Wireless Sensor Network Optimization for Multi-Sensor Analytics in Smart Healthcare System

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Abstract

In the twenty-first century, the Internet of Things (IoT) has assisted in the mainstreaming of automation. By boosting bandwidth, communication protocols, and redundancy, the integration of IoT, WSNs, and health monitoring systems with a multi-cloud environment can improve sensor networks. The proposed design is compared to current health infrastructure and monitoring systems, as well as alternative network architectures. Machine-to-machine health monitoring methods have also been investigated, as well as how they relate to communication protocols. The objective of this study is to find out more about how sensor data analytics may be used to multi-cloud sensor communication protocols directly. When the supplied prototype and the one-of-a-kind communication mechanism are merged, a model is created that is 98 percent more accurate than traditional techniques

Keywords:*Multi-cloud, WSNs, machine to machine*

1. Introduction

Although cloud computing is a complete service that provides clients with ease, it is not without flaws. One of the advantages of the Internet of Things is its ability to quickly analyze and evaluate enormous amounts of data generated by a variety of applications [1]. In today's fast-paced society, smart care systems are essential. When fog computing and IoT are combined with medical equipment, the efficacy of operations in such healthcare systems may be improved.[2].

The new systems surpass older or traditional systems because they combine more reliable and cost-effective technology with secure data transfer techniques. When fog computing and IoT are used, healthcare expenses are decreased [3]. The quality of services has increased as high-speed computers and processing have become more widespread. Health monitoring conducted with a fog computing-enabled IoT device has a much higher value [3]. The primary benefit of using IoT into medical health care is that it makes tracking important health indicators easier while also saving money [4]. Wearables are widely used in the healthcare industry because they are the most convenient and comfortable method of collecting data, monitoring health, and interacting with general practitioners on a regular basis.

IoT-enabled gadgets and equipment are transforming the face of medicine with their operations and processes. IoT gadgets that rely on the assistance of an IoT platform include armbands and ECG monitors [5]. For data generation, collecting, and administration, planning and control activities are critical components of IoT. The devices also examine data using a series of rules and processes that are required for assessment.

Cloud computing is a comprehensive service that brings convenience to customers, but it is not without faults. One of the benefits of the Internet of Things [6] is its capacity to analyze and assess massive volumes of data provided by a range of applications fast. Smart care systems are critical in today's fast-paced world. The efficacy of operations in such healthcare systems may be increased when fog computing and IoT are coupled with medical equipment [7].

The new systems surpass older or traditional systems because they combine more reliable and cost-effective technology with secure data transfer techniques. When fog computing and IoT are used, healthcare expenses are decreased [8]. The quality of services has increased as high-speed computers and processing have become more widespread. Health monitoring conducted with a fog computing-enabled IoT device has a much higher value [8]. The most significant benefit of implementing IoT in medical health care is that it simplifies the tracking of vital health indicators while also saving money [9]. In the healthcare industry, wearables are popular because they are the most convenient and comfortable method to collect data, monitor health, and interact with general practitioners on a regular basis[10].

Distributed Computational Framework Health Monitoring Environments

Modern healthcare monitoring activities have been revolutionized by the Internet of Things idea. Consumers and professionals are being transformed by the latest smart sensor devices. Sensing technologies and smart mobile devices in general can aid in the administration of new healthcare apps that were previously only accessible via hospital computers.

Athletes and the general public have utilised smart watches, smart phones, and tablets to track everyday sports activities and collect movement and routine data [11,12]. Professional sports may test players' activity in high-stress scenarios in other spirited situations, such as medical staff. Sports events include football games, cycling races, and running races. Light portable gadgets, such as a laptop or tablet, are commonly used in these scenarios. It is tough to build strong workstations or servers in the actual world.Furthermore, the computational support of a cloud-hosted server is not always available for rapid monitoring. The vast bulk of cloud resources are dedicated to storing data for later processing. The types of programmes that may be built are limited by these operational constraints. As a result, today's doctors and athletic coaches prefer to utilise a simple monitoring system.

The suggested framework increases health monitoring by using the computing capability of emerging wearable and other IoT devices for sophisticated healthcare applications. The most important effort is made by BAN devices (wearable or sensors) to analyse applications prior to providing high-level data to medical staff equipment for evaluation. Figure 2 shows the suggested computational components of the framework in general. Unlike previous BANs [13], this one requires the user to wear the device rather than use the device's computer capabilities. The capabilities of BAN' things' are combined with sensing and computing in this technique. That is, there are things that can only detect (for example, biosensors), calculate (for example, cellphones), and perceive and compute (for example, computers) (i.e., smart watch). They may all connect to establish a wireless network and share information.

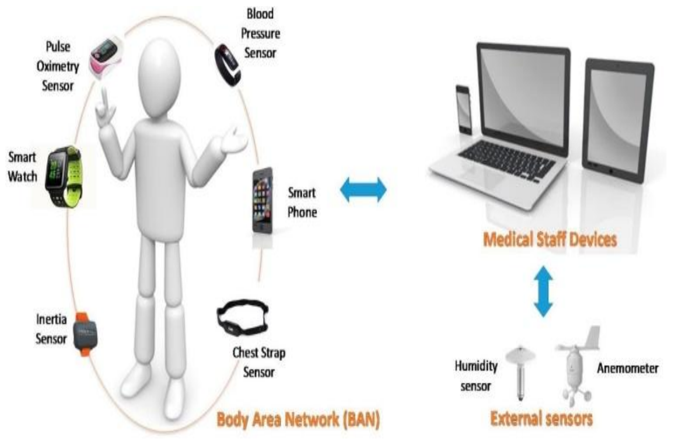

Figure 1.Diagram of the computing elements of the framework.

The Internet of Things (IoT) is a collection of devices computer components. A LAN (Local Area Network) is widely used to connect the devices (LAN). As a result, a wireless local area network is created by such equipment. The objective of creating WLAN standards was to provide ubiquitous internet access while improving network performance at the same time. Table 2 outlines some of the most important elements of the most recent modifications to the standard [14, 15].

Table1. Current WLAN standards feature.

Technology(Release Date)	Frequency Band	Data Rate	Application
802.11ac(2014)	5.4GHz	1.3 Mbps	High speed scenarios
802.11n(2009)	2.4; 5.4GHz	600Kbps	Standard scenarios.
802.11ah(2016)	0.9GHz	100Kbps	Indoor/outdoor IoT scenarios.
801.11ad(2012)	60GHz	7 Gbps	Highdensity and extra-highspeedindoor Scenarios

Because they must divide the available bandwidth, the maximum number of mobile platforms or terminals connected to a WLAN is restricted by the connection's transmission speed. By gazing at the access point, any device's current transit speed may be ascertained. However, the entire bandwidth of the instrument must be used to determine relative importance. When computer terminals are mobile and connected via typical wireless networks, estimating how much more bandwidth is available in a set of connections is challenging. The amount of bandwidth available is affected by the location of mobile devices on traditional networks, which swap capacity between linked devices. In such cases, estimating total bandwidth using average values received by devices during routine inspections is a viable technique.

Frame work Specification

The framework makes job allocation and sharing in apps simple to organize and set up. Table 2 shows the inputs and outputs for each proposal stage in general. There are three essential steps to the suggested architecture for developing distributed applications:

1. Breakdown of tasks and data flows

2. Planning for resources

3. Implementation and modifications based on empirical data

Table2. Frame work methodology

Design State	Input	Output
(i)Application analysis for tasks and dataflows	State-of-the-art techniques Implementations	Granularity unit Application partitioning

breakdown	Workingenvironmentconstraints Application requirements	Data-flow diagrams
(ii)Planning for resources	Network architecture Cloud market IOTenvironment	wearables,Sensors, mobile devices, and other IoT devices are configured in the IoT environment.
(iii)Implementation and modifications based on empirical data	Test Configuration setup	Distributed architecture for IoT Environment

After that, there are descriptions of how the framework works. SD detection in mobile situations is the subject of this demonstration. This approach might be used to a wide range of complicated healthcare monitoring applications or scenarios, especially those that need a great quantity of data collection and processing.

In the state-of-the-art portion, applications based on ECG analysis, particularly SD detection, were examined to emphasize the need for solutions that can be used in mobile situations when a hospital monitoring environment is not available.

1. Breakdown of tasks and data flows

The overall activity of the programme can be split down into individual activities in a variety of ways. This responsibility varies depending on the application area and kind. This time period has two unique characteristics.

To get started, devise an application breakdown strategy for assigning code for remote and local processing. The approach can be dynamic or static: in the former, smart device-friendly elements of the candidate programme are identified during the design stage; in the latter, the application code is reviewed on the fly to identify which parts of the programme can be handled outside of the device.

Second, the granularity must be determined. This option defines the application's size unit, which can be calculated discretely. Process, module, component, class, and technique are the most common choices. The application is divided using this granularity. This is the scenario due to the data transportation needs as well as the abstraction level. Although a coarse-grained model allows for a great deal of abstraction, it also needs a great deal of communication and synchronization. Fine-grained planning, on the other hand, takes considerable work. The application task is used as a granularity unit in this technique.

An assessment of existing implementations and state-of-the-art methodologies is necessary to determine the correct application split. In addition, the requirements of the application, as well as the constraints of the working environment, all influence the design of acceptable data-flow diagrams. Wearables and sensor devices, for example, are intended to function with minimal resources. In these circumstances, several essential factors, such as enhanced communication skills and energy use, must be addressed.

As a consequence, a directed graph is used to describe the target application= {T, F}

T stands for vertex set, which is a collection of data collection, monitoring, and processing application activities. After then, the application is broken down into a sequence of tasks: $=\{t1,t2,\ldots,tn\}$

The edge set F denotes the data flows that are switched between the tasks. The data flows specify the sequence in which tasks are completed and the quantity of data that is provided. The quantity of data exchanged between tasks I and j is denoted by F (i, j).

To develop an acceptable data flow decomposition for the SD application example given in this segment, this study took much time and effort. As a consequence, the jobs found are consistent with the most common SD detection processes as specified by existing methodologies.

Figure 3a shows a data flow diagram of an application that was simulated using this method. This assignment might be any of the sizes listed above, or it could be variable in size and completed in a sequential order.

2. Planning for resources

After analyzing the compute load, the following step is to identify where each job will be handled. According to the framework's concept, data is transmitted from BAN devices to other devices outside of the framework. The network architecture, as well as the IoT ecosystem, are important inputs for resource preparation at this level.

The devices D involved are specified as follows in line with the proposed framework:

- Assume that B represents the BAN's "things" or gadgets. The users must wear these gadgets at all times. One of their tasks is to identify and transfer data. They may also be able to process information.
- Assume M is a list of computers that the user may access from beyond his BAN. Computers and other mobile devices with processing capability fall into this group. As a result, the gadgets in this collection can show and process information.

• Assume E is a collection of external sensors. This package also includes an external device that allows the user to identify additional programme data. Environmental factors such as humidity and temperature are two examples, for example.

$$\text{Thatis:}=\{B\}\cup\{M\}\cup\{E\}$$

Processing starts at the BAN, where data is collected, and continues in more sophisticated devices spanning from B to M in this method. Data feedback from the M to the B devices is not planned, despite the fact that it is feasible. The optimal setup distributes the application's processing across time, with the goal of computing raw bio-signals in the user's closest location while lowering the number of M device connections required.

This has two key advantages: the user can keep track of more precise data, and the medical equipment can manage several users at the same time. In complex systems with a high number of users, such as a football club, this is a particularly valuable feature. A running tournament may draw hundreds of spectators, despite the fact that there are only eleven participants in this game. As a result of the proposed design, a smart BAN emerges, capable of improving medical monitoring and health analysis by accelerating the processing of complex healthcare applications.

This technique transforms the programme into a distributed application that can run on a group of D devices, as shown in the directed graph. Figures 2b–d, for example, demonstrate a variety of distributed computing configurations. Rather than giving the data to the medical staff's PCs, the application may be shared in these instances.The first three phases of Figure 2b can be carried out by BAN devices that display user data on a graph created immediately from the collected data, such as the number of heartbeats and their progression over time. Figure 2c depicts how data is processed further before being submitted for anomaly detection in order to acquire more comprehensive and accurate information. The setup is really simple. Figure 2d shows a system with two peripheral devices in addition to the BAN: the computation begins in the BAN, an intermediate device does a single work, and the second device completes the remaining tasks.

3. Implementation and modifications based on empirical data

Distributed system software components can each run on their own device, with their own set of capabilities. A multitude of criteria must be considered while selecting the right computer for each job, including CPU resources, battery life, network bandwidth availability and latency, and so on. Many of these factors, such as network capacity, might change over time.

Each machine or computer model must be configured with the resources indicated in the preceding unit. After that, the main devices' performance should be extensively evaluated for each profile and application situation. It's critical to make sure that the device can always meet the criteria. Furthermore, based on the data-flow and distributed features supplied, the distributed application must alter data flows between devices to accomplish the desired effects. System modelling and simulation may be useful in this scenario. Until the entire system is working, the resource planning stage should be evaluated and fine-tuned.

At-Home IoT Patient Monitoring System Structure:

The topology of the IoT system utilized in this study to monitor patients at home is depicted in Figure 3. The system was designed to deal with the large number of Personal Healthcare Devices (AICLOUDs) that will be required. Some of the system's components include Middle Nodes—Common Service Entities (MN-CSEs),Application Dedicated Nodes—Application Entities (ADN-AEs), Infrastructure Node—Application Entities (IN-AEs) (IN-AEs) and Infrastructure Node—Common Service Entity (IN-CSE).

The name of a piece of software put in a sensor is ADN-AE. It collects and analyses environmental signals in order to create data, which it subsequently sends to the IN-CSE on the IoT server for patient monitoring. MN-CSEs are traffic controller and procedure adaptation gateways in an IoT network, and an ADN-AE is a (Artificial Intelligent cloud programme on a) AICLOUD in the proposed system. They use an AICLOUD to deliver biological data to the IN-CSE in this investigation. IN-AEs are used by health-care workers and system officers to get access to patient data on the IoTserver. An MN-CSE manages or monitors MN-ADN-AEs, CSEs, and the processing necessary for effective multiclass communication between the IN-CSE and ADN-AEs. By connecting to a patient monitoring IoT server through an IoT network, an IN-AE may collect patient data.

This study's oneM2M-based IoT system adheres to the oneM2M standards. Two modules are then inserted, as seen in Figure 4. (Protocol Converter and MQL Scheduler). The Sensing and Network Manager modules make up an ADN-AE. In order to create biomedical data, the Sensing module receives and analyses biological signals from AICLOUD users. The biological information is sent to the Network Manager module, which converts it into oneM2M messages. The three modules that make up a CSE are the Network Manager, Message Handler, and Resource Manager. During the CSE process, the Network Manager module controls and communicates with ADN-AEs. Resource trees, which contain information about all of the objects in the IoT system, are managed by the Resource Manager module.

The CMDH (Communication Management and Delivery Handling),NSE (Network Service Exposure), , CSFs (Common Service Functions) and NSSE (Network Service Exposure Execution and Triggering) Controller are all part of the Network Manager module. The MQL Scheduler was built in response to the study's suggestions for multiclass Q-learning scheduling. Sending oneM2M messages is handled by the NSE module, whereas communication (policies) and buffer management are handled by the CMDH module. The NSSE module is in charge of the CSF and NSE connection sessions. The MQL Scheduler module makes biological data transfer scheduling decisions using the MQL scheduling method.

The Message Handler module is made up of the Message Handler/Protocol Converter and Reference Point modules. Before transforming incoming messages to HTTP and oneM2M basic messages, the Message Handler module analyses them. The Reference Point segment is in charge of HTTP headers and XML documents. The mapping between HTTP messages and oneM2M Request/Response basic messages is shown in Tables 1 and 2.

There is now more freedom and opportunity to build unique and semantically based data structures and representations that may support and integrate diverse activities, processes, and operations in healthcare systems, thanks to the introduction of business analytics and Big Data. A number of techniques may be used to produce data and meta-information regarding healthcare cuboid structures, which can subsequently be used for visualization and data mining[18, 19]. As a result of the development of frameworks for healthcare systems, particularly those with complicated disease systems, new views on healthcare representation have arisen. Data science and the exchange of fresh information assist medical practitioners[19].

The protocol conversion software components that were added to the existing oneM2M system for this investigation are depicted in Figure 5. The system's gateways (MN-CSEs) convert between the oneM2M protocol and ISO/IEEE 11073. The protocol adaptation module is made up of three C# classes that operate with Windows 7.

• AI CLOUD Message Manager class: This command controls the protocol conversion procedure from beginning to end. It also accepts and transmits information to the AI CLOUD Message Handler from the protocol conversion module.

• AI CLOUD Message Handler class: Converts protocols and sends the results to the Resource Tree Manager, who is in charge of building the gateway's resource trees.

• AI CLOUD Message Template class: There are a number of ISO/IEEE 11073 message templates available. Using templates, suitable messages may be readily produced, and protocol changeover time can be minimized.

Results:-

The methods presented in Figure 5 are used to send messages between nodes in two different cloud setups, one with one source and 50 destination nodes and the other with 100 destination nodes. The whole simulation model was run for each of the 100 permutations and combinations. In the result description, we've listed the top 5 best choices for each cloud environment. Message communications for cloud 1 with 50 nodes are shown in Figures 2, while message communications for cloud 2 with 100 nodes are shown in Figures 3.The precision and accuracy model in a cloud for communication protocol upgrading is more efficient the more nodes in a communication network.

Description	Precision	Accuracy
Cloud1(50 nodes)	97.2%	98.1%
Cloud 2(!00 nodes)	98.8%	99.4%

Table 3:- Shows the result analysis for Cloud 1 and Cloud 2 framework as per new messenger algorithm proposed

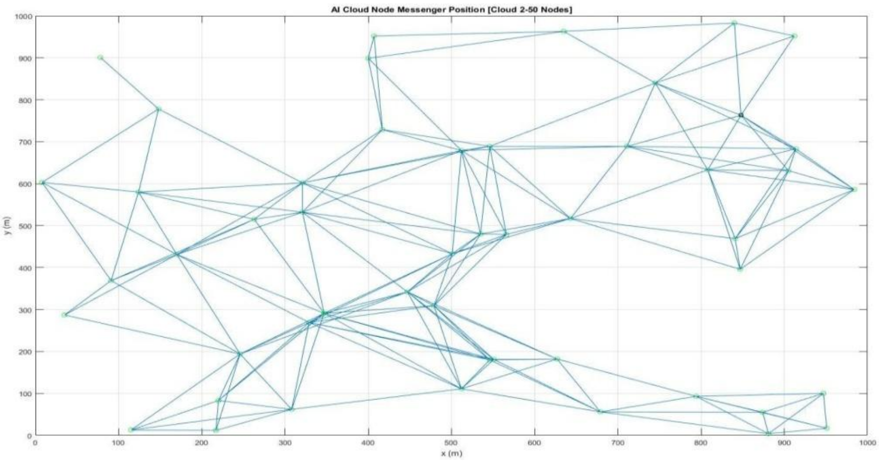

Figure 2 :-ShowingtheAICloud messenger positionfor Cloud1with 50nodes.

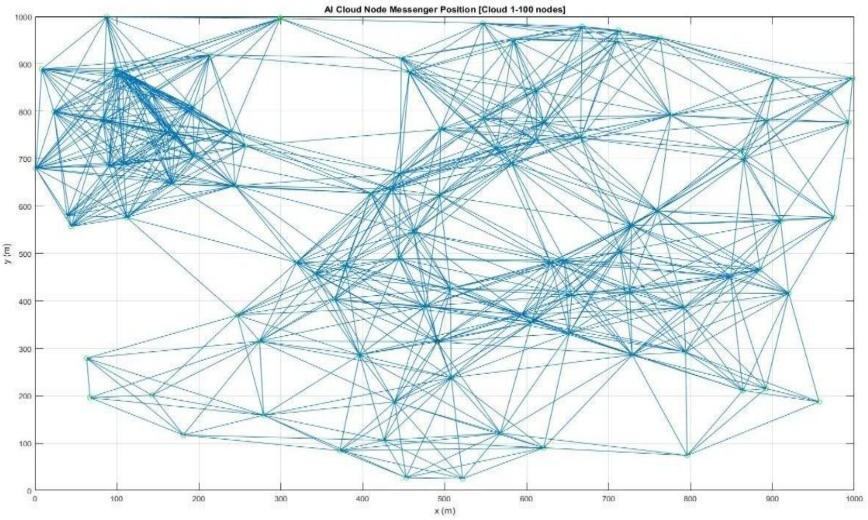

Figure3:-Showing the AI Cloud messenger position for Cloud 2with 100nodes.

Conclusion

Automation is often ascribed to the Internet of Things (IoT) for bringing it into the mainstream of 21st-century civilization. In a multi-cloud context, for example, integrating IoT, WSNs, and health monitoring systems enhances bandwidth, communication protocols, and sensor network redundancy. Current health infrastructure and monitoring systems, as well as a range of network frameworks, are all taken into account in the proposed design. The common entities involved in building communication protocols, as well as machine-to-machine protocols for health monitoring, have been explored. The purpose of this research is to demonstrate how sensor data analytics may be utilized directly in multi-cloud sensor communication protocols as well as for multi-level computing.Using encryption methods for the recommended message scheduler or message handler, the HTTP protocol may be made universal for data authentication. When a given prototype is modelled using the unique communication system, it produces a more efficient model than the traditional method, with a 98 percent more accurate system.

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