A Model for Pervasive Computing and Wearable Devices for Sustainable Healthcare Applications

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***Abstract*—The user's demands in the system supported by the Internet of Things are frequently controlled effectively using the pervasive computing system. Pervasive computing is a term used to describe a system that integrates several communication and distributed network technologies. Even so, it properly accommodates user needs. It is quite difficult to be inventive in the pervasive computing system when it comes to the delivery of information, handling standards, and extending heterogeneous aid for scattered clients. In this view, our paper intends to utilize a Dispersed and Elastic Computing Model (DECM) to enable proper and reliable communication for people who are using IoT-based wearable healthcare devices. Recurrent Reinforcement Learning (RRL) is used in the suggested model and the system that is connected to analyze resource allocation in response to requirements and other allocative factors. To provide effective data transmission over wearable medical devices, the built system gives managing mobility additional consideration to resource allocation and distribution. The results show that the pervasive computing system provides services to the user with reduced latency and an increased rate of communication for healthcare wearable devices based on the determined demands of the resources. This is an important aspect of sustainable healthcare. We employ the assessment metrics consisting of request failure, response time, managed and backlogged requests, bandwidth, and storage to capture the consistency of the proposed model.**

Keywords*—Internet of Things; wearable devices; pervasive computing; sustainable healthcare; healthcare applications; public health; health system

I. INTRODUCTION

The world has been modernized and changed into a pervasive computing system environment because of recent advancements in many applications that are capable of sensing and interacting everywhere. The devices that can work wirelessly and are enhanced with sensing, processing, and decision-making capabilities are integrated with real-world items to generate the correct service delivery for the Internet of Things. This kind of service is in high demand among businesses in the healthcare, IT, communication, and multimedia sectors. The needs of the user are met through rapid service delivery and improved "querying requests."

Integrating a wide range of devices, from sensors to intelligent machines, is necessary to access the network and all its resources. Consumers were granted unrestricted, global freedom to use resources anywhere in the world through increasing communication through the end users' devices. The device allowed a wide range of applications by connecting to the clients through external networks and services and employing adaptive conveyance mechanisms.

To provide pervasive services, it is crucial for users to concentrate on the service and receive reliable services that meet their needs. The ability to employ heterogeneous devices as a form of service is enabled by a pervasive computing environment. The services are delivered through networks that integrate the communication interface of various service systems and the fundamental systems to expand communication.

In a distributed system, pervasive computing has the authority to employ several computing paradigms to meet user expectations. It offers a variety of services, including simultaneous user access, service configuration, computer-related inquiries, resource allocation, and resource distribution. The data were scattered throughout numerous healthcare sectors, and the Internet of Things' flexible sensor network was used to combine a variety of sensors to facilitate data conveyance. The software-defined network (SDN), mobile networks, medical sensor data centers, distributed servers, and edge processing networks were all included to achieve a resilient service for edge users.

Extending trustworthy and adaptable communication is crucial but difficult and complex in the case of the large-scale pervasive computing environment. A novel dispersed and elastic computing model (DECM) has been created by previous researchers at [1] for the IoT-based wearable healthcare device in the pervasive computing environment. The developed system uses Recurrent Reinforcement Learning (RRL) to analyze how resources are distributed in accordance with demands and other allocative factors.

The pervasive computing system delivers services to the user in the end with a reduced amount of latency and an increased rate of communication for the medical wearable devices based on the calculated resource requirements. The designed system places additional attention on managing mobility in addition to resource distribution and distribution for proper data transmission over the wearable healthcare device.

By balancing the flow of requests across the network, the planned layout accelerates the processing of requests. The RRL is used in the request balancing process. As a result, the volume of requests handled increases while the response time decreases. By employing RRL to optimize the storage, the bandwidth rate is increased. Additionally, this paper analyses the design empirically and compares the results to existing methods.

This paper is organized as follows. Section II explains related works done by the previous research. Section III discusses the computing model used in our study. Section IV highlights the results and discussion of our experiments. Section V is the conclusion and a brief of future works.

II. Related Works

Azariadi et al. [2] have suggested a method for deciphering the heartbeat from the ECG and further implemented the method to a wearable medical device that does continuous 24x7 monitoring. The review of WHCD is presented by Haghi et al. [3] in both academic publications and for-profit endeavors. The method was developed to get around the challenges in device data mapping and matching using the enhanced petri net service model, according to Lomotey, et al.'s [4] presentation of an IoT architecture for data streaming delivering traceability of data route from the originating source to the Health data center."

Al-Makhadmeh, et al. [5] use the deep learning method to learn from past analyses and predict the course of cardiac disease. Higher-order Boltzmann deep belief neural networks were used by the system. A "Systematic Review of Wearable Sensors and IoT-Based Monitoring Applications for Older Adults-a Focus on Ageing Population and Independent Living" is presented by Baig et al. in their paper [6].

Yang et al.'s [7] "introduced a new method for ECG monitoring based on IOT techniques, in which ECG data are gathered using the wearable monitoring node and are directly transferred to the IOT cloud using Wi-Fi. In the IOT cloud, both HTTP and MQTTP are utilized to provide consumers with timely and illustrative ECG data. The "Smart wearable system for safety-related medical IoT application: Case of epileptic patient working in an industrial environment" was carried out by Hayek, et al. [5]. The remote care-taking applications Silva, et al. [8] "designed could be implemented for patients. This system is used as a waist belt and shoe with embedded sensors.

The Compact Wearable Meta Materials Antennas for Energy Harvesting Systems, Medical, and IoT Systems are done by Sabban, Albert, et al. Dey, Nilanjan, and colleagues [9,10] described the difficulties and potential uses of implantable and wearable medical devices. The IoT-Based Noninvasive Wearable and Remote Intelligent Pervasive Healthcare Monitoring Systems for the Elderly People were presented by Balasubramaniam, et al. Greco, Luca, and colleagues in [11] presented Trends in IoT-based solutions for health care: moving AI to the Edge. Big Data Business Analytics as a Strategic Asset for the Health Care Industry was explored by Smys, S., et al. The Cloud based Internet of Things for smart connected objects"was presented by Duraipandian et al. The "Effective Fragmentation Minimization by Cloud Enabled Back up Storage" was carried out by Pandian, A. Pasumpon, et al. The Special Section on Innovative Engineering Solutions for Future Health Care Informatics" has been discussed by Joy Iong-Zong Chen et al. [12]. Recurrent Neural Networks and Nonlinear Prediction in Support Vector Machines were presented by Raj, Jennifer S. et al. [13].

These previous works have highlighted the need for more experiments, especially for people who are using IoT-based wearable healthcare devices or employ heterogeneous devices as a form of service.

Our study is narrower in scope and restricted to IoT devices utilized in healthcare, as opposed to earlier research. The figures are provided by a startup business that works on Internet of Things devices in one of Malaysia's cities, and they receive 600 inquiries on average. With our method, we aim to outperform the existing system while maintaining the same configuration environment.

III. Computing Model for Pervasive Computing: IoT Healthcare

The pervasive computing's flexibility and elasticity are inherent qualities that enable the operation of heterogeneous devices and encourage interoperability. DECM is utilized to provide service help to many users at once. By computing the requests and optimizing the storage with RLL, the delivery rate of the service is increased.

The cloud, device, substructure, and ubiquitous layer are significant planes that make up the laid-out design. Numerous users and mobile IoT wearable devices that request resources from the cloud plane augment the ubiquitous layer. The aircraft accepts mixed-applications usage and conveyance methodologies that assess user requirements in accordance with information storage standards. Additionally prevalent on this level are computing and data analytics.

The proposed framework is presented in a block diagram in Fig. 1.

As in SDN, the device plane makes up the control plane and performs the crucial computation of requests and storage optimization to increase the communication rate. The substructure plane is equipped with access points, gateways, and BS that support heterogeneous communication by integrating a variety of data conveyance technologies based on Internet of Things-related sensor technology. The potential of the substructure plane to cover a wide geographic region and provide users with ubiquitous communication is what makes it significant. The information that has been gathered is stored on the cloud plane for later use. The committed cloud services handled the clients' requests for access to the information that was stored and oversaw computation and resource allocation. Even though the cloud offers authenticated customers the anytime, anywhere right to use, it still only functions as a third party.

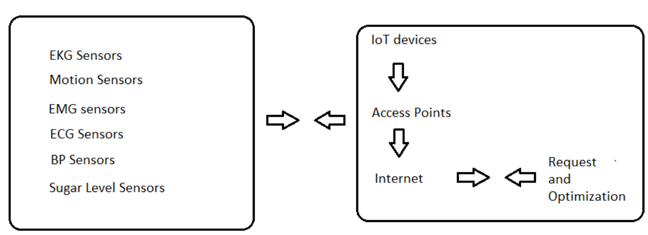

Fig. 1. Proposed workflow.

The proposed system analyses the request and optimizes the storage using RRL to increase the rate of conveyance. Utilizing a personal device that uses Wi-Fi or Zig-Bee to upload the requests, the processing of the request enables one to organize the requests and transport them to the cloud plane.

This reduces the amount of time needed to process requests, eliminates blocking scenarios, and ensures a constant flow of data into the pervasive computing environment. Eq. (1) provides an approximation of the request processing rate.

$$Request\ of\ Processing\ Rate = \frac{Requests\ from\ x\ number\ of\ devices}{Maximum\ time\ limit} \quad (1)$$

Eq. (2) and Eq. (3) use the two parameters of device connectivity probability and the rate of request arrival to achieve the scalability function.

$$Probability\ Device\ Connectivity\ = \rho\ devices^{\frac{1}{\tau}}\ \forall \geq maximum\ connectivity \quad (2)$$

where, ρ = normalization factor τ = exponent for connectivity.

$$Rate\ of\ arrival\ = \sum_{i=1}^{number\ of\ devices} rate\ of\ arrival_i \quad (3)$$

Eq. (4), which is based on the above equations, is used to balance the rate at which requests enter and exit the network to reduce delivery delays.

$$balancing\ rate = \begin{cases} Request\ processing\ rate\ X, \max time\ taken\ X\ processing\ tin \\ \frac{(1-\Delta)X\ service\ time}{rate\ of\ arrival\ time}\ , for\ processed\ requ \end{cases} \quad (4)$$

Recurrent learning is used to manage the discrepancies in the conveyance. By controlling the defects in the hidden layers, the learning process for request processing, and storage optimization are used to obtain the desired outcome, as shown in Fig. 2.

Eq. (5) illustrates how the learning process is used to estimate the prerequisite storage for the request.

$$Required\ Storage = \frac{1}{number\ of\ requests} \log\left(\frac{\frac{1}{l+1}\ request * rate\ of\ arrival}{1-\frac{changes\ on\ request\ rate}{l-1}}\right) \quad (5)$$

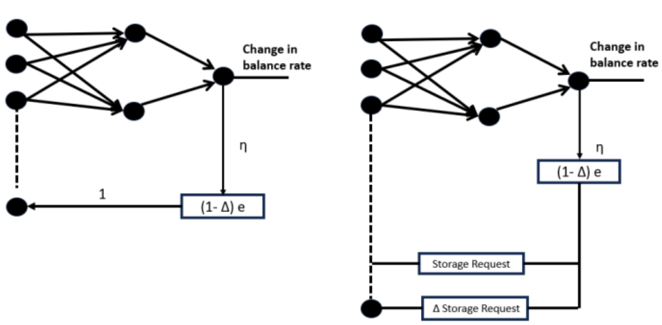

Fig. 2. Recurrent Learning for request processing (left) and storage (right).

IV. Results and Discussion

In a network simulator, we conducted the experiment using 200 IoT devices, and the settings used are listed in the table. The evaluation of the established model consistency utilizes metrics like request failure, response time managed and backlogged requests, bandwidth, and storage. The results are compared to those from other approaches to show how robust the intended DECM model is. The parameters and configurations of the experiments are depicted in the Table I.

TABLE I. Parameters and Configuration

Parameters	Configuration
Wearable Healthcare Devices	200
Flow of request	50
Pause Time	5ms
Bandwidth	2MBps
Maximum Time	20s
Storage size	60 requests/second
Number of requests	600 requests/second

A time-based map of how long it took to produce the response is shown in Fig. 3. The backlog is decreased, and the process is sped up as the request is computed, lowering the amount of time that must elapse between requests and the required average response time.

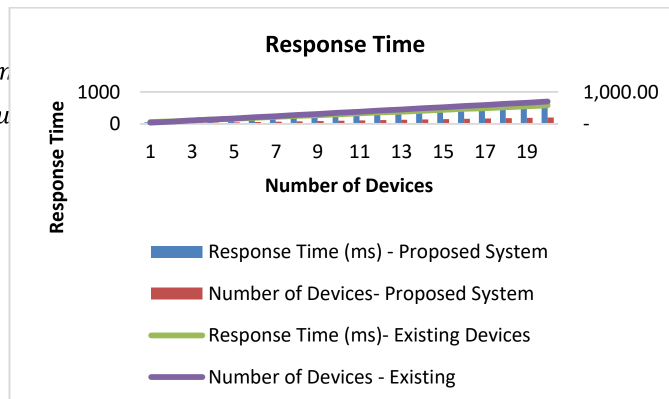

Fig. 3. Response time.

To minimize the time it takes to respond, the balancing rate makes sure that the greatest number of requests may be handled within the allotted service period. The requests are given the appropriate resources with the aid of the storage optimization procedure, which considers the storage units and modifies the succeeding requests.

The resource allocation process is improved, the dormancy in managing the requests is improved, and the count of requests handled and computed by the system is increased, which is used to reduce errors in the requests received and to optimize storage. The table compares the resources handled, the backlogs created, and the failures associated with the current and suggested in Table II.

The resource allocation process is enhanced by the RRL process, which is used to reduce errors in received requests and to optimize storage. It also improves dormancy in managing requests and increases the count of requests handled and computed by the system's architecture. Table II compares the number of resources handled, the number of backlogs, and the failures suffered in the current and planned designs.

TABLE II. HANDLED REQUESTS, BACKLOGS, AND ERRORS

Request Handled	Existing		Proposed	
	Failures	**Backlogs**	**Failure**	**Backlogs**
5000	0.30	400.00	0.13	166.67
7000	0.34	526.32	0.15	169.49
9000	0.38	555.56	0.17	172.41
11000	0.43	588.24	0.19	175.44
13000	0.49	909.09	0.21	178.57
15000	0.55	1,000.00	0.24	181.82
17000	0.62	1,111.11	0.27	192.31
19000	0.71	1,250.00	0.31	196.08
21000	0.80	1,428.57	0.35	199.20
23000	0.90	2,000.00	0.39	198.81

V. CONCLUSION

The delivery robustness of pervasive computing systems for the Internet of Things wearable devices has been increased because of the DECM introduced in this research in response to earlier work. The approach used computes the requests, optimizes the storage, and helps the flow of requests by removing bottlenecks in their transportation. Additionally, optimized storage distributes the storage for a variety of requests with different densities, preventing bottlenecks in resource allocation. The experiment's findings demonstrate how consistently the suggested architecture works better than the existing one. The future focus of this paper is to create a system with other improvements to help multiple heterogeneous applications run simultaneously.

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