can be adjusted. Energy consumption can be reduced by integrating BIM and IOT in smart and green buildings. Costs can also be reduced with energy efficient buildings. In addition, recommendation and warning systems can be created by analyzing real-time data transferred to BIM using deep learning algorithms such as LSTM. Based on BIM and IOT integration, a digital twin of the buildings is created and facility management is ensured in an easy, effective and efficient manner. Within the scope of the digital twin, activities such as maintenance, operation, reinforcement, and ensuring the comfort of building occupants are ensured to be effectively, easily and digitally monitored. Table 2.1 presents the major studies in BIM research area.

TABLE 2.1 – Overview of existing studies on BIM

Authors	Integration Method	Main Focus	Key Findings
Desogus et al. (2021)	BIM-WSN Integration	Structural Health Monitoring	Use of IoT sensors and BIM for real-time monitoring of building structures.
Chang et al. (2018)	BIM-Sensor Integration	Data Collection and Analysis	Automatic collection of sensor data, storage in BIM, and visualization for decision-making.
Villa et al. (2021)	BIM-IoT Cloud Integration	Preventive Maintenance	Use of IoT sensors and BIM for preventive maintenance and fault detection.
Kim et al. (2018)	BIM-IoT Cloud Integration	Real-Time Data Correction	Correction of real-time building data using IoT sensors and BIM.
Wu et al. (2019)	BIM-IoT COZy-BIM Integration	Comfort and Energy Efficiency	Integration of BIM, IoT, and COZyBIM for comfort and energy efficiency in buildings.
Scianna et al. (2022)	BIM-IoT Database Integration	Real-Time Data Transmission	Establishment of real-time connection between IoT sensors and BIM for data transmission.
Tripathi et al. (2023)	BIM-IoT-GIS Integration	Post Occupancy Evaluation	Integration of BIM, IoT, and GIS for post-occupancy evaluation of buildings.
Su et al. (2021)	BIM-IoT Visualization Integration	Fault Detection	Development of a visualization tool for fault detection in HVAC systems using BIM and IoT.
Waas et al. (2022)	BIM Software Comparison	Software Comparison	Comparison of Graphisoft Archicad and Autodesk Revit for BIM integration.
Malagnino et al. (2021)	BIM-IoT Best Practices	Integration Best Practices	Review of best solution practices for BIM-IoT integration and interoperability.
Chen et al. (2018)	BIM-IoT Fire Rescue Integration	Fire Rescue	Integration of BIM and IoT for fire rescue, including real-time monitoring and evacuation alerts.

2.2 Pervasive Environment Management Systems - PEMS

In recent years, the Pervasive Environment Management System (PEMS) has gained attention as a practical solution for monitoring and controlling environmental conditions across diverse settings. PEMS leverages pervasive computing technologies to create a system that seamlessly integrates with the environment, enabling efficient management of various parameters. This section explores the application and significance of PEMS in environmental management, aiming to provide a clear understanding of its potential benefits in ensuring environmental sustainability. By employing a user-friendly and accessible approach, this research investigates valuable insights into the practical implications of implementing PEMS for effective environment management (Colace et al., 2015).

Ambient assisted living (AAL), which is an ecosystem of different technologies and applications for pervasive and ubiquitous computing and monitoring of personal health care to protect and improve people's quality of life, especially for the elderly, at all stages of life, refers to the multidisciplinary field. The concept of enhanced living environments (ELEs) refers to the ambient assisted living area associated with information and communication technologies. ELEs require information and communication technologies that include algorithms, platforms and systems to design and develop innovative applications and services to sustain independent living. ELE creates information and communications solutions using the latest IoT technologies to improve people's health and well-being. ELE allows people to receive healthcare services at home rather than moving to institutional settings. In addition, these systems offer effective methods that will improve the independence of individuals and facilitate medical treatments. Currently, there are different health systems that use wireless technologies such as ZigBee, Wi-Fi 3G, Bluetooth and Ethernet, which enable monitoring of various human physiological states and environmental parameters. Monitoring the human physiological state provides the perception of the medical condition and is important in detecting symptoms at the appropriate time, especially for the elderly and newborn individuals at risk. Human well-being and health do not depend solely on physiological state. The conditions of a person's environment also affect their well-being and health. Doctors can analyze both physiological and environmental data in real time to support clinical symptoms. For example, the effect of air quality on human health in the indoor environment where people spend most of the day can be evaluated. This data can be

monitored and controlled in real time. There are many open issues in the design and implementation of healthcare systems, such as usability, user interface, data structure, ubiquitous design, ergonomics, and data access. Privacy and confidentiality of information are currently recognized by most healthcare systems. Here it must be ensured that technological innovation does not replace human care. Instead, this technological innovation should be used to support medical decisions and monitor health/diseases from anywhere, anytime. IoT applications are in close contact with healthcare systems thanks to remote monitoring, smart homes, wearable devices and smart medical equipment. To support high-quality healthcare systems, IoT must embrace standardization, including efficient wireless protocols, improved mobile and wearable sensors, and cost-effective and low-power microprocessors. (Marques et al., 2019) aims to make an introduction to health systems, to review the current state-of-the-art technology, to examine IoT-based technologies, applications, challenges, opportunities, IoT open source platforms and operating systems in this field. In addition, in this study, a comprehensive and comparative review was made on existing IoT platforms and operating systems and solutions were proposed, especially for the healthcare field.

The new area of interest being studied in the field of health is preventive and predictive medicine. In general, behavioral, physical and environmental factors are effective parameters in preventive and predictive medicine studies. By analyzing, combining and monitoring the data obtained according to these parameters, the effects of the parameters on human health are examined by medical experts and it is aimed to prevent or predict the disease before it occurs. IoT technology can be used to obtain, analyze and combine personal health data and environmental data in real time in preventive and predictive medicine studies in the field of healthcare. (Haghi et al., 2020) aim to create a configurable and adaptable platform that provides comprehensive parameter monitoring according to the appropriate wearability mode. In this context, an IoT-based platform that measures, combines, synchronizes and processes environmental, behavioral and physical parameters in real time has been developed for medical examinations. This platform also includes a flexible IoT gateway structure so that different products can be integrated into the platform. For this purpose, an innovative wrist-worn prototype that measures environmental parameters has also been developed. Thus, users will be able to use this platform with their own products.

Recent advances in wireless communications, solid-state circuits, and high demands on sensing capability have led to the emergence of a new technology, integrated sensing

and communications (ISAC). ISAC provides 2 important advantages. The first one provides the advantage of integration for efficient use of wireless/hardware resources. The other is to balance dual function performance and provide coordination benefits for mutual aid. In the ubiquitous IoT architecture triggered by ISAC, the sensing and communication layers have also experienced a paradigm shift, evolving into a new layer, the signaling layer. This signaling layer enabled by ISAC has the advantages of low hardware cost, low power consumption, low signal delay, small product size and improved spectral efficiency. ISAC technology also enables existing communications networks to provide detection and surveillance services with minimal standard modifications. ISAC technology has many use cases. Some of those; autonomous vehicles, smart cities, smart homes, cellular networks for beyond 5G. With the study (Cui et al., 2021), we tried to create a resource to understand the role of the ISAC concept in the IoT architecture through the signaling layer. Then, the factors affecting ISAC were analyzed and usage scenarios and situations were examined. Scenarios and situations include remote sensing, environmental sensing, human computer interaction, sensing as a service, smart home, vehicle to everything and in-cab sensing. Finally, ISAC solutions are classified and categorized according to the layer where the integration takes place.

While urbanization increases economic growth, it also causes air pollution and climate change. Increasing urban air pollution and the resulting health and economic impacts are met with concern worldwide. Main pollutants such as particulate matter (PM), sulfur dioxide (SO₂), nitrogen oxide (NO_x), carbon monoxide (CO), ozone (O₃), volatile organic compounds (VOCs) that cause air pollution; It is emitted from sources such as automobiles, energy production, construction, industrial activities, open burning, and dust. Exposure to these pollutants has socio-economic impacts such as death, healthcare costs and reduced productivity. Considering the effects of air pollution and climate change, it is necessary to reduce and manage the efficiency of urban emissions with certain strategies. With the spread of information and communication technologies in all areas of life, the smart city framework has emerged. When considered within the framework of a smart city, it can be possible to ensure good air quality through the integration of low-cost sensors, satellite data, data mining tools and open data portals. 4th Industrial Revolution technologies such as IoT, big data, artificial intelligence, smartphones, social and cloud computing have reshaped urbanization conglomerates around the world. Cities can use these technologies in concert with traditional methods to improve air quality. (Kaginalkar et al., 2021) explores the role of urban computing in urban air quality management (UAQM) from various sources and provides a pers-

pective on this subject. The article is a repository of interdisciplinary knowledge about urban computing applications for air quality functions. In this study, technologies that enable urban air quality management and are used within the framework of smart cities are explained comparatively. In addition, open issues, challenges and opportunities in this regard are also analyzed and presented.

The industrial internet of things has entered almost every aspect of our lives today. Many devices, systems and applications in the environment we use or live in contain sensors connected to the internet and provide convenience to our lives. This effect is seen in almost every area of society. It is possible to see the impact of IIoT not only in work but also in individual or corporate lifestyle. IIoT, the concept of connecting to the internet through any device, seems to be the new rule of the future. (Malik et al., 2021) present an IIoT architecture by examining the current status of Internet of Things-based pervasive computing and IIoT application areas. IIoT architecture is classified as perception(sensors), preprocessing, communication(networking), middle-ware, applications. According to this classification, the standards, frequency rate, data rate, transmission range, energy consumption and cost of Bluetooth, Wi-Fi, LoRA, Wimax and LRWPAN technologies as communication (networking) technologies were comparatively examined. Another comparative study is about revealing the compatibility between existing boards to be used in IoT-enabled devices and IoT-supported platforms such as Arduino and Raspberry Pi. In addition, in this study, applications of IIoT in different fields such as environmental monitoring, agriculture, smart home/building, construction industry, disaster management, automotive industry, robotic technology were examined.

IoT can identify, control and monitor every object in the world over the internet by connecting physical and virtual objects to each other and communicating and connecting over a specific protocol, based on the interoperability of information and communication technologies. The main purpose of IoT is to support the sharing of real-time information through autonomous networked devices, sensors, and services. Nowadays, a huge amount of data is produced through IoT-based applications and services. These data are often called "Big Data" and are large-scale data. New architectures and technologies are needed to manage data at this scale. By managing this data, guiding values can be produced for decision making and understanding. IoT and its integration with big data are applied in a wide variety of fields such as smart cities, smart healthcare, smart warning systems, disaster management. Although there have been tremendous

advances in smart environmental applications for IoT, capturing, storing, analyzing and processing large volumes of data are still challenging tasks. Additionally, the rapidly increasing volume and variety of new sensors available makes it difficult for users to analyze, share, and extract information from big data. (Hajjaji et al., 2021) present the existing literature on IoT and big data within the scope of smart environmental applications was examined. The main purpose of this study is to explain how IoT and big data integration can lead to promising solutions and insights for smart environmental applications, to reveal yet unrealized challenges and opportunities of this technology, and to identify future research opportunities. It is thought that thanks to this study, the concept of IoT and big data will be better understood and implemented by other researchers and practitioners.

Users' comprehensive demands for higher efficiency, larger capacity, lower latencies and lower energy consumption are expected to be met by the 5G network. To reach the milestone where all of these will be met, both the research and industrial communities have suggested that the future will leverage new technologies, including the Millimeter-Wave (mm-wave) frequency band, IoT, wireless sensor networks, big data and cellular cloud computing technologies. Next-generation networks will provide ubiquitous internet and cellular services to the estimated billions of internet-enabled devices, including human- and machine-type communications systems. IoT is considered as an expanding technique used in a wide range of applications and functions, from smart environment and homes to personal healthcare. The concept of IoT is summarized as connecting everyone, anytime, anywhere. The application of the IoT concept gets objects and people closer and makes everyday life easier. (Hassan et al., 2020) aim to systematically categorize and investigate research on IoT application methods and approaches. Additionally, the growth and development of IoT, as well as IoT applications in various fields, have been investigated. The scope of the study includes health, environment, smart city, commercial, industrial and infrastructure areas where IoT is applied. In addition, the IoT architecture and the protocols used were also examined in the study. Additionally, challenges and open issues in IoT application areas are also included in the scope of the study.

The IoT paradigm refers to a system of devices that are interconnected, have computational capacity, are identifiable, and have the ability to transfer data over a network without human interaction. The concept behind this paradigm is the widespread existence of smart devices that achieve common goals by collaborating with each other

and interacting with people. Today, an enormous amount of data is produced from smart devices and systems in different fields that incorporate the IoT concept. There is no standard IoT architecture in the infrastructure of complex IoT systems in different areas. Since the requirements and complexity of different IoT systems in different areas are different, there is no uniform architecture. However, there are various architectures that are widely used and experienced, such as 3-layer architecture, SoA-based architecture, middleware architecture, server-based architecture, cloud-based architecture, edge computing-based architecture. In IoT architectures, scalability, interoperability, distributed, resource-constrained operability and security are essential requirements. Different protocols are used for connection and communication from different layers of IoT architectures. For example, RFID, Wireless Sensor Network (WSN) in the perception layer, Wi-Fi, Bluetooth, NFC, LTE, Z-wave, LoRA in the network layer. We can see the use of IoT in many areas such as big data, cloud computing, healthcare, smart city, smart home, mobile application, cyber security industry, smart agriculture, autonomous vehicles. What is important here is that IoT is suitable for naturally interconnected applications such as mobile applications, as well as ubiquitous computing applications. (Lombardi et al., 2021) present a review and analysis was made about IoT architectures, protocols used in different layers of the architectures, and IoT applications. In this regard, the study constitutes a reference source.

By making people aware of the quality of the environment they live in every day, they can be encouraged to transform their behavior to improve environmental and economic sustainability. For example; People can benefit from cost-effective, efficient IoT solutions that provide up-to-date information about air pollution in the area where they live, adapted to different situations according to dynamically selected different levels of detail (e.g. home/region/city). In line with this information, they can have information about the environment they are in and determine their activities and behaviors according to this information. (Bellavista et al., 2017) presents a Pervasive Environment Sensing and Sharing (PRESS) project that was designed and developed to increase people's awareness of the natural environment they live in and to contribute to improving sustainability. The primary goal of this project is to obtain real-time and user-centered information about environmental conditions in the environment, and especially air pollution. The PRESS project also features the ability to integrate heterogeneous monitoring data, from air pollution perceived from the environment to quality perceptions provided by the user, flexibility (plugging and playing of new hardware without requiring manual installation and configuration on the server and user side)

and scalability. In addition, the PRESS project includes an automatic and dynamic mechanism to detect and overcome the situation that causes traffic congestion in case of over load. In this way, bottlenecks can be overcome and service interruptions can be prevented. There are 3 components in the PRESS project architecture : gateway module, web-app module and user interface module. Gateway module component ; It is the part where interaction with the physical environment is ensured and data is collected. The web-app module component is the core component of the project framework and this component provides communication between the Gateway module component and the user interface module over certain protocols. The user interface module component is the part where data is presented to the end user via the web browser. The PRESS project is an effective design and resource in terms of collecting, processing and monitoring heterogeneous data by the end user.

Wireless sensing and communication are basic needs in IoT technology, which enables thousands of interconnected devices to work together for the same purpose. RFID and Wireless Sensor Networks (WSN) technologies are technologies that focus on wireless sensing and communication. While RFID is a technology for identifying and tracking objects, WSN collaboratively provides information to and collects information from these sensors. By working together, RFID and WSN technologies can benefit from each other's technologies and complement their deficiencies or limited parts. RFID and WSN technologies can be integrated together and help create new IoT applications. (Landaluce et al., 2020) include a review of RFID and WSN technologies and the challenges and applications of these technologies. Additionally, in this review, the integration of RFID and WSN technologies was also examined.

In IoT architecture, middleware is the foundational layer that bridges the gaps between applications and devices to improve application development and solve many common IoT problems. From this perspective, developing the appropriate middleware, combining heterogeneous hardware and software in IoT as an integrated system and ensuring functionality and required quality emerge as the main challenge. Considering the experience of distributed system development, it is necessary to create a ubiquitous middleware that brings together network hardware, operating systems, network stacks and applications. In this study, IoT middleware requirements, challenges and the current state of research in this field are discussed. A technical classification has been made for IoT middleware based on the approach to abstracting and processing data. Three perspectives from which the IoT paradigm is evaluated and the charac-

teristics of these perspectives are presented. These perspectives are : internet-oriented features, things-oriented features, and semantic-oriented features. The feature of heterogeneity in things-oriented features includes three aspects : heterogeneity of devices, data, and communication. Semantic-oriented features include location awareness and high-level knowledge aspects in the collected data. (Zhang et al., 2021) presents an IoT middleware requirements of interoperability, self-adaptation, real-time, scalability, reliability and lightness. Technologies that enable IoT middleware are discussed in detail under the headings of context-aware computing, knowledge discovery and self-adaptive technologies. In the light of this information examined, the existing middleware types are explained in detail as service-based middleware, event-based middleware, virtual machine-based middleware, database-based middleware and agent-based middleware. Finally, open issues in this field are revealed. This study provides a comprehensive overview of IoT middleware and serves as a guide for those who want to develop or research in this domain.

What turns real-world things into smart objects will actually shape the future of communication. The functional aspect of IoT is to connect objects in the world under a common infrastructure. Thus, people have the ability to both control these objects and receive regular and timely updates about the current situation. The concept of IoT is not a very old concept and has now become a reference for communicating between objects. (Khanna and Kaur, 2020) present a comprehensive literature review conducted on various aspects of IoT such as its technology, applications, and challenges. An in-depth review has been made of the current situation of IoT, starting from its origins. In this study, we examine the communication technologies of sensors and devices used in IoT (RFID, LTE, Z-Wave, NFC, etc.) and today's IoT applications (smart mobility, smart home, smart building, environment monitoring, medical and healthcare, industrial processing, agriculture and breeding, etc.) and use cases, as well as reviews of IoT's challenges, open issues, and future research directions, have been created as an important resource for researchers.

IoT is a system of millions of interconnected smart devices that influence and analyze our daily activities. The devices and sensors that compose the IoT system can seamlessly integrate with the environment for information interaction and sharing. IoT includes personal, enterprise, automation and cloud computing services. There is ubiquitous connectivity between various IoT sensors, devices and services, such as smartphones, computers, Android-based mobile applications, web services, cloud services,

lighting services, air conditioners with heating and cooling features. There are different types of communication technologies for IoT-enabled sensors, devices, applications and services to communicate and connect with each other. For example, 3G, LTE, Wi-Fi, Bluetooth, ZigBee etc. (Lohiya and Thakkar, 2020) present a systematic research was conducted on the basic structure of IoT technology, its use in different application areas (health, transportation, security, energy efficiency, agriculture, home devices), how IoT is implemented in applications in these areas, and its data structure on a field basis. Data is used as a source for evaluating IoT performance. In addition, commercial IoT solutions developed by different organizations and the challenges and research aspects that need to be addressed to align the IoT field with the needs of the real world are also examined in this study. The study examined studies between 2015 and 2019.

Pervasive computing can be defined as the trend towards embedding computational capability into everyday objects, usually in the form of microprocessors, requiring minimal interaction from the end user with the computer. Pervasive computing devices are networked and constantly available. Pervasive computing can be created with any device, anytime, anywhere, in any data format. Examples of pervasive computing devices are smartphones, tablets, wearable devices, sensors, and actuators. IoT technology is the most important technology in the implementation of pervasive computing. Pervasive computing with IoT technology can be seen in many different areas, from smart cities to agriculture, from healthcare to autonomous vehicles and industry. Thanks to the wearable device (bracelet) connected to the IoT network in the field of healthcare, patients' vital sign data such as temperature, blood pressure, and heart rate can be measured and analyzed in real time, and preventive measures can be taken before the disease occurs or the disease can be diagnosed early. The industrial internet of things (IIoT) also manifests itself in every aspect of daily life. It has applications in many areas such as agriculture, smart building, smart city, disaster management and robotic technology. With the Internet of Industrial Things, efficiency can be achieved by reducing energy consumption. Indoor air quality can be measured and kept at an ideal level. Thanks to real-time environmental data measured with IoT technology, people can be made aware of the conditions of their environment and encouraged to take action for a sustainable environment. IoT networks can contain many different devices, sensors, and actuators. These devices are wirelessly connected to the network and measure data continuously. The amount of actual data they measure is huge and nowadays it is called Big Data. By managing Big Data, guiding outputs can be produced for decision making and understanding. Thousands of interconnected devices in IoT tech-

nology can work together for the same purpose. The basic needs of these devices are wireless sensing and communication. RFID for wireless sensing and wireless sensor network (WSN) technologies for communication are widely used. The shortcomings can be completed by ensuring that RFID and WSN (such as 3G, WiFi, LTE, Bluetooth, ZigBee, LoRA) work together. Since the complexity and requirements of IoT systems differ, they can be created in different architectures. There is no standard architectural framework for IoT architecture. However, there are various architectures, including the most commonly used 3-layer architecture, SOA-based architecture, middleware architecture, cloud-based architecture, edge and fog computing. The main requirements of IoT architectures are scalability, interoperability, distributed, resource-constrained operation and security. Different protocols are used for different communication and connection at different layers in IoT architectures. Table 2.2 present major existing studies in the literature on PEMS research domain.

TABLE 2.2 – Overview of existing studies on PEMS

Authors	Integration Method	Main Focus	Key Findings
Waas et al.	BIM Integration	Examines functions, features, potentials, and limitations of Graphisoft Archicad and Autodesk Revit for BIM.	Identified advantages and disadvantages of each software for different aspects of building information management.
Tripahi et al.	BIM-IoT-GIS Integration	Explores the use of digital twins with BIM-IoT-GIS integration for post-occupancy evaluation.	Demonstrated how integrated BIM-IoT-GIS systems can enhance building performance evaluation and management.
Su et al.	BIM-IoT Integration	Develops integration between BIM and IoT sensors for real-time data transfer and fault detection in HVAC systems.	Showed improved facility management efficiency and reduced downtime through real-time monitoring and fault detection.
Scianna et al.	BIM-SHM-IoT Integration	Establishes real-time connection between BIM model and digital twin using SHM and IoT sensors.	Demonstrated how real-time monitoring of structural health can improve safety and maintenance planning for buildings and infrastructure.
Hajjaji et al.	IoT-Big Data Integration	Reviews literature on IoT and big data integration for smart environmental applications, identifies challenges, and future research directions.	Identified potential of IoT and big data integration for smart environmental monitoring and management, highlighted challenges in data processing and analysis.
Khanna et al.	N/A	Conducts a literature review on various aspects of IoT including technology, applications, and challenges.	Provides an overview of IoT technology, applications across different domains, and challenges in IoT implementation and deployment.
Lohiya et al.	N/A	Systematic research on the basic structure and application areas of IoT technology, including health, transportation, security, energy efficiency, etc.	Identified key application areas and implementation challenges for IoT technology in various sectors.
Bellavista et al.	IoT Environment Sensing	Presents the PRESS project for real-time environmental monitoring and congestion detection using IoT sensors and dynamic mechanisms.	Demonstrated the effectiveness of IoT-based environmental sensing for real-time monitoring and congestion detection in urban areas.
Landaluce et al.	RFID-WSN Integration	Includes a review of RFID and WSN technologies, their integration, challenges, and applications in IoT.	Highlighted the complementary nature of RFID and WSN technologies for IoT applications and identified integration challenges.
Zhang et al.	IoT Middleware	Presents an IoT middleware requirements of interoperability, self-adaptation, real-time, scalability, reliability and lightness.	Provided a comprehensive overview of IoT middleware and served as a guide for those who want to develop or research in this domain.
Malik et al.	IIoT Architecture	Analyzes the current status of Internet of Things-based pervasive computing and IIoT application areas.	Classified IIoT architecture into perception, preprocessing, communication, middleware, and applications, and evaluated various communication technologies for networking.
Hassan et al.	IoT Applications	Investigates research on IoT application methods and approaches, growth, development, and applications in various fields.	Explored IoT applications in health, environment, smart city, commercial, industrial, and infrastructure areas, and examined IoT architecture and protocols used.
Haghi et al.	Wearable IoT Platform	Develops an IoT-based platform for real-time monitoring of environmental, behavioral, and physical parameters.	Designed a configurable platform with flexible IoT gateway structure and wearable prototype for comprehensive parameter monitoring.
Cui et al.	ISAC Technology	Explores the role of integrated sensing and communications (ISAC) technology in IoT architecture.	Classified ISAC solutions and examined usage scenarios in various applications such as autonomous vehicles, smart cities, and smart homes.
Kaginalkar et al.	Urban Air Quality Management	Investigates the role of urban computing in managing urban air quality with IoT technologies.	Explored technologies enabling urban air quality management, analyzed open issues, challenges, and opportunities, and provided a comparative overview of urban computing applications.
Lombardi et al.	IoT Architectures	Reviews and analyzes IoT architectures, protocols used, and applications.	Presented a review of IoT architectures, protocols, and applications, including a discussion on different architectural frameworks and protocol usage at different layers.

2.3 Data Aggregation Models

With the increasing use of technologies such as wireless networks, smart devices equipped with different sensors, radio frequency identification tags (RFID) and near field communication (NFC), the concept of the Internet of Things (IoT), a new technology, has emerged in people's daily lives. There is interest in using wireless sensor technologies in various IoT scenarios. The idea of the internet of things offers a perspective that includes communication, data exchange, data collection and integration between the objects around us. Considering the tremendous growth of smart objects and applications, collecting and analyzing data therein emerges as the main challenge. It is critical that operations be energy efficient in battery-powered sensor nodes in IoT technologies. In networks formed by wireless sensor nodes (WSN), energy is largely consumed while data packets are received from neighboring nodes and transmitted to the central station. To reduce energy consumption in sensor networks, techniques can be applied to reduce the size of data packets by removing redundancies in transmitted or received data. Data aggregation is an important technique in getting rid of data redundancy and ensuring energy efficiency. It also extends the life of wireless sensor networks thanks to energy efficiency.

In the context of the IoT, the Data Aggregation Module plays a crucial role in collecting and consolidating information from diverse sources. As IoT ecosystems continue to expand, the need for efficient data handling becomes increasingly essential. Such module serves as a pivotal component in this process, facilitating the aggregation of data generated by various IoT devices. This section examines the significance of the Data Aggregation Module within the IoT framework, focusing on its practical applications and contributions to streamlining data management. By offering a simplified exploration, this research aims to enhance the understanding of the role played by module in the context of IoT and its implications for effective data handling.

(Abbasian Dehkordi et al., 2020) introduces data aggregation techniques, which are an effective method in reducing energy consumption, which is the most important challenge of wireless sensor networks and are examined in depth in order to ensure the continuity and long life of the IoT system. Major techniques for data aggregation and integration in terrestrial, underground, underwater and body area wireless sensor networks are presented. In addition, the usage applications, advantages, disadvantages and difficulties of each technique are also explained.

The Internet of Things (IoT) allows any entity to send and receive data over a communication network. However, network lifetime is a critical challenge in IoT, affecting the longevity of IoT applications. To overcome this difficulty, data aggregation is used as an efficient method in networks where nodes are limited in terms of resources and energy. The main purpose of the data aggregation method is to effectively combine and aggregate data packets to improve energy consumption, network lifetime, traffic bottleneck and data accuracy. Additionally, removing redundancies in data and reducing the amount of data transfer also reduces energy consumption. Efficient collection of data depends on the network design and the size of the sensed data. Because the size of the data creates a burden on network communication. Although data aggregation is of vital importance in IoT, a systematic general study examining the important techniques in this regard has not been conducted and organized. (Pourghebleh and Navimipour, 2017) presents current data aggregation methods in IoT. In this study, data collection methods were examined under 3 classes. These; tree-based, cluster-based and centralized data aggregation. These data aggregation methods are divided into classes according to the placement of sensor nodes in the network and data communication strategy. In the tree-based data aggregation method, the data sensed from the environment is transmitted from leaf sensors to the middle node, where the aggregated data is transmitted to the sink node. In the cluster-based method, all sensor nodes are clustered in the network. And each cluster has a cluster head. The data sensed from the sensors is transmitted to this cluster head, and from there to the nearest sink node. In the centralized method, all sensor nodes transmit data packets to the central node via the shortest route and the aggregation takes place at this node. After aggregation, the data is transmitted as a single packet. In addition, data aggregation methods are analyzed according to various metrics such as energy efficiency and latency. Additionally, challenges and issues regarding data aggregation in IoT were also evaluated.

In IoT, there are different types of sensors and actuators that connect to the internet through different access networks, such as wireless sensor networks. Billions of objects can be found in IoT through these sensors and actuators. Thanks to the ability to connect objects to the Internet through sensors and actuators, IoT provides the opportunity to access physical objects in the environment anytime and anywhere. Wireless sensor networks (WSN) play an important and active role in the integration of information in the environment. In IoT applications, large amounts of data are sent from one point of the network to another. Sensor nodes are inherently energy limited as they operate on power such as batteries. Therefore, it is not effective and efficient in terms of

energy consumption for sensor nodes to transmit all collected data directly to the sink node. Data generated from neighboring nodes is often correlated and highly redundant. By combining this related and redundant data with valid, high-quality information at intermediate nodes, the data collection method can be followed. This form of data collection has been shown to be beneficial in terms of power consumption, bandwidth usage, load balancing, network lifetime, and data accuracy. With proper data collection technique, energy consumption and network traffic volume can be reduced. In addition, it can increase network lifetime and data accuracy. (Rahman et al., 2016) compares several data collection techniques for some parameters considered important using the NS-2 simulation tool. And the obtained simulation results were analyzed and evaluated according to the selected performance measurements.

The IoT network consists of interconnected sensors, devices, actuators, and other connected nodes. These sensors and actuators connected in the IoT network are usually equipped with various types of transceivers, microcontroller devices and protocols necessary for control and communication of sensor data. Sensors in the network are connected to a central repository (server) to store measured data in real time and transmit the data there. Authorized persons access the data from this center. Therefore, without human intervention, IoT networks can operate safely and sustainably for a long time. This topology is called wireless sensor network (WSN). Heterogeneous WSN has become the cornerstone of IoT-based systems by connecting a wide variety of smart sensors. The rapid development of devices in WSN also brought energy consumption problems. Communication and data sharing in WSNs are the operations that cause the most energy consumption. A sensor node typically consists of 4 units. These; the sensing/identification unit, which detects and collects data from the work area, the processing unit, where the detected data is manipulated, the communication unit, where the processed data is transmitted, and the power supply unit, which provides power to all components of the node. A sensor node can have 3 states based on its operating state; active, sleeping and idle. According to these situations, the maximum energy consumption is in the active state. In the idle state, the node waits for a data packet to transmit data to another node. This causes energy consumption. Sleeping is the state with the least energy consumption since no action is taken and communication is turned off. Battery energy sources are used to power IoT systems. Therefore, efficient use and management of these resources is important. In this study, the role of WSN in IoT systems, its difficulties and data collection issues were investigated by conducting a literature review. (Gulati et al., 2022) present a research on the conservation of

energy required for the operation of WSN and therefore the IoT system and various data collection techniques for this purpose are also presented.

With the influence of the Internet of Things, there has been a rapid growth in digital health applications, which has increased the efficiency of healthcare services and the quality of life of patients. For example; vital values of the patient can be measured with IoT body devices. Wireless body sensor networks (WBSN); Wearable mobile devices and lightweight implantable medical devices help to diagnose the disease efficiently and produce better statistical results by measuring the patient's vital signs such as heart rate and blood pressure and presenting them to doctors. Since values such as body temperature, heart rate, and blood pressure are measured regularly and repeatedly with WBSN, the size of the data is very large. Therefore, these health data aggregation services play a critical role in terms of efficiency and verification. However, in wireless body sensor networks, a malicious attacker can obtain the patient's health status by eavesdropping on the communication network and accessing and analyzing real-time data on the IoT health device. Thus, it is important to protect the patient's data security and privacy. Encryption schemes are widely used in IoT body sensors to meet security and privacy requirements. A signature scheme is needed for data verification. Typically, data is digitally signed and then encrypted. However, an additional computational resource is needed for a scheme that performs both signature and encryption. Considering energy-constrained wearable devices, resource efficiency must be ensured when implementing these schemes. In this article, a new encryption accumulator based on a lightweight encryption scheme is proposed to enable secure collection of data from IoT body sensors in healthcare. This accumulator consists of pieces of data collected from sensors and is encrypted and signed before being sent to the data server. The data server cannot decrypt or modify the data, but it can compute the sum without decryption. In this way, the security feature of the data is ensured without the healthcare provider having to deal with data collection and aggregation. (Rezaeibagha et al., 2020) presents an IoT-based wearable monitoring system with cryptographic accumulator. In addition, the performance evaluation is made by comparing the computation and communication costs of this system with other IoT-based solutions.

Despite significant advances in hardware and software technologies, there are many challenges in meeting the requirements of IoT applications in fields such as industry, agriculture, transportation, smart buildings, healthcare systems, and security. For example, since most sensor-based IoT devices still run on low-power batteries, the batte-

ries need to be discharged. In addition, sensor-based IoT devices must be used in harsh and inaccessible areas for a long time without the possibility of charging or replacing the batteries. Therefore, energy constraint is the primary challenge in IoT networks. However, ensuring Quality of Service (QoS) requirements, including data transmission delays and high reliability issues, are other challenges of IoT. To overcome these challenges, data aggregation is the primary process of IoT. Data aggregation is defined as the process that collects data from various sensors and IoT devices and then integrates it using an aggregation function and attempts to minimize traffic on the system network. Advantages of the data aggregation process ; These can be listed as minimizing traffic in the system, reducing delays in data transmission and improving energy consumption of IoT devices. There are some research papers on data aggregation in IoT. Some of these articles ignored mobile agent-based data aggregation mechanisms and focused only on client-server-based mechanisms. It is thought that the various review studies on existing client-server based data aggregation mechanisms do not meet the current and comprehensive needs of the existing literature (Yousefi et al., 2021). With this motivation, authors present a systematic literature review of both client-server-based and mobile agent-based data aggregation approaches. In this study, data aggregation is divided into two main categories : client-server based and mobile agent based. Client-server based data aggregation includes three groups : clustering-based, tree-based and centralized. The ultimate goal of the study is to provide a detailed comparison of data aggregation mechanisms and provide recommendations for future studies.

Data aggregation is vital in wireless sensor network design as it reduces the number of packets that need to be transmitted by increasing energy efficiency as data is collected from nodes to the sink. With the emergence of the Internet of Things and machine-to-machine communication, new architectures and use cases are evolving. In addition, advances in edge and fog computing have also led to improvements in network architecture design. In fog computing, control, computation, and storage are moved to nodes close the network edge. In WSN, a single sink is generally used in aggregation algorithms. However, in architectures where fog computing is used, multiple sinks are needed to collect data. For example, in machine-to-machine communication scenarios, there may be actuators subscribing to sensors. In this case, data is not only aggregated and processed within the network, but also distributed to the actuators. As heterogeneity in IoT networks increases, the use of a single sink for data aggregation has been abandoned. Instead, there may be multiple gateways with connections located at the

network edge, possibly operated by different parties. Most of the existing literature on data aggregation in WSNs is on single-sink scenarios. Therefore, it is necessary to develop solutions that combine both gateway selection and routing for data aggregation for optimal energy efficiency. (Fitzgerald et al., 2018) presents two new models for data aggregation in IoT. In the first model, called 1K, it is possible to aggregate data in any of the networks where there is more than one gateway. The second, called nK, is better applicable to scenarios where network actuators are used. This model allows joint data aggregation and distribution to all or a minimum number of multiple target nodes. These models are formulated as an optimization problem using mixed integer programming (MIP) for both wireless transmissions and the computation of the data aggregation function. While making the formulation, energy costs were taken into account and the minimum total energy target was achieved. In the study, network lifetime optimization was used as the key performance indicator metric. In addition, in this study, formulations for minimum-maximum energy optimization per node were provided for both models and their impact on network lifetime optimization was evaluated. In addition to sensor and gateway selection, routing subgraphs for data aggregation and distribution are also included in the optimization using models. In this study, a numerical study was carried out to compare the energy and solution times required for both models in different topologies and network scenarios with 10 to 40 nodes.

IoT includes sensors, actuators and devices that connect to the internet through different access networks, such as wireless sensor networks. Thanks to the wireless sensor network, there can be millions of connected devices in the network and they can work integrated for the same purpose. Devices, sensors and actuators in the wireless network can connect physical objects in the environment to the Internet, which allows access to physical objects anytime and anywhere. Sensors and devices in the wireless IoT network use sensing and communication technologies to work together and detect and access physical objects. In the IoT network, large amounts of data are transmitted from one point in the network to another. Currently, sensors are energy limited because they work with power such as batteries. In addition, sensors have to work actively for a long time in the physical environment, sometimes in conditions where battery replacement is not possible. This requires that the power they consume be used with maximum efficiency. It has been determined that the highest power consumption in IoT networks is during communication. At this stage, there are studies showing that if the data transmitted in packages is aggregated and transmitted to ensure energy efficiency, it

TABLE 2.3 – Overview of existing studies on Data Aggregation

Authors	Method	Main Focus	Key Findings
Bellavista et al. (2017)	PRESS project architecture	Environmental sensing	Real-time environmental monitoring and congestion detection
Landaluce et al. (2020)	Integration of RFID and WSN	RFID and WSN technologies	Synergies between RFID and WSN for IoT applications
Zhang et al. (2021)	IoT middleware requirements	Middleware for IoT	Interoperability, self-adaptation, scalability, reliability
Khanna et al. (2020)	Various IoT applications	IoT technology	Smart mobility, smart home, healthcare, agriculture, etc.
Lohiya et al. (2020)	Basic structure of IoT technology	IoT applications	Health, transportation, security, energy efficiency, etc.
Rahman et al. (2016)	Comparison of data collection techniques	NS-2 simulation	Evaluation of data aggregation techniques
Gulati et al. (2022)	Conservation of energy in WSN	WSN and IoT	Energy-efficient data collection techniques
Rezaeibagha et al. (2020)	Secure IoT-based wearable monitoring	Cryptographic accumulator	Lightweight encryption for secure data collection
Yousefi et al. (2021)	Literature review on data aggregation	Client-server vs. mobile agent-based	Comparison of aggregation approaches
Fitzgerald et al. (2018)	Data aggregation in IoT	Optimization models	Energy-efficient data aggregation with multiple gateways

consumes less power. It has been shown to be beneficial in terms of power consumption, bandwidth, load balancing, network lifetime and data accuracy in a wireless IoT network by using appropriate data aggregation methods. Table 2.3 presents existing studies on the data aggregation models in IoT.

3 PROPOSED APPROACH

3.1 Experiment Design And Architecture

The Internet of Things (IoT) paradigm is a system of interconnected devices and protocols that have computational capabilities, can operate without human interaction, and can transfer data. The background of the IoT concept is the widespread presence in daily life of smart devices and systems that work in collaboration with each other and interact with people to serve a common purpose. Nowadays, a large amount of data is produced from smart devices and systems in different areas based on the IoT concept. In the applications of IoT in different areas, there is no standard IoT architecture in the infrastructure of IoT systems. Different IoT applications in different domains require different levels of complexity and system infrastructure because they are built according to different requirements. Therefore, it is not possible to talk about a single architecture. Therefore, it is not possible to mention a single architecture. However, there are several architectures that are widely used and tested. Examples of architectures include SoA-based architecture, middle-ware architecture, server-based architecture, cloud-based architecture, and edge computing-based architecture. Today, IoT architectures aim to provide the needs of systems such as scalability, interoperability, reliability, security, efficiency, quality and speed. Middle-ware architecture is one of the architectures that provide these requirements. This architectural approach consists of 5 layers : physical layer, network layer, middle-ware layer, application layer and business layer. The middle-ware architecture is shown in Figure 3.1.

The physical layer is the layer that contains devices such as sensors and actuators, which measure and collect physical quantities in the environment. The middle-ware layer performs as the layer that provides the connection between applications, users, and data in the architecture. IoT architecture-based middle-ware is supportive in creating more efficient applications. In general, the middle-ware can be a software or service programming positioned between IoT technologies and applications. The middle-ware layer has important features such as aggregating data received from the physical layer, filtering, discovering information, and providing access control. In addition to these

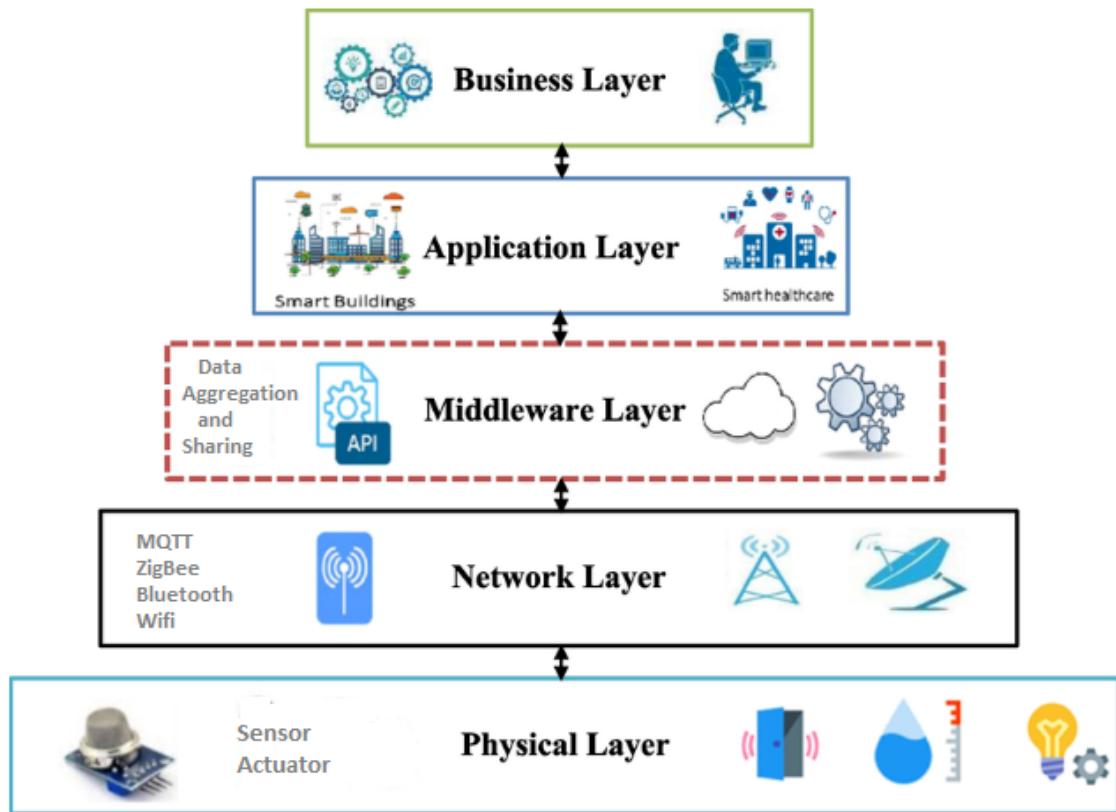


FIGURE 3.1 – The middle-ware architecture

features, the middle-ware has several other advantages. These are ;

- Supporting different applications,
- Ability to run on various operating systems and platforms,
- Providing access to services across heterogeneous networks, devices, applications and distributed computing,
- Supports standard protocols

Thanks to the features and advantages of the middle-ware, it has played an important role in the development of new services and the integration of existing legacy services with new technologies in recent years.

The application layer is the layer that defines how the system will communicate with the user. This layer is responsible for providing application service to the user. For example, in a building management system, alarms are activated when the amount of CO₂ measured in the environment reaches high levels. The application layer is responsible for generating alarms.

Business layer includes application control, change management and process manage-

ment of stored information and user privacy management.

Approaches in IoT architectures enable features such as efficiency, continuity, interoperability, reliability and speed in IoT networks. In this direction, increasing energy efficiency and effectiveness, speed and network life in IoT networks can be addressed within the framework of IoT architectures.

In IoT networks, the most energy consumption occurs during data transmission and sharing. In order to increase the efficiency, effectiveness, speed and network life in IoT networks, methods such as minimizing data packets, collecting data, etc. can be followed to reduce energy consumption and increase efficiency during the data transmission and sharing phase, where energy consumption is most intense.

The energy consumed in data transmission can be reduced by minimizing or aggregating the data packets to be transmitted. Data can be transmitted faster and more effectively. In particular, ensuring energy efficiency in resource-limited IoT networks is critical for increasing IoT network life, collecting and transmitting more efficient and accurate data, and ensuring effective operation of IoT systems. Functions such as data aggregation, filtering and transmission are performed in the middle ware in IoT architectures. Accordingly, a software can be created to run on the middle ware to reduce energy consumption.

In the study we present, it is aimed to develop a program that aggregates data collected from the physical layer in the IoT network and reduces the size of the data packet to be transmitted in order to reduce energy consumption in limited-resource IoT networks. This program can be run as a middleware in the IoT network.

The program basically takes customer requests as input and dynamically reads the following information based on the customer requests : ;

- How frequently will the physical data collected be received and transmitted,
- Which data aggregation method will be applied,
- Which physical quantity data will be processed ?

As output, the data previously collected from the environment is calculated at the desired data transmission frequency according to the desired data collection method and given as output. At this stage, instant memory usage is measured according to the data aggregation method, data transmission frequency and data number and transmitted as output by the program.

High current memory usage also causes intense energy consumption. In the approach we present, very simple algorithmic or mathematically complex methods are used to see the fundamental change in the current memory usage used in the data aggregation process. If the simple aggregation method makes a difference on current memory usage, methods with higher algorithmic or mathematical complexity will have a greater impact on current memory usage. From this point of view, our approach uses 4 simple aggregation methods that give the maximum, minimum, average of the value and compare a value with a threshold value. Among these methods, the averaging method has the highest algorithmic complexity. These 4 aggregation methods are included in customer requests.

Another parameter that we want to measure in the approach we present and that may affect the current memory usage is the transmission frequency. In our approach, the transmission frequency parameter is chosen randomly. And its effect on current memory usage is observed by trial and error method. Here, when the transmission frequency is reduced and the data is aggregated and transmitted, the minimum values at which the change in the instantaneous memory occurs will be used. When the transmission frequency is changed, the data size to be transmitted at each transmission moment will also differ. As the transmission frequency decreases, the size of the data to be transmitted per unit time will also decrease.

In the approach we present, as the amount of data read by the program at a certain frequency increases, it is also measured whether there is a change in the current memory usage. Increasing the number of requests made to the program increases the number of data aggregation and transmission operations performed by the program. If this causes a change in current memory usage, it will also cause a change in energy consumption.

Current memory usage is measured when the program transmits data collected from the environment without using any data aggregation method. Then, the current memory usages are measured for different aggregation methods, different transmission frequencies and different record numbers. Changes in current memory usage measured according to different parameter values were compared and examined. The developed program will be written in C language so that it can be deployed to a micro-controller such as ESP8266 Nodemcu and run on the gateway.

According to the approach we presented, while simulating the program, the dataset estimated in Kaggle was used as the data source, based on the dataset of temperature, humidity, light, movement and CO2 quantities previously measured from sensors placed

in 30 rooms in the Galatasaray University C Block building. The data set for each quantity consists of time (Timestamp) and the measured physical value.

3.2 Data Flow and User Requests

Nodes in IoT networks measure physical quantities such as temperature, humidity, and motion in the environment. The measured quantities are transmitted according to a data transmission structure in the IoT network. According to this transmission structure, nodes transmit the measured quantities to the gateway in the network. Data is transmitted from nodes to the gateway at regular intervals. Data from the Gateway is transmitted to the cloud using specific network protocols. IoT applications also fetch data from the cloud. The diagram of data transmission in IoT networks is shown in Figure 3.2.

In IoT networks, the data transmission structure continues as long as data is collected from nodes. Nodes are devices with limited resources and continue to collect data until they run out of power. Therefore, the power and energy consumption of the nodes affects the lifetime of IoT networks. If the consumption during data transmission from nodes is reduced or its efficiency is increased, the lifetime of the node in the network will increase. This will also support the long-term operation of IoT networks. In addition to the efficiency and effectiveness of data transmission at the nodes, the data transmission speed will also increase as the size of the transmitted data decreases.

Ensuring effective, efficient, and fast data communication in IoT networks is a critical challenge, given the resource limitations of nodes within these networks. Data aggregation emerges as a promising solution to address this challenge by consolidating data from multiple sources before transmission, thereby reducing memory consumption, enhancing energy efficiency, and improving transmission speed. Various data aggregation methods can be used to reduce the size of the data measured from the nodes and transmitted to the gateway. The data aggregation methods to be used may have different mathematical complexity. The level of mathematical complexity of data aggregation methods can affect the current memory usage and processing capacity.

This study proposes an approach to examine the impact of different data aggregation methods and transmission frequencies on memory usage in resource-limited sensor

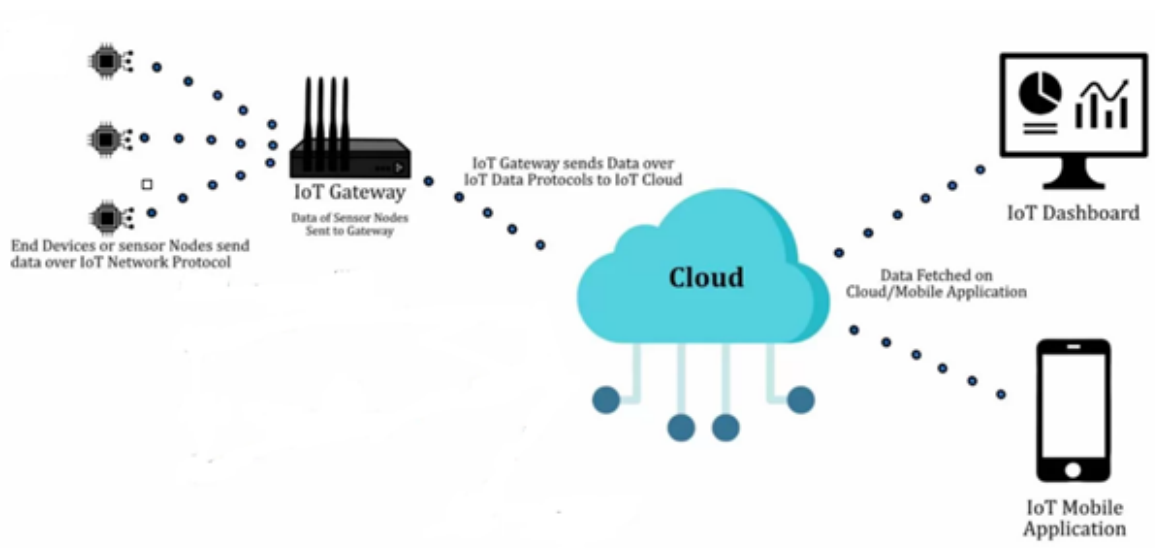


FIGURE 3.2 – Data Transmission in IoT Network

nodes, considering these client requests. Specifically, we will investigate how memory consumption changes when data is transmitted to the sink node/gateway at various frequencies using different aggregation techniques. Additionally, memory usage is measured when the aggregation method and transmission frequency are dynamically determined, and aggregated data is transmitted to the requested server or service. In this approach, data will be aggregated at a certain transmission frequency and transmitted to the gateway. The size of the data transmitted to the gateway will be reduced. Therefore, the data to be transmitted from the gateway to the cloud will be smaller in size and will be transmitted faster. The data transmission scheme according to the reduced data size is shown in Figure 3.3.

The process begins with sensors deployed in the IoT network collecting various types of data, such as temperature, humidity, CO2 levels, and luminosity, according to their predefined sampling and sending frequencies. Each sensor node continuously collects data from its environment and stores them locally.

When a client connects to the system and submits a request, such as "Room 10, temperature, every 10 seconds, average," the central management unit orchestrates the data aggregation process accordingly. It instructs the sensors to aggregate the temperature data specifically from Room 10, ignoring all other data.

The sensors aggregate the temperature data according to the specified parameters (e.g., average) and the designated time intervals (e.g., every 10 seconds). Once aggregated,

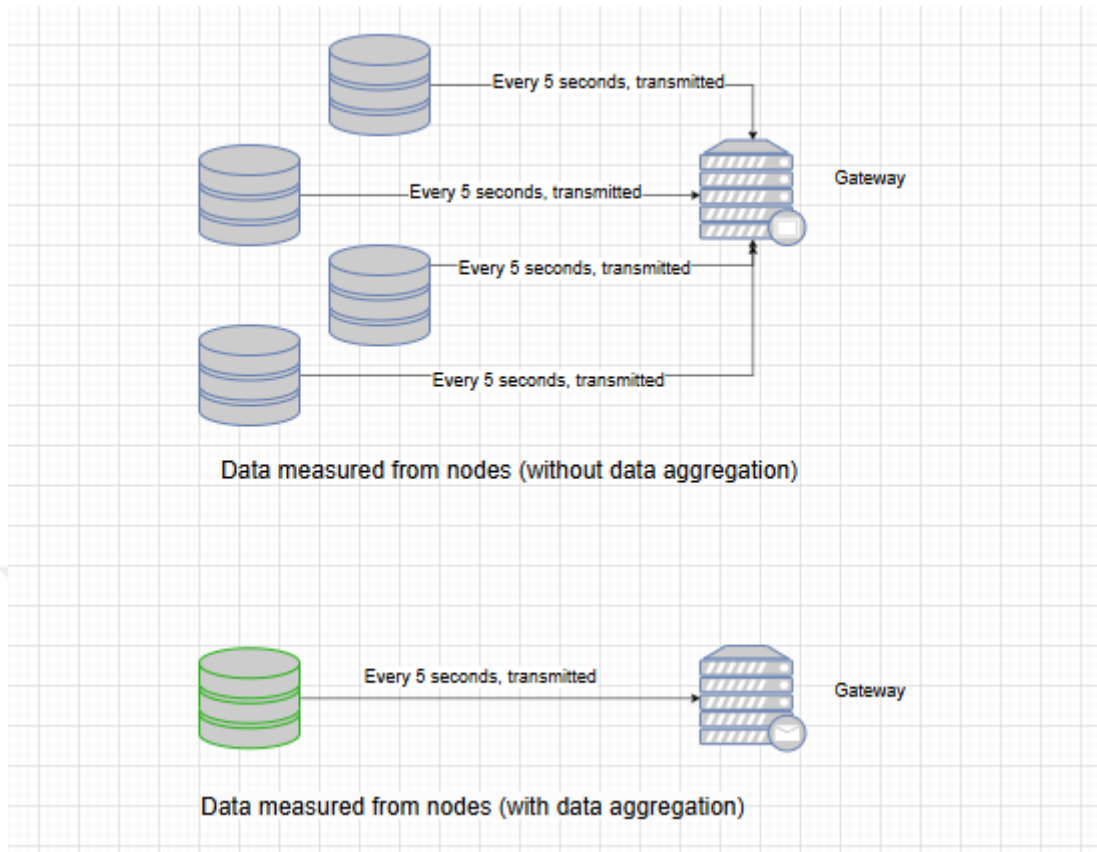


FIGURE 3.3 – Transmission diagram of reduced data

only the relevant temperature data from Room 10 is transmitted to the sink node.

The sink node receives the aggregated temperature data from Room 10 and calculates the average temperature for every 10-second interval. It then informs the client of the calculated average temperature at each interval.

If no client is connected to the system, the sink node ignores all incoming data, and no processing occurs.

In the proposed system for user-request driven smart data aggregation in IoT networks, the data flow follows a structured process to efficiently handle client requests while optimizing resource usage. Based on these requests, sensors will aggregate the data and transmit it to the sink node, the client system, or the server at the specified frequency. By comparing the measured memory usage values, we aim to identify the aggregation method and transmission frequency that result in the least memory usage. These optimal values are expected to enhance energy efficiency and memory usage efficiency in the IoT network, consequently prolonging its lifespan.

The workflow of our proposed approach is illustrated in Figure 3.4. Following this workflow, experiments are conducted to monitor changes in memory usage based on specific data aggregation methods and transmission frequencies.

Throughout the process, memory usage in the sensor nodes is monitored to evaluate the efficiency of different data aggregation methods and transmission frequencies. By comparing memory usage values under various conditions, the system can identify the most resource-efficient approach to data aggregation.

The proposed data flow ensures that client requests are efficiently handled while minimizing resource consumption in the IoT network. By dynamically aggregating and transmitting data based on user demands, the system optimizes memory usage, energy efficiency, and network performance.

In the proposed approach, if there is no request from the client or if a request does not come in the specified format/pattern, the system will not be able to perform an aggregation operation and will not send a response to the client. A specific format/pattern has been determined while receiving the client requests specified in the workflow figure. And it is accepted that the requests will be transmitted in the specified format/pattern. Additionally, client requests will be listened to dynamically. When the request arrives, the program will aggregate and transmit the measured data.

In summary, this study aims to contribute insights into optimizing memory usage in IoT networks through efficient data aggregation and transmission strategies, considering client requests. By experimentally evaluating the proposed approach, we seek to identify the most effective combination of aggregation methods and transmission frequencies for resource-constrained sensor nodes.

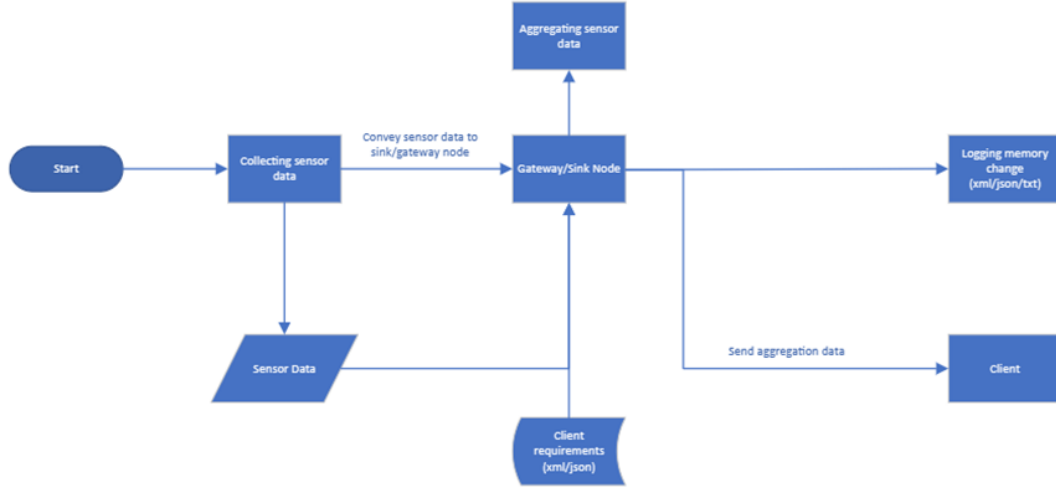


FIGURE 3.4 – Data flow of the Proposed Approach

3.3 Deployment of the program

The program we developed in line with the approach we presented can be easily deployed to the IoT network. In a wireless IoT network, sensors at the physical layer make standard measurements at the current transmission frequency according to the IoT architecture and send them to the gateway node. The program is not deployed to the sensors.

Data aggregation and sharing operations are performed in the middleware layer of which the gateway node is a part. Data collected from sensors are subjected to data aggregation and filtering processes by the program before being transmitted to the cloud/internet. The program we developed is deployed to the gateway node, performs data aggregation and filtering operations, and sends the data to the cloud/internet. Since the program is written in C language, it is supported by the gateway node and can be easily deployed.

4 EXPERIMENTS

4.1 Dataset

Data were collected from sensors placed in 30 different classrooms in the Galatasaray University C Block building for use in the experiments. Sensors that measure the physical quantities of CO₂, temperature, humidity, light and movement are placed in each classroom, and measurements are taken at 5-second intervals.

The dataset contains physical quantities measured for 1 week between 23.08.2023 and 31.08.2023. When the data measured in the 1-week measurement period was examined, no unmeasured or erroneous records were found. The data is regular and continuous within the measurement range. The maximum, minimum and average values of the data we used in the simulation of the approach we presented are shown in Figure 4.1.

CO₂, temperature, humidity, light and motion quantities measured every 5 seconds are written to the csv file. There are approximately 130k records measured every 5 seconds for each physical quantity as test data. Data is stored in a csv file as timestamp and measured value. Sample data sections for CO₂, temperature, humidity, light and movement of the C110 class are given in Table 4.1.

In line with the proposed approach, the measured CO₂, temperature, humidity, light and motion quantities were used as test data. During the experiment, the records measured every 5 seconds from each class were divided into certain record numbers as 100, 10000 and 130000. And these were stored in separate csv files.

	Maximum	Minimum	Average
Temperature	25,65	22,63	23,9444
Humidity	54,45	42,38	49,3952
Co2	768	415	485,29
Light	333	0	53,6625
Movement	30	0	0,45584

FIGURE 4.1 – Maximum, minimum and average values of the data used in the simulation

Co2	Tempeture	Light	Humidity	Pir
1377299107, 488.00	1377299107, 23.93	1377299107, 97.00	1377299107, 45.34	1377299108, 0.00
1377299108, 495.00	1377299108, 23.94	1377299108, 97.00	1377299108, 45.34	1377299126, 0.00
1377299110, 487.00	1377299126, 23.93	1377299126, 97.00	1377299126, 45.34	1377299127, 0.00
1377299127, 496.00	1377299131, 23.93	1377299131, 97.00	1377299131, 45.31	1377299130, 0.00
1377299130, 495.00	1377299136, 23.92	1377299136, 97.00	1377299136, 45.34	1377299139, 0.00

TABLE 4.1 – Dataset

4.2 Programs used and developed in the experiment

In this experiment, in accordance with the data aggregation approach, the requirement requests containing the customers' needs are submitted as a file by the customer. The sent file format is json. It is saved in the directory specified as the requirements directory. And the file includes customer ID, measurement type, data aggregation method and data transmission frequency information.

The developed data aggregation program is run manually on the computer. The program reads the requirements documents sequentially from the request directory and reads the measurement type, aggregation method and transmission frequency from the document content. The values of physical quantities measured from sensor data are also kept in a different directory. Sensor data is read from the file and aggregated by the program according to the measurement type, data aggregation method and data transmission frequency in the customer request file. When each sensor data value is read and aggregated by the program, measurement type, sensor data value, data aggregation method, aggregated value and current memory usage are written on the program screen in kB.

The program reads the sensor data in the file line by line and continues to work until all the row values are read and writes them to the screen by measuring the current memory usage. Once the reading and aggregation of all sensor data in the file is complete, the program stops working. It writes the latest current memory usage information, along with the measurement type, data aggregation method, and aggregated value, to the result file in json type and saves it in a separate directory. Finally, the processed sensor data file located in the sensor data directory is moved to a different directory. This prevents reprocessing of the same sensor data.

The program was developed in C language. The following libraries are used for various operations in the program.

"dirent.h" is used to find files in the directory.

"stdlib.h" is used to move the file from one folder to another.

"cJSON.c" is used to read data from the JSON file.

"windows.h", "psapi.h", "processthreadsapi.h" are used for current memory usage measurement.

"time.h" is used for delaying the time.

C code is developed for methods that find the maximum, minimum, threshold value control and averages of the value for data aggregation and is used by calling in the program. In the Maximum method; it returns the largest value among the incoming sensor data.

In the minimum method; it returns the smallest value among the incoming sensor data.

In the average method; it returns the average value of the incoming sensor data.

In the Threshold method; if the incoming sensor data is different from the threshold value, it returns the sensor data, otherwise it returns the threshold value.

The C code developed for data aggregation methods is shown in Figure 4.2 and Figure

4.3

If the program can not find any files in the client request directory, it still writes the current memory usage to the screen. However, if the client finds a file in the request directory and there is no data aggregation method information in the file content, it will still measure and write the current memory usage to the screen, but will not process the sensor data.

```

1  #include <stdio.h>
2
3  //Function to return the self value
4  float selfValue(float value)
5  {
6      printf("selfValue: %.2f\n", value);
7      return value;
8  }
9
10
11 //Function to return the average value
12 float avgFunc(float avgValue, float newValue, int count)
13 {
14     printf("Current average value: %.2f\n", avgValue);
15     printf("New sensor value: %.2f\n", newValue);
16     printf("Row count: %d\n", count);
17     float tempAvgValue = (avgValue + newValue)/count;
18     printf("Calculated average value: %.2f\n", tempAvgValue);
19
20     return tempAvgValue;
21 }
22
23 //Function to return the maximum value
24 float maxFunc(float maxValue, float newValue)
25 {
26     printf("Current maximum value: %.2f\n", maxValue);
27     printf("New sensor value: %.2f\n", newValue);
28     if(newValue > maxValue)
29     {
30         printf("Calculated maximum value: %.2f\n", newValue);
31         return newValue;
32     }
33     else
34     {
35         printf("Calculated maximum value: %.2f\n", maxValue);
36         return maxValue;
37     }
38 }
39

```

FIGURE 4.2 – Source code of data aggregation methods

```

40 //Function to return the minimum value
41 float minFunc(float minValue, float newValue)
42 {
43     printf("Current minimum value: %.2f\n", minValue);
44     printf("New sensor value: %.2f\n", newValue);
45     if(newValue < minValue)
46     {
47         printf("Calculated minimum value: %.2f\n", newValue);
48         return newValue;
49     }
50     else
51     {
52         printf("Calculated minimum value: %.2f\n", minValue);
53         return minValue;
54     }
55 }
56
57 //Function to control and return the threshold value
58 float thresholdFunc(float thresholdValue, float newValue)
59 {
60     printf("Current threshold value: %.2f\n", thresholdValue);
61     printf("New sensor value: %.2f\n", newValue);
62     if(newValue != thresholdValue)
63     {
64         printf("Calculated threshold control value: %.2f\n", newValue);
65         return newValue;
66     }
67     else
68     {
69         printf("Calculated threshold control value: %.2f\n", thresholdValue);
70         return thresholdValue;
71     }
72 }
73

```

FIGURE 4.3 – Source code of data aggregation methods

4.3 Testing of the developed program

How power and resource consumption (such as memory consumption) in IoT networks changes during the transmission of data to clients, and the effects of data aggregation methods and data transmission frequency on this change were observed by testing with the developed program.

During the test, the result data was not transmitted to the client via Bluetooth, internet, etc. It is saved in a local directory on the device. For this reason, the effect of data transmission methods such as Bluetooth and the Internet on current memory usage could not be measured.

The following test cases were tested to see the impact of data aggregation method and data transmission frequency on memory usage. For each test case, the current memory usage was measured by running the program. During testing, it was not taken into account how long the program had been running.

During the test, CO₂ measurement data measured from room C110 was used. Average,

Row Count	Aggragtion Function	Transmission Frequency(sec)	Memory Usage(kB)
0	Self Value	1	3012
100	Self Value	1	3036
10000	Self Value	1	3036
130000	Self Value	1	3024

TABLE 4.2 – Test results for transmission frequency 1.

Row Count	Aggragtion Function	Transmission Frequency(sec)	Memory Usage(kB)
0	Self Value	30	3012
100	Self Value	30	3036
10000	Self Value	30	3036
130000	Self Value	30	3024

TABLE 4.3 – Test results for transmission frequency 30.

maximum, minimum and threshold value control methods are used as aggregation functions and the data transmission frequency is 1 and 30 seconds.

The test results of the test cases are shown in the tables below. Data aggregation method and transmission frequency are dynamically taken from the client request file. Each test case was tested according to the data aggregation method, data transmission frequency, and the number of measured data. The test cases run for each scenario are as follows. Test cases are below.

- Measurement of current memory usage for data type co2 when sensor data record count is 0.
- Measurement of current memory usage for data type co2 when sensor data record count is 100.
- Measurement of current memory usage for data type co2 when sensor data record count is 10000.
- Measurement of current memory usage for data type co2 when sensor data record count is 130000.

Test results are the average value of the result of 100 trials for each test case.

Scenario 1 : Transmitting sensor data without any data aggregation method.

The test results for this scenario are shown in Table 4.2 and Table 4.3. According to this test case, as the number of records to be transmitted increases, the current memory usage increases up to a certain point. However, after a certain number of records (10000), there is a slight decrease in memory usage.

Scenario 2 : Measuring the current memory usage when the program is run after the

Row Count	Aggragation Function	Transmission Frequency(sec)	Memory Usage(kB)
0	Maximum	1	3020
100	Maximum	1	3044
10000	Maximum	1	3044
130000	Maximum	1	3032
0	Minimum	1	3020
100	Minimum	1	3044
10000	Minimum	1	3044
130000	Minimum	1	3032
0	Average	1	3020
100	Average	1	3052
10000	Average	1	3052
130000	Average	1	3040
0	Threshold Value Control	1	3020
100	Threshold Value Control	1	3044
10000	Threshold Value Control	1	3044
130000	Threshold Value Control	1	3032

TABLE 4.4 – Test results for transmission frequency 1.

Row Count	Aggragation Function	Transmission Frequency(sec)	Memory Usage(kB)
0	Maximum	30	3012
100	Maximum	30	3036
10000	Maximum	30	3036
130000	Maximum	30	3024
0	Minimum	30	3012
100	Minimum	30	3036
10000	Minimum	30	3036
130000	Minimum	30	3024
0	Average	30	3012
100	Average	30	3044
10000	Average	30	3044
130000	Average	30	3032
0	Threshold Value Control	30	3012
100	Threshold Value Control	30	3036
10000	Threshold Value Control	30	3036
130000	Threshold Value Control	30	3024

TABLE 4.5 – Test results for transmission frequency 30.

device is restarted and sensor data is aggregated and transmitted with a specific data aggregation method.

The test results for this scenario are shown in Table 4.4 and Table 4.5. In this test case, it was observed that the current memory usage was the same when data was aggregated using the Maximum, Minimum and Threshold Value Control data aggregation methods. When the average data aggregation method was used, the current memory usage increased compared to other methods. As the number of records to be transmitted increases, the current memory usage increases to a certain point. However, after a certain number of records, there was a slight decrease in memory usage. As the data transmission frequency decreases, the current memory usage also decreases. However,

Row Count	Aggragation Function	Transmission Frequency(sec)	Memory Usage(kB)
0	Maximum	1	3024
100	Maximum	1	3044
10000	Maximum	1	3044
130000	Maximum	1	3032
0	Minimum	1	3024
100	Minimum	1	3044
10000	Minimum	1	3044
130000	Minimum	1	3032
0	Average	1	3024
100	Average	1	3052
10000	Average	1	3052
130000	Average	1	3040
0	Threshold Value Control	1	3024
100	Threshold Value Control	1	3044
10000	Threshold Value Control	1	3044
130000	Threshold Value Control	1	3032

TABLE 4.6 – Test results for transmission frequency 1.

Row Count	Aggragation Function	Transmission Frequency(sec)	Memory Usage(kB)
0	Maximum	30	3024
100	Maximum	30	3044
10000	Maximum	30	3044
130000	Maximum	30	3032
0	Minimum	30	3024
100	Minimum	30	3044
10000	Minimum	30	3044
130000	Minimum	30	3032
0	Average	30	3024
100	Average	30	3052
10000	Average	30	3052
130000	Average	30	3040
0	Threshold Value Control	30	3024
100	Threshold Value Control	30	3044
10000	Threshold Value Control	30	3044
130000	Threshold Value Control	30	3032

TABLE 4.7 – Test results for transmission frequency 30.

using the data aggregation method increases the current memory usage compared to the case where data is not aggregated.

Scenario 3 : Measuring the current memory usage when the program is run for a certain period of time and sensor data is aggregated and transmitted with a certain data aggregation method.

The test results for this scenario are shown in Table 4.6 and Table 4.7. When this test scenario was compared with the second test scenario (running the program after the device was restarted), it was observed that the current memory usage increased up to a certain level. The instantaneous memory usage consumed by the program is also increased the current memory usage. However, decreasing the data transmission

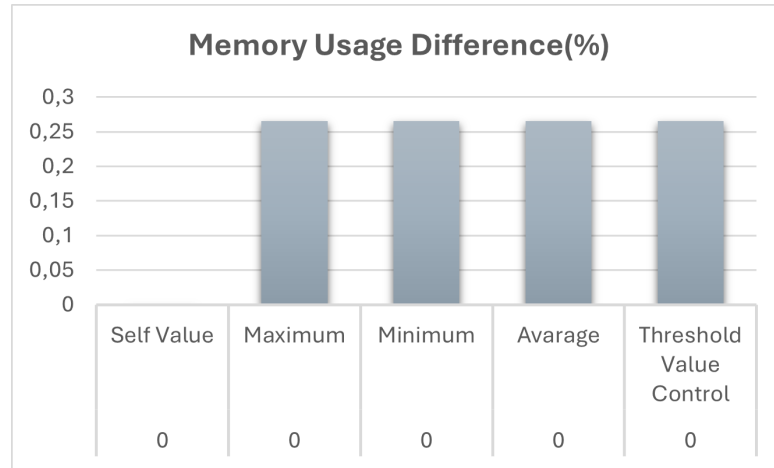


FIGURE 4.4 – Transmission Frequency : 1 and Row Count : 0

frequency did not change the current memory usage.

When the results of the test scenarios were evaluated, the current memory usage without using any middleware layer was compared as a percentage with the current memory usage when the data aggregation process was performed. And the results are visualized as in the figures below.

According to the results, when the number of requests increases and the transmission frequency is reduced, the current memory usage decreases. As the algorithmic complexity of the aggregation method increases, the current memory usage also increases.

The current memory usage when the transmission frequency is 1 and row count is 0 is shown in Figure 4.4.

The current memory usage when the transmission frequency is 1 and row count is 100 is shown in Figure 4.5.

The current memory usage when the transmission frequency is 1 and row count is 10000 is shown in Figure 4.6.

The current memory usage when the transmission frequency is 1 and row count is 130000 is shown in Figure 4.7.

The current memory usage when the transmission frequency is 30 and row count is 0

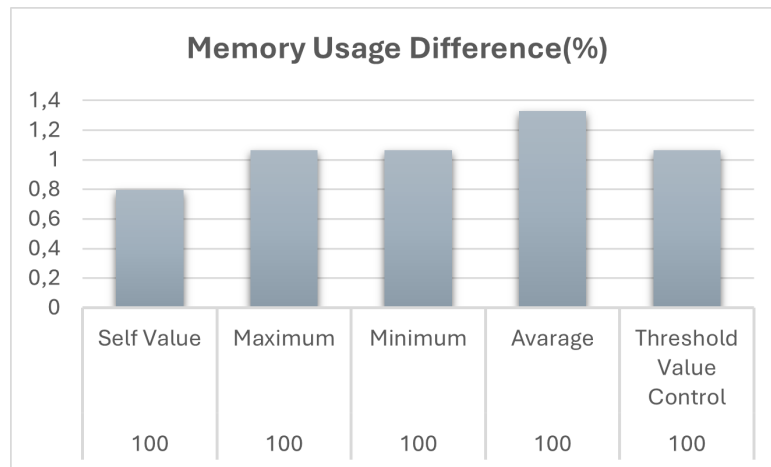


FIGURE 4.5 – Transmission Frequency : 1 and Row Count : 100

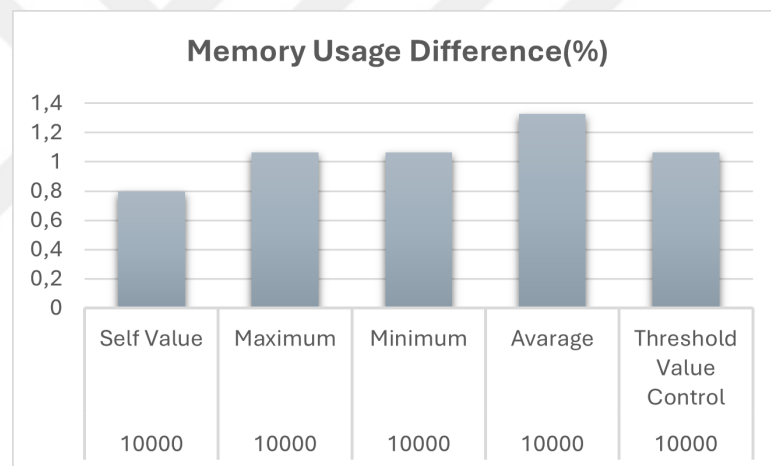


FIGURE 4.6 – Transmission Frequency : 1 and Row Count : 10000

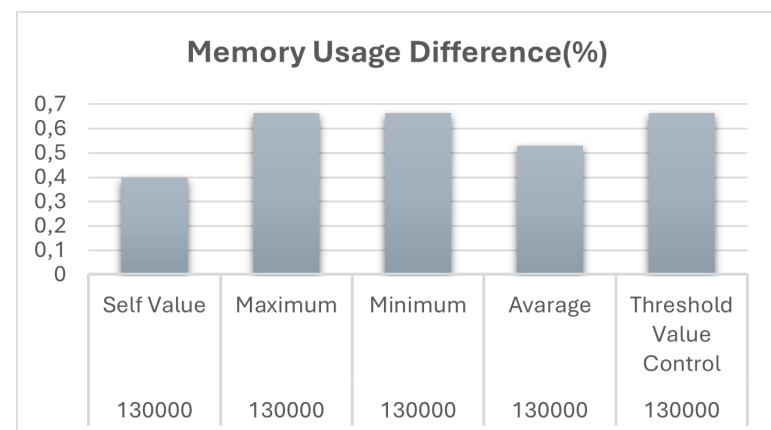


FIGURE 4.7 – Transmission Frequency : 1 and Row Count : 130000

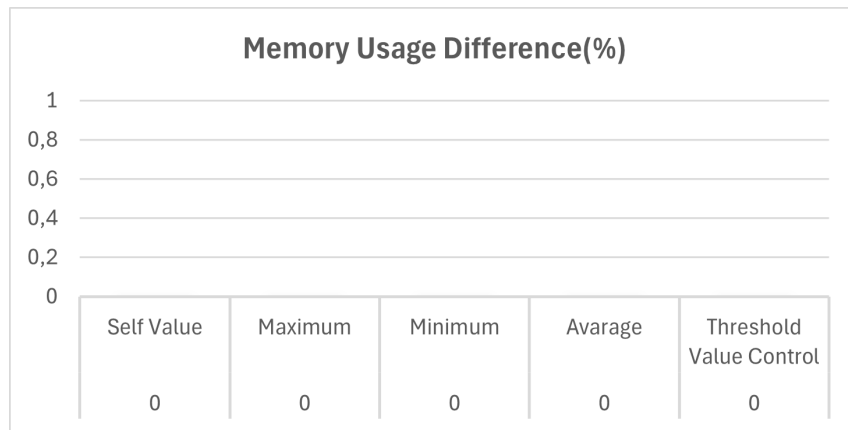


FIGURE 4.8 – Transmission Frequency : 30 and Row Count : 0

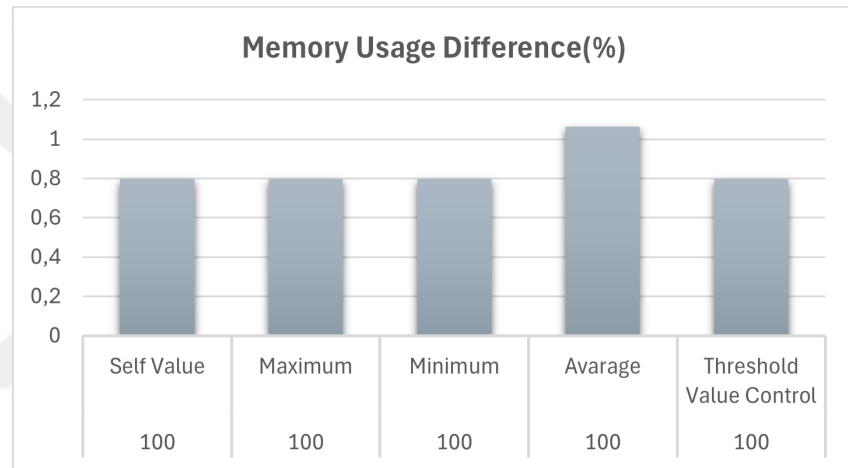


FIGURE 4.9 – Transmission Frequency : 30 and Row Count : 100

is shown in Figure 4.8.

The current memory usage when the transmission frequency is 30 and row count is 100 is shown in Figure 4.9.

The current memory usage when the transmission frequency is 30 and row count is 10000 is shown in Figure 4.10.

The current memory usage when the transmission frequency is 30 and row count is 130000 is shown in Figure 4.11.

In this experiment, data of 5 different physical quantities, namely CO₂, temperature, humidity, light and motion, collected from 30 classes, were transmitted at regular intervals without using any middleware, and the sizes of the transmitted data were measu-

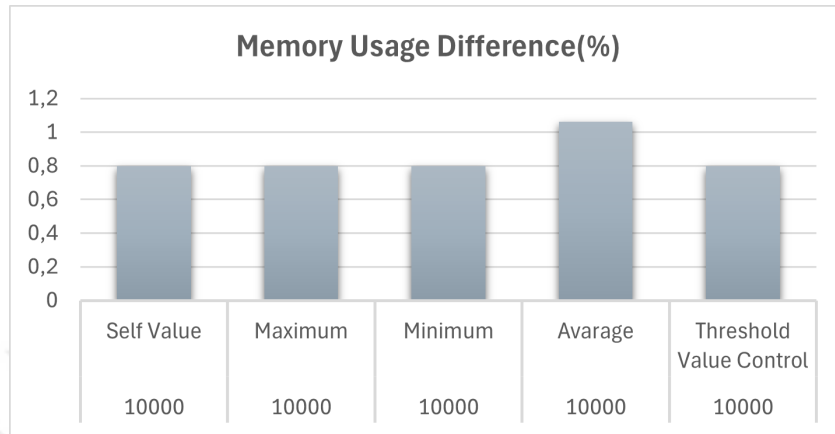


FIGURE 4.10 – Transmission Frequency : 30 and Row Count : 10000

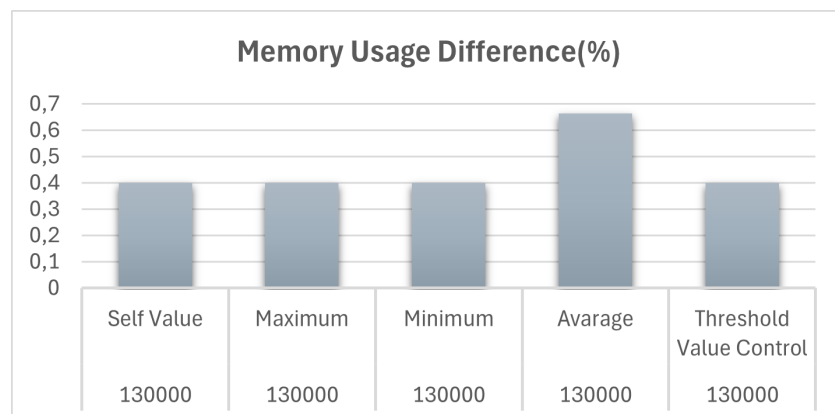


FIGURE 4.11 – Transmission Frequency : 30 and Row Count : 130000

	Default (bytes)	With our framework (bytes)	Gain (%)
5 sec	89	18	79,78
10 sec	179	18	89,94
30 sec	538	18	96,65
60 sec	1000	18	98,20

TABLE 4.8 – Data size gain table

red. In addition, the data size is measured when the collected data is aggregated with an intermediate software by applying an aggregation method. In this context, the size of the data sent without any middleware at intervals of 5, 10, 30 and 60 seconds and the size of the data transmitted when there is middleware and the data is aggregated are shown in the table below. In the table, it is observed that there are large gains in the size of the data to be transmitted when the data is aggregated. As the transmission frequency decreases, the gain from the size of the data to be transmitted increases. Data size gain is shown in Table 4.8.

5 CONCLUSION AND DISCUSSION

With the developed program, suggestions for aggregating and transmitting data and reducing the transmission frequency were tested in order to increase efficiency and effectiveness in IoT networks where nodes with limited resources are present.

The program was run according to various test scenarios. In the scenario of data aggregation and transmission, the current memory usage was measured when the maximum, minimum and threshold value control methods of the measured sensor data were applied. At the same time, the current memory usage was also measured in cases where data was transmitted without being aggregated. When the results of these two conditions were compared, no difference in memory usage was observed. However, when the Average data aggregation method was used, the current memory usage increased. That is, the mathematical complexity level of the data aggregation method affects the current memory usage. As the level of mathematical complexity increases, the use of current memory usage also increases.

The number of records of test data also affects memory usage. As the number of records to be processed increases, the current memory usage also increases. Just reducing the data transmission frequency reduced the current memory usage. From here, it can be said that reducing the data transmission frequency increases the efficiency on the limited resources in the node.

In data transmission; the size of the data to be transmitted has decreased when the data is aggregated. In this way, the data to be transmitted will be transmitted faster.

In the tests on the developed program, data transmission was done by writing the results to a text file and storing them in a directory on the device. In order to measure the impact of both the use of data aggregation methods and the reduction of data transmission frequency on efficiency, effectiveness and data transmission speed in IoT networks, more accurate results can be observed by transmitting data using transmission methods such as Bluetooth/Internet etc. instead of writing the results to a text file.

This study could not conclude that transmitting data by applying only data aggregation

methods has a direct positive effect on efficiency, effectiveness and data transmission speed. However, it has been observed that reducing the data transmission frequency along with the data aggregation method has a positive impact on limited resources. It should also be examined whether the data transmission type (Bluetooth/Internet, etc.) affects efficiency in resource-constrained nodes. In the future study, it is recommended to examine the effects of data aggregation method, data transmission frequency and data transmission type on efficiency, effectiveness and data transmission speed in IoT networks when applied together.



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Enhancing Healthcare Services through User-Centered Data Collection and Analysis

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Abstract—The advent of real-time data processing applications has revolutionized monitoring and analysis capabilities across diverse operational domains, including big data and healthcare. This study focuses on the development and evaluation of a prototype application designed for real-time data processing in dynamic environments. The application parses configuration files, processes real-time sensor data and outputs calculated values at user-defined intervals, ensuring accuracy and timeliness in data analysis. Experimental evaluations under varied conditions validate the application's robust performance in managing pipeline operations, computational efficiency, response times and data aggregation precision. Optimizations, including data type adjustments, significantly enhance network communication efficiency and reduce latency, critical for supporting real-time applications. The application's flexibility in user-configured settings for data storage and aggregation proves essential for adapting to specific application requirements. This adaptability is particularly beneficial for handling the complexities of big data and the sensitivity of healthcare data. Overall, this study contributes a robust solution for real-time data processing and continuous monitoring, demonstrating its feasibility and applicability across dynamic operational environments, including those requiring rigorous data handling and precise analytics.

Index Terms—User-Centered Design, Internet of Medical Things (IoMT), Big Data Analytics in Healthcare, Predictive Health Analytics, Patient Engagement and Data Privacy

I. INTRODUCTION

In recent years, the integration of the Internet of Things (IoT) and big data analytics into the healthcare sector has revolutionized the way health services are delivered and managed. The proliferation of IoT devices, such as wearable health monitors, smart medical devices and connected home care systems, has facilitated the continuous collection of vast amounts of health-related data. These advancements, when combined with the powerful capabilities of big data analytics, offer multiple opportunities to enhance healthcare services, improve patient outcomes and optimize operational efficiency.

IoT devices in healthcare, often referred to as the Internet of Medical Things (IoMT), enable real-time monitoring of patients' physiological parameters, medication adherence and overall well-being. These devices collect a diverse array of data, including vital signs (such as heart rate, blood pressure and glucose levels), physical activity, sleep patterns and more. This continuous data stream provides healthcare providers with

a comprehensive and dynamic picture of a patient's health status, allowing for timely interventions, personalized treatment plans and proactive management of chronic conditions.

For example, a wearable device that monitors heart rate and activity levels can detect irregularities and alert both the patient and their healthcare provider, potentially preventing serious cardiac events. Similarly, smart insulin pumps can adjust dosages based on real-time glucose readings, significantly improving diabetes management. These IoMT applications not only enhance patient safety and quality of life but also reduce the bottleneck on healthcare systems by decreasing hospital admissions and emergency room visits.

Big data analytics involves the systematic analysis of large and complex datasets to uncover hidden patterns, correlations and insights. In healthcare, big data analytics can be applied to improve clinical decision-making, predict disease outbreaks, enhance treatment efficacy and streamline administrative processes. By analyzing data from various sources, including electronic health records (EHRs), medical imaging, genomic data and IoT devices, healthcare providers can gain actionable insights that drive better health outcomes [1]–[3].

One of the significant advantages of big data analytics is its ability to support predictive analytics. For instance, by analyzing historical patient data and current health metrics, predictive models can identify patients at high risk of developing conditions such as heart disease or diabetes. This enables healthcare providers to implement preventive measures and early interventions, ultimately reducing the incidence and severity of these conditions [4]–[6].

While the technological advancements in IoT and big data analytics hold immense potential, the effectiveness of these technologies hinges on a user-centered approach to data collection and analysis. User-centered design focuses on the needs, preferences and behaviors of the end-users—in this case, patients and healthcare providers. By prioritizing the user experience, data collection methods can be tailored to ensure high-quality, reliable and meaningful data [7]–[9].

In healthcare, user-centered data collection involves engaging patients in the monitoring process, ensuring that devices are easy to use and seamlessly integrate into their daily lives. For example, wearable devices should be comfortable, non-intrusive and provide clear feedback to the user. Additionally,

healthcare providers must be equipped with user-friendly data visualization tools that enable them to interpret and act on the collected data effectively.

Furthermore, addressing privacy and security concerns is paramount in user-centered data collection. Patients must trust that their data is handled with the utmost care, confidentiality and compliance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA). Transparent communication about data usage, consent and protection measures is essential to fostering this trust.

This study aims to explore the impact of user-centered data collection and analysis on enhancing healthcare services. By examining pilot implementations of IoT and big data analytics in healthcare settings, this research tries to provide actionable insights and recommendations for integrating user-centered approaches into the design and deployment of health technologies.

Through this investigation, we aim to demonstrate that placing users at the heart of data collection and analysis processes not only enhances the effectiveness of health interventions but also empowers patients and healthcare providers to achieve better health outcomes.

The remainder of the paper is structured as follows: Related works are given in Section II. Section III presents the methods used. Section IV gives a brief description of our experimental platform to implement our approach and describes the experiments we conducted. Finally, conclusion and discussion are given in Section V.

II. RELATED WORK

A. The Importance of Data Aggregation in Enhancing Healthcare Services

Data aggregation plays a critical role to present the full potential of IoT and big data analytics within the healthcare sector. As the volume of health-related data generated by IoT devices continues to grow exponentially, the ability to effectively collect, integrate and analyze this data becomes increasingly critical. Data aggregation, the process of gathering and combining data from various sources into a comprehensive dataset, is fundamental to deriving meaningful insights that can enhance healthcare services, improve patient outcomes and optimize operational efficiencies [4], [10], [11].

B. Enabling Comprehensive Patient Monitoring

One of the primary benefits of data aggregation in healthcare is the creation of a holistic view of patient health. IoT devices, such as wearable fitness trackers, smart medical devices and remote monitoring systems, generate diverse datasets encompassing vital signs, physical activity, sleep patterns, medication adherence and more. Individually, these data points provide valuable information; however, when aggregated, they offer a comprehensive and continuous picture of a patient's health status. This aggregated data enables healthcare providers to monitor patients more effectively, identify patterns and trends and make informed clinical decisions [12], [13].

For instance, by aggregating data from a wearable heart rate monitor, a glucose sensor and a physical activity tracker, healthcare providers can gain insights into the interplay between a patient's cardiovascular health, blood sugar levels and physical activity. This holistic view facilitates personalized treatment plans, timely interventions and proactive management of chronic conditions, ultimately enhancing patient care [6], [14].

C. Supporting Predictive Analytics and Early Intervention

Data aggregation is also crucial for the development and application of predictive analytics in healthcare. Predictive analytics relies on large, diverse datasets to build models that can forecast future health outcomes and identify individuals at risk of developing specific conditions. By aggregating data from multiple sources, healthcare providers can create robust predictive models that account for a wide range of factors influencing health [15], [16].

For example, aggregated data from electronic health records (EHRs), IoT devices and patient-reported outcomes can be used to predict the likelihood of hospital readmissions, the onset of chronic diseases, or the progression of existing conditions. These predictive insights enable early intervention strategies, such as lifestyle modifications, preventive treatments and closer monitoring, which can significantly reduce the incidence and severity of health issues. Consequently, data aggregation not only enhances individual patient care but also contributes to the overall efficiency and sustainability of healthcare systems [4], [17].

A notable example is the use of predictive analytics in managing chronic diseases like diabetes. By aggregating data from continuous glucose monitors, dietary logs and physical activity trackers, predictive models can identify trends and patterns that precede hyperglycemic or hypoglycemic events. This allows healthcare providers to recommend adjustments in diet, exercise and medication before adverse events occur, significantly improving patient outcomes and quality of life.

D. Improving Data Quality and Reliability

The aggregation process also plays a vital role in improving the quality and reliability of health data. By integrating data from multiple sources, inconsistencies, errors and missing values can be identified and addressed, resulting in cleaner and more accurate datasets. Moreover, aggregated data can be subjected to advanced statistical methods and machine learning algorithms that further refine and validate the data [18], [19].

This improvement in data quality is particularly important in healthcare, where decisions based on inaccurate or incomplete data can have serious consequences. High-quality aggregated data ensures that healthcare providers have access to reliable information, thereby enhancing the accuracy of diagnoses, the effectiveness of treatments and the overall quality of care delivered to patients [20], [21].

For instance, data from various sensors and devices may sometimes be incomplete or contradictory. Through data aggregation, these discrepancies can be reconciled by cross-referencing multiple data points, thus ensuring a more reliable

dataset. This process not only improves the integrity of the data but also builds greater confidence in the insights derived from the data.

E. Facilitating Research and Innovation

Lastly, data aggregation is essential for advancing research and innovation in healthcare. Aggregated datasets provide a rich resource for researchers to explore new medical hypotheses, identify emerging health trends and develop innovative solutions. By pooling data from various sources, researchers can conduct large-scale studies that yield statistically significant results and drive evidence-based advancements in medical science and healthcare practices.

For example, during the COVID-19 pandemic, aggregated data from various sources, including health records, mobile apps and social media, helped researchers track the spread of the virus, understand its transmission patterns and develop effective containment strategies. This rapid aggregation and analysis of data were crucial in informing public health responses and vaccine distribution strategies.

Additionally, aggregated data supports the development of personalized medicine. By combining genomic data with clinical and lifestyle data, researchers can identify genetic markers associated with specific diseases and tailor treatments to the individual characteristics of patients. This approach promises to improve treatment efficacy and reduce adverse effects, ushering in a new era of precision medicine.

In conclusion, data aggregation is hugely important for modern healthcare analytics, enabling comprehensive patient monitoring, supporting predictive analytics, improving data quality and facilitating research. As healthcare systems continue to embrace IoT and big data technologies, the importance of effective data aggregation will only grow, making it a critical component in the pursuit of enhanced healthcare services and improved patient outcomes. By integrating user-centered approaches into data aggregation processes, healthcare providers can ensure that the collected data is not only accurate and reliable but also relevant and actionable, ultimately leading to better health outcomes for patients.

Recent literature underscores the effectiveness of various data aggregation techniques in addressing energy consumption challenges in WSNs. [20] provide a comprehensive review of data aggregation methods tailored to different IoT environments, including terrestrial, underground, underwater and body area networks. Their study evaluates tree-based, cluster-based and centralized aggregation approaches, highlighting their advantages, disadvantages and application contexts.

Pourghepleh et al. examine the role of data aggregation in enhancing energy efficiency, network lifetime and data accuracy in IoT systems. They emphasize the significance of selecting appropriate aggregation methods to optimize resource utilization and mitigate network congestion [22]. Similarly, Rahman et al. compare various data collection techniques based on metrics such as energy efficiency and latency using simulation tools. Their findings underscore the importance of

deploying efficient aggregation strategies to improve overall network performance [23].

Implementing effective data aggregation in IoT networks poses several challenges, including scalability, security and interoperability. Yousefi et al. conduct a systematic review of client-server and mobile agent-based data aggregation approaches, offering insights into their comparative advantages and limitations. They highlight the need for scalable and adaptable aggregation frameworks capable of supporting diverse IoT applications and environments [24].

In healthcare applications, Wireless Body Sensor Networks (WBSNs) leverage IoT technologies to monitor and transmit vital signs such as heart rate and blood pressure in real-time. Rezaeibagha et al. propose a secure data aggregation framework using cryptographic accumulators to protect sensitive health data transmitted over IoT networks. Their approach ensures data integrity and confidentiality, addressing privacy concerns associated with healthcare IoT deployments [25].

The evolution of IoT has catalyzed advancements in various application domains, including smart cities, industrial automation, agriculture and environmental monitoring. Fitzgerald et al. introduce novel models for data aggregation in IoT networks, considering the emergence of edge and fog computing paradigms. Their models optimize energy efficiency by integrating multiple gateways for data aggregation and distribution, enhancing scalability and reliability in heterogeneous IoT environments [26].

III. PROPOSED APPROACH

A. Optimizing Data Aggregation for Efficient Healthcare Data Transmission in IoT Networks

In the IoT research area, ensuring effective, efficient and fast data communication poses a significant challenge, particularly given the resource constraints of sensor nodes. This challenge is exacerbated in healthcare applications, where real-time data collection and transmission are critical for monitoring patient health and facilitating timely interventions. Data aggregation emerges as a promising solution to address these challenges by consolidating data from multiple sources before transmission, thereby reducing memory consumption, enhancing energy efficiency and improving transmission speed.

B. Context and Problem Statement

In our scenario, wireless sensors deployed in our university building environment (considered as an emulator of a hospital environment) continuously collect data such as temperature, humidity, CO₂ levels, motion and luminosity at predefined sampling frequencies (e.g., every minute). These data are crucial for monitoring patient conditions, ensuring environmental safety and optimizing healthcare delivery. However, transmitting raw data from each sensor node to a centralized server or monitoring system can overlap the network bandwidth and consume excessive resources.

Moreover, clients—such as healthcare providers or medical staff—often require specific subsets of data tailored to their

needs. For instance, a client may request aggregated temperature readings from a specific room at regular intervals to monitor patient comfort or detect environmental anomalies. Fulfilling these requests efficiently while minimizing resource usage poses a significant operational challenge.

C. Proposed Methodology

The proposed approach focuses on examining the impact of different data aggregation methods and transmission frequencies on memory usage in resource-limited sensor nodes within healthcare IoT networks. Specifically, we aim to investigate how memory consumption varies when data is aggregated and transmitted to the central server at different intervals using various aggregation techniques. Furthermore, we evaluate dynamic aggregation and transmission strategies based on real-time client requests to optimize resource utilization and enhance network efficiency.

In this study, the goal is to address the fact that the hardware capabilities of gateway devices used for transmitting sensor data in IoT networks are not significantly different from those of the sensors themselves. Therefore, it is crucial to consider the memory and computational capacities of the gateways. This attention to hardware limitations ensures that the gateways can efficiently manage the data processing and transmission tasks without becoming bottlenecks in the network.

1) *Design of IoT Data Aggregation Framework:* The first step involves designing an IoT data aggregation framework for healthcare applications. In our proposed approach for optimizing data aggregation in healthcare IoT networks, we focus on efficiently managing data collection, aggregation and transmission processes. Sensors deployed in the environments continuously gather diverse data types, such as temperature, humidity, CO2 levels and luminosity, at predefined intervals. This continuous monitoring ensures that patient health and environmental conditions are consistently observed.

When clients, such as healthcare providers or medical staff, submit requests, gateways perform data aggregation based on specific parameters defined in the request. For instance, a client might request average temperature readings from a particular room at regular intervals. This aggregation process filters and processes the data to derive relevant subsets, such as average temperature or minimum humidity, optimizing the data for transmission.

Our approach relies on efficient transmission protocols, which help us send combined data smoothly to central servers or client systems. These protocols prioritize minimizing latency and optimizing bandwidth usage, ensuring timely and reliable data transfer. By dynamically adjusting aggregation methods and transmission frequencies based on real-time client demands, our approach maximizes resource utilization and network efficiency.

This methodology not only enhances data management in healthcare IoT networks but also supports the integration of advanced analytics for deriving actionable insights from aggregated data. Predictive analytics and machine learning

algorithms can benefit from these aggregated data to forecast patient outcomes, optimize resource allocation and improve overall healthcare service delivery.

2) *Dynamic Data Aggregation and Transmission Strategies:* Unlike traditional static approaches, our method dynamically adjusts data aggregation and transmission based on real-time client demands. This adaptive strategy involves:

Our proposed approach for optimizing data aggregation in healthcare IoT networks revolves around efficiently managing data collection, aggregation and transmission processes. Sensors deployed in healthcare environments continuously collect various data types like temperature, humidity, CO2 levels and luminosity at predefined intervals to ensure continuous monitoring of patient health and environmental conditions.

3) *Evaluation Metrics and Experimental Setup:* Our proposed approach for optimizing data aggregation in healthcare IoT networks focuses on efficiently managing the entire data lifecycle, from collection through to transmission and analysis. Sensors deployed in environments continuously gather a variety of data types such as temperature, humidity, CO2 levels, motion and luminosity at predetermined intervals. This ongoing monitoring is essential for maintaining real-time awareness of patient health statuses and environmental conditions within the facilities.

Our methodology incorporates rigorous evaluation metrics to assess the performance of different aggregation strategies. Memory consumption is meticulously monitored across gateway nodes under varying aggregation methods and transmission frequencies. This analysis aims to pinpoint optimal configurations that minimize memory usage while maintaining data integrity and responsiveness to client requests.

Energy efficiency is another key focus area, where we evaluate how different aggregation strategies impact sensor node energy consumption. Optimizing energy usage is pivotal for prolonging sensor node battery life and reducing operational costs in healthcare environments where continuous monitoring is essential.

Additionally, network performance is examined through detailed analysis of transmission speed and latency metrics. These metrics ensure that aggregated data is delivered promptly without compromising its quality or the reliability of healthcare services. Maintaining robust network performance is critical for supporting real-time decision-making and enhancing overall healthcare service delivery.

By integrating advanced analytics into the aggregation process, such as predictive modeling and machine learning algorithms, our approach unlocks the potential to derive actionable insights from aggregated healthcare data. These insights can inform predictive healthcare strategies, optimize resource allocation and improve patient outcomes through proactive intervention and personalized care.

In summary, our proposed approach aims to establish best practices for optimizing data aggregation in healthcare IoT networks. By prioritizing efficiency, scalability and responsiveness to client needs, we seek to advance healthcare data man-

agement and operational effectiveness in IoT-driven healthcare environments.

In conclusion, our proposed approach aims to optimize memory usage and enhance data transmission efficiency in healthcare IoT networks through innovative data aggregation and dynamic transmission strategies. By accommodating real-time client requests and adapting to changing network conditions, our method ensures that healthcare data is transmitted efficiently while preserving resource-constrained sensor node capabilities. This chapter outlines a structured methodology to implement and evaluate the proposed approach, emphasizing its potential to advance healthcare data management and operational efficiency in IoT environments. Through empirical validation and real-world implementation, we seek to establish best practices for optimizing healthcare data aggregation in IoT networks, contributing to enhanced patient care and healthcare service delivery.

D. Proposed Framework and Algorithm

In response to the existing gap in academic literature concerning efficient user-configured data aggregation and optimized storage in aggregated memory, this study introduces a framework aimed at exploring these critical aspects within IoT sensor networks. The research is motivated by the observation that optimizing data types can significantly enhance network communication efficiency. Initial experiments, based on real-world sensor data provided by Galatasaray University, focus on key metrics such as CO₂ levels, light intensity, occupancy, humidity and temperature.

In this environment, sensor nodes periodically transmit collected data to a gateway, including timestamped measurements. Notably, optimizations in data types, such as transitioning from double precision to unsigned short integers for sensor readings, demonstrate substantial improvements in data transmission efficiency. This optimization not only reduces data size but also minimizes latency, conserves bandwidth and reduces memory usage in transmitted data. Figure 1 presents the different packet size based on the data types.

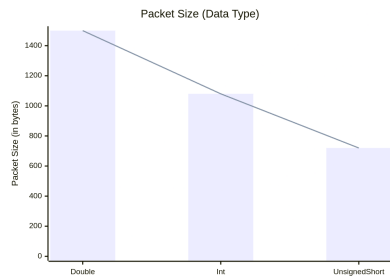


Fig. 1. The packet header code snippet

Furthermore, the framework supports user-configurable settings for data pairing and aggregation, emphasizing adaptability to specific application requirements and constraints. This flexibility is crucial for customizing data management strategies to optimize sensor node performance effectively. Figure 2 presents the config header file where users may request MIN, MAX, AVG, VAL of a physical measurement (CO₂, HUM, LIG, PIR, TEM).

```

1  #ifndef CONFIG_H
2  #define CONFIG_H
3
4  #include <stdint.h>
5  #include <stdio.h>
6  #include <time.h>
7
8  #define PORT 8080
9  #define MAX_ROOMS 30
10 #define MAX_MEASUREMENTS 5
11 #define MAX_FILENAME_LENGTH 500
12 #define MAX_LINE_LENGTH 100
13 #define MAX_ROOM_LENGTH 8
14 #define MAX_DATA 1200
15 #define MAX_HISTORY 100
16
17 #define MAX_USER UINT32_MAX
18 #define MAX_REQUEST UINT8_MAX
19
20 typedef enum { CO2, HUM, LIG, PIR, TEM, DATA_TYPE_LEN } Data_type;
21 typedef enum { MIN, MAX, AVG, VAL, AGGR_TYPE_LEN } Aggr_type;
22
23 #define MAX_REQUEST_TYPE_LENGTH (DATA_TYPE_LEN * AGGR_TYPE_LEN)
24
25 typedef struct UserConfig
26 {
27     uint32_t user_id;
28     struct UserConfig *next;
29 } UserConfig;
30
31 typedef struct Request
32 {
33     uint16_t req_id;
34     Data_type data_type;
35     Aggr_type aggr_type;
36     uint32_t interval;
37     uint8_t room_idx;
38     UserConfig *head_user;
39     size_t len;
40     struct Request *next;
41 } Request;
42
43 typedef struct GwayConfig
44 {
45     Request *head_req;
46     size_t len;
47 } GwayConfig;
48
49 int parse_config(GwayConfig *config, time_t *last_mod);
50
51 #endif

```

Fig. 2. The config header code snippet

Upon receiving data, the gateway employs a structured file storage approach that preserves the integrity and format of the original data. This strategic storage mechanism ensures that data is managed efficiently while adhering to predefined storage limitations. Configuration files parsed by the gateway define data aggregation parameters, specifying maximum intervals (e.g., hourly, daily, weekly) for each data type aggregation. Consequently, only data within the specified aggregation intervals is stored, ensuring optimal use of storage resources without compromising data fidelity.

In summary, the integration of optimized data types and structured storage mechanisms in IoT sensor networks represents a critical advancement towards enhancing network

performance and resource utilization. Future research aims to expand the simulation framework by incorporating additional sensor types and advanced aggregation methods, further validating the efficacy of these optimization strategies in diverse IoT applications.

This study introduces a prototype application designed to efficiently process and analyze real-time data, emphasizing critical functionalities aimed at enhancing data accuracy and operational reliability. The application operates through a series of synchronized stages to ensure timely processing and output of processed information.

At the outset, the application initializes by parsing a configuration file, which is crucial for defining user requests and operational parameters. This initial setup phase involves loading configuration details into memory to facilitate seamless access and operational continuity.

Following configuration setup, the application provides real-time monitoring and periodic data retrieval from designated files. Data retrieval intervals are strictly synchronized with gateway updates, ensuring that the application consistently accesses the most recent data. This real-time data acquisition process is fundamental in maintaining the accuracy and relevance of the processed information.

Upon capturing the required data, the application proceeds to execute predefined calculations specified in the configuration file. These calculations are designed to extract meaningful insights from the raw data, highlighting the critical role of accuracy in generating reliable analytical results.

The final operational phase involves timed output of the calculated results. As configured, the application outputs processed values and associated user IDs to the main program console at fixed intervals. This stage not only delivers results but also signifies the completion of an operational cycle within the application.

Subsequently, the application resets and initiates a cyclic loop, perpetuating continuous updates and recalculations based on new data and user requests. This iterative process ensures ongoing data integrity and responsiveness to dynamic operational demands.

In summary, this prototype application exemplifies robustness and dynamism in real-time data processing. By parsing configuration files and executing periodic data updates and calculations, the application adheres to a structured approach essential for continuous monitoring and timely data analysis. Such capabilities are pivotal for applications requiring real-time insights and continuous operational efficiency.

IV. EXPERIMENTS

Following the design of the simulation and implementation of a fully functional prototype application, a series of comprehensive experiments were undertaken to evaluate its performance under realistic conditions. The primary objective of these experiments was to validate the functionality, reliability and usability of the prototype across diverse environments.

The experiments were pivotal in assessing how effectively the application performs with real data and its resilience in

overcoming operational challenges. Deployment in various environments provided insights into its operational behavior and highlighted any potential shortcomings that needed addressing. These evaluations were crucial steps in validating the application's design and functionality, ensuring it meets operational expectations. Figure 3 introduces the time comparison graph.

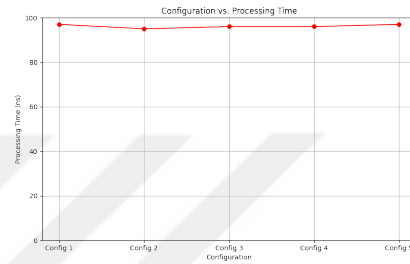


Fig. 3. The configuration and processing time comparison graph

Additionally, the experiments aimed to validate the efficiency of algorithms integrated into the prototype. Various scenarios and workloads were tested to evaluate computational efficiency, response times and the accuracy of data aggregation processes. Through detailed analysis and comparisons of gathered data, strengths and weaknesses of existing algorithms were identified, guiding improvements for optimal operational efficiency. Figure 4 introduces the time comparison graph for parsed configuration.

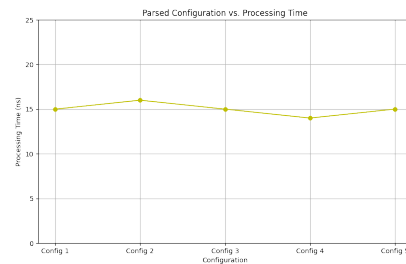


Fig. 4. The parsed configuration and processing time comparison graph

Moreover, the experiments highlighted the impact of optimizations on parsing configurations. Significant enhancements were observed in parsing efficiency, demonstrating the tangible benefits of optimizing configurations for improved performance. Such optimizations are critical for enhancing overall system responsiveness and resource utilization. Figure 5 presents the memory usage of parsed configuration.

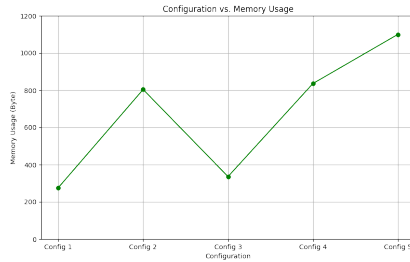


Fig. 5. The parsed configuration and memory usage comparison graph

A. Interpretation of the Results

While the C programming language offers advantages in terms of speed and flexibility, the experimental results also underscored challenges related to memory efficiency. However, the inherent flexibility of C allows for customized adjustments to optimize memory management according to specific requirements and contexts. This adaptability ensures that the language remains suitable for addressing diverse computational challenges, despite potential inefficiencies in memory usage.

In conclusion, the experimental evaluations provided crucial insights into the performance and capabilities of the prototype application. By validating its functionality across varied conditions and optimizing critical algorithms, these experiments contribute to ensuring the application's readiness for real-world deployment and continuous improvement.

V. CONCLUSION AND DISCUSSION

In this study, we developed and evaluated a prototype application for real-time data processing, aiming to fulfill the demands of continuous monitoring in dynamic operational environments. The application successfully parsed configuration files, processed real-time data and provided timely outputs of calculated values, ensuring accuracy and reliability in data analysis. Experimental evaluations under varied conditions demonstrated the application's robust performance in managing pipeline operations, computational efficiency, response times and data aggregation precision.

Key findings from our experiments underscored the significant impact of optimizations, such as data type adjustments, on enhancing network communication efficiency and reducing latency. These optimizations are crucial for supporting real-time applications across diverse operational scenarios. Moreover, the application's flexibility in user-configured settings for data storage and aggregation proved instrumental in adapting to specific application requirements and constraints, enhancing its versatility.

While our results are promising, there are notable opportunities for further enhancement. Improving memory management strategies and fine-tuning algorithms are critical next steps to

maximize the application's efficiency and effectiveness. Given the powerful capabilities of the C programming language, optimizing memory usage remains pivotal for mitigating inefficiencies associated with varying user configurations.

In conclusion, the prototype application presented in this study offers a robust solution for real-time data processing and continuous monitoring in dynamic environments, validated through comprehensive experimental evaluations. Moving forward, future research efforts will focus on refining memory management techniques and optimizing algorithms to elevate the application's performance and broaden its applicability across diverse operational domains.

ACKNOWLEDGMENTS

This work is supported by Galatasaray University Research Foundation under the Grant No. FBA-2024-1257.

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