

RESEARCH ARTICLE

Simulation and Assessment of Vertical Scaling for a Smart Campus Environment Using the Internet of Things

MIRZA ABDUR RAZZAQ¹, JAVED AHMAD MAHAR¹, ARIF MEHMOOD²,
GYU SANG CHOI³, AND IMRAN ASHRAF³

¹Institute of Computer Science, Shah Abdul Latif University Khairpur, Khairpur Mir's, Sindh 66111, Pakistan

²Department of Computer Science and Information Technology, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan

³Department of Information and Communication Engineering, Yeungnam University, Gyeongsan 38541, South Korea

Corresponding authors: Gyu Sang Choi (castchoi@ynu.ac.kr) and Imran Ashraf (ashrafimran@live.com)

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ABSTRACT The concept of scaling in the Internet of things (IoT) refers to the capacity of expanding the number of Internet-connected devices. From the perspective of exponentially increasing IoT devices, scaling is an important research topic. According to a future flexibility point of view, a smart campus holds significant importance and requires an in-depth study. This study presents a new scalability categorization, comprising the device layer, gateway layer, communication layer, and server/cloud layer. Furthermore, the transport system of the smart campus is assessed and analyzed at the server layer using a custom-based simulator created in Visual Studio. According to the outcomes, raising the workload causes the server's response time to increase. Response time is reduced as a result of scaling up. When scaling up to a specific point and raising the workload, response time further increases resulting in demanding horizontal scaling in the future. This study is expected to aid in determining the capabilities of current and upcoming smart transport systems in the context of smart campuses.

INDEX TERMS Internet of Things, scaling taxonomy, vertical scaling, horizontal scaling, smart campus.

I. INTRODUCTION

The Internet of things (IoT) implements the concept of anything to anybody from anywhere at any time and connects them using the network service to frame objects as more smart, efficient, and productive communicators [1]. The IoT is the most potent technology available today for integrating numerous heterogeneous devices into a central network for information access and sharing. The device has sensors and is networked with computers and mobile devices to share data. In the last few years, the number of IoT devices are increased exponentially. With the aid of IoT, the whole world is getting digital and intelligent enhancement. The cloud provides a platform to remotely access, retrieve and store data while IoT devices transmit data over a network resource. In addition,

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cloud computing is envisioned as the leading player in the fourth industrial revolution to enhance IoT [2]. Devices are connected to the Web via communication channels such as Wi-Fi and mobile data connections such as 3G, 4G, long term evolution (LTE), 5G, and so on. The wide use of IoT devices for health, transportation, etc. has increased their applications in different fields of life. Figure 1 depicts the breadth of varied applications of IoT devices in the real world.

IoT is a superset of the most recent generation of wireless sensors and actuators networks. The basic concept is that everything (devices, items, gadgets, objects, or nodes) may be connected to the Internet at any moment and job. It can link up to any device over any network by employing some services for making lives smarter and easier. Some examples are IoT in home automation, all smart home devices are connected to the internet in the smart home environment to save energy. While in industries IoT provides a platform to build

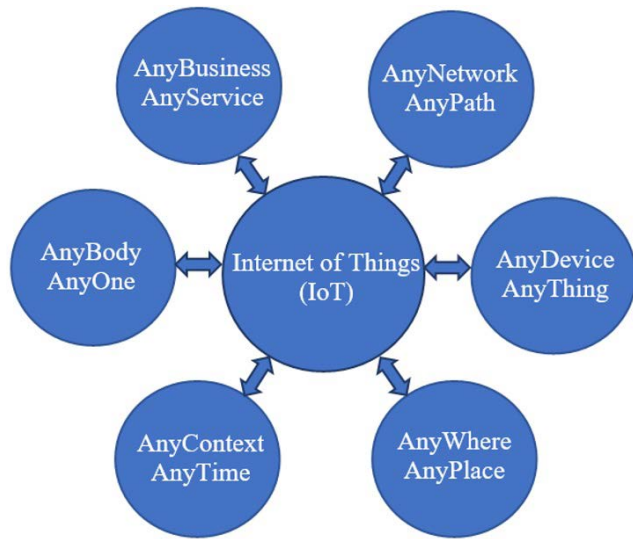


FIGURE 1. Diverse applications of the internet of things [1].

automated industrial systems and applications like assembly line management. Whereas in the medical field, IoT devices are being utilized in the smart health care systems for the assessment and monitoring of patients [1]. It was predicted in 2010 that as the rate of expansion accelerates, the number of connected gadgets will outnumber the number of possessors. In 2030, it is expected that the number of linked devices will reach approximately 90 billion [3], [4], [5]. Table 1 shows the rapid expansion of IoT devices from 2010 to 2030. Smart transportation, road condition monitoring, traffic management, smart logistics, smart city, unintentional measures, urban management, smart sports, smart tourism, smart atmosphere, mobile-Learning, smart manufacturing, smart grids, smart health care, municipal administration, smart homes, and home entertainment, are all areas where IoT devices are used in smart societies [6], [7], [8]. IoT infrastructure also includes wireless sensor networks, in fact, they are considered the pivotal element of this infrastructure. IoT objects are linked to IoT gateways, switches, or hubs, which send data to IoT cloud servers over a communicating network. IoT idea functions as a link between the physical and digital worlds, allowing objects to interact with one another in ways such as machine/human to human/machine with maximum possible alternatives [9].

TABLE 1. Estimated annual increase in IoT devices.

Year	Globe populace	IoT gadgets	IoT gadgets per human
2010	6.8 billion	12.5 billion	1.84
2015	7.2 billion	25 billion	3.47
2020	7.6 billion	50 billion	6.58
2025	8.1 billion	75 billion	9.27
2030	8.5 billion	90 billion	20.5

IoT is a system of networked objects such as sensors (smartphones, vehicles, buildings, etc.) and actuators that generate a significant amount of data, which results in big Data. The sensing devices continually gather and transfer data to the IoT server. Big data is termed as 4Vs: volume,

value, velocity, and variety. In the decade 2010-2020, the data capacity rose forty-four times and reached 35 ZB from 0.8 ZB. As a result, future IoT applications may face scaling difficulties due to the massive influx of data from IoT objects [10]. Scaling, in the IoT, refers to the future expansion of linked objects with the Internet which are used for detecting, updating, monitoring, and sending data in order to create information and gain understanding to accommodate more data processes over the normal case.

The discussed research works are analogous to such research highlights in terms of framework, a number of gadgets, gateways/routers, transmission technologies, and server types; however, the layout of the selective campus, the number of gateways, devices, transmission technologies, and the kind of server machines are all dissimilar. The created system uses instantaneous methods and transmits available data to make decisions, which is the research’s main innovation. Keeping these points in view, this study participates toward scalability solutions and makes the following key contributions

- A new scaling classification approach is presented which is divided into four layers: device layer, gateway layer, communication layer, and server layer. The classification is based on IoT infrastructure. Gateways are used at the edge to provide wired or wireless connectivity to IoT objects. Devices are employed so that vertical and horizontal scaling may be implemented, much like at gateways. The cloud/server is connected to the gateways via wired or wireless connection. As a result, scalability may be used at both the communication and server levels.
- The vertical scaling is performed and assessed of the transport system for the smart campus at the server layer. A custom-built simulator is utilized, as a case study, for accessing the vertical scaling of a smart transport system at the server layer.
- Performance is analyzed regarding different parameters like the number of buses, response time, etc. Performance with existing studies is also carried out to analyze the efficiency of the proposed approach.

The remainder of the article is explained as follows. Related work is presented in Section II, Scaling is explored in-depth in Section III. Section IV discusses scaling testing. Results and discussion are presented in Section V, and the conclusion is ultimately finalized in Section VI.

II. RELATED WORK

The number of research studies has boomed for IoT during recent years and several important aspects of IoT technology have been investigated. For example, a container technology is suggested by Aruna and Pradeep in [11] to link many IoT objects at gateways for IoT applications. The technology is utilized to store and process data, allowing the network to grow while improving network proficiency. The container technique is utilized in clusters in a distributed fashion. In [12], the authors suggested a decentralized method for scalability in which a hybrid cloud computing environment

(private for delicate and public for large data) is used for the management of data to exchange data among many partners. Gharbieh *et al.* [13] presented a tempo-spatial mathematical framework stochastic geometry and queuing theory to get over the restricted uplink bandwidth of mobile networks, which is a scaling challenge at the communication layer. To entertain vertical scaling in communication channels, the framework enforced three communication techniques: back off, communication consistency, and energy ramping. IoT devices are connected gateways to upload collected data using uplink bandwidth. The uplink bandwidth should be scalable to accommodate varying requirements of more captured data. So, this technique impacts IoT technology to enhance scalability. In [14], Lenka *et al.* developed a method for making the IoT network scalable by separating clusters as sensing regions, accumulating the gathered data, and communicating to decrease power consumption.

Diyan *et al.* [15] presented a Data Loading and Storing Module (DLSM)-based scalable multitasking Internet of Things Gateway (IoTGW) for the contemporary IoT era (DLSM). A highly dynamic distributed framework is made possible by the combination of the offered DLSM module with the Gateway module's services, which include an orchestrator, versatility in the sensing domain, and application domain. Additionally, a hybrid Adaboost-Multilayer Perceptron data classifier module was added to the proposed work to improve the service delivery of IoT gateways to numerous IoT application facilities and protocols and to support IoT requirements for multitasking, classification, interoperability, and quick data distribution between multiple modules.

Raj and Srinivasulu [16] created a working prototype for a Raspberry Pi VPN gateway that connects the local network to the ISP network. Through this network employing the suggested prototype assured security and scalability.

People's lives are changing as a result of intelligent things and applications that are used in every aspect of life. One of the crucial technical supports among them is the location service. Location prediction is a crucial component of location-based services and is essential to both the recommender system and the design of urban resources. Currently, position prediction tasks make extensive use of GPS-based trajectory data. The category of spatiotemporal series data, which also includes time and location information, includes GPS trajectory data. The intelligent optimization algorithm significantly improves optimization technology and offers a workable solution for those combinatorial optimization issues that conventional optimization technology finds challenging. GPS trajectory data offers the benefits of extensive coverage, rapid updating, simple collecting, and low cost, and it also denotes a variety of road network data. In turn, this has led to the steady emergence of GPS user trajectory data as a fresh source of information for the automatically generated urban road network and as a popular area of study for many researchers [17]. In order to address the drawbacks of current GPS tracking and positioning, the scholars also introduced the notion of a swarm intelligence algorithm. A Swarm

intelligence algorithm is used to create and implement a data analysis and behavior prediction system for computing GPS user trajectory.

After identifying the required criteria of a smart university/campus, Fernández-Caramés and Fraga-Lamas [18] explored state-of-the-art transmission techniques and blockchain-type architecture. In [19], Marques *et al.* discussed the scaling, mobility, and availability of IoT improvements in health care, as well as portability and privacy issues of IoT. In [20], the authors looked into the security trade-offs of the smart home.

Nie [21] introduced the use of cloud computing and the IoT in education. The discussion of the current state of smart campuses was followed by an explanation of how digital campuses differ from smart campuses in terms of both old and new technologies. By developing a model and application structure for a smart campus based on cloud computing and the IoT, examining how to use it, and lastly talking about how to implement it extensively.

Cloud computing and associated technologies were presented by Li [22], who then examined the requirements for a smart campus service platform and, in light of those findings, created a smart campus service platform based on cloud computing technology to support the growth of smart campuses.

Innovative tracking methods in automobile or transportation systems, among other IoT-based applications, demand the movement of the IoT device across various IoT technologies. Ayoub *et al.* [23] analyzed two multi-attribute decision-making procedures, TOPSIS and SAW, and examined four LPWAN strategies to determine the best IoT solution based on factors like bit rate, coverage, energy consumption, etc. In terms of selecting and organizing the technologies, the TOPSIS technique outperforms SAW. SAW has a shorter running time, though.

III. SCALING IN IoT

Scalability is separated into two kinds, are further subdivided into several sorts and layers.

A. SCALABILITY IN CASE OF IoT FUTURE FLEXIBILITY

In an IoT system, scaling also discusses the upcoming flexibility. In case the setup does not fulfill varying needs, it is necessary to restructure it, which is budget and time-intensive. Vertical and horizontal scaling are the two forms of scaling that may be distinguished with respect to flexibility [24]. The next sections go through the specifications of each kind.

1) VERTICAL SCALING

Vertical scaling is also termed scaling up. Vertical scalability implies the capacity of an IoT server, transmission media bandwidth, gateways, and devices to facilitate additional data than typical function [25]. It belongs to the capability and efficacy of assets such as executing capability, communication bandwidth, and storage ability of linked devices in fulfilling varying desires. The advantages of this form of scaling are that it involves less energy than many nodes, it is simpler to control owing to a single machine unit, and cost, software implementation, arrangement, installation, and all are

manageable. There are also particular problems, such as the probability of machine malfunction, a greater working expense, and so on.

2) HORIZONTAL SCALING

Horizontal scaling also called scaling out, implies a setup that can control huge expansion in the number of IoT servers, devices, gateways, and hardware-software nodes and tackle greater info process whilst running as a unified node [26]. The notion is that with the increasing number of IoT cloud servers, routers/gateways, and devices, the setup should adapt to accommodate varying upcoming needs. The cluster of nodes in a workload balancing system that spreads data uniformly across numerous nodes is an illustration of horizontal scaling. Horizontal scalability is advantageous with a bigger collective performance than an individual typical system and the reality that if one machine crashes, the whole scheme does not get worse.

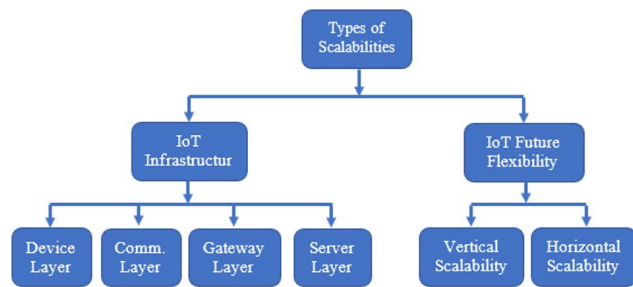


FIGURE 2. Classification of various scaling layers utilized in IoT.

B. SCALABILITY IN CASE OF IoT INFRASTRUCTURE

The suggested taxonomy is divided into four categories based on the usage of scaling at dissimilar layers in the case of IoT infrastructure: device layer, communication layer, gateway layer, and server layer scaling. The proposed classification of scaling layers utilized in IoT is also shown in Figure 2. Figure 3 explains the application of vertical or horizontal scaling at device, gateway, communication, or server layers.

1) DEVICE LAYER

Vertical scaling is utilized at the device layer as the sensing devices' ability is enhanced. Sensor capacity is often enhanced by substituting earlier sensing devices with the latest, greater-ability equivalents. Horizontal scalability is applied as the number of sensing devices is expanded. This is applied when the surrounding area of installed sensors inflates. Because of the system's scalability, it is simple to add or detach sensing nodes from an existing system and customize each sensing node's purpose (what data to produce) [27].

2) GATEWAY LAYER

Vertical scaling is also applied at the gateway layer when processing ability, volatile storing space, memory, and other components are raised. When the number of gateways expands, horizontal scaling is applied. Scalability is guaranteed at gateway in [16].

3) COMMUNICATION LAYER

Normally, the communication channel's uplink capacity is relatively lower [13]. IoT sensors collect data from the environments and transmit it to the IoT server/cloud through an uplink bandwidth. Vertical scaling is applied as the transmission capability of a communication link is raised. Horizontal scaling is applied as the number of transmission links is expanded.

4) SERVER/CLOUD LAYER

Vertical scaling is applied as the processing capability, storage capability, and hard disk space of a server at the server/cloud layer are raised, while horizontal scalability is used when the number of servers is increased.

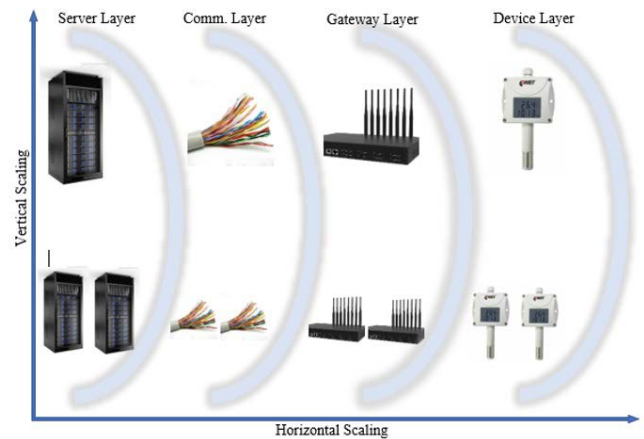


FIGURE 3. Distribution of scaling layers.

IV. TESTING OF SCALING FOR SMART CAMPUS TRANSPORT SYSTEM

The transport system of a smart varsity campus is nominated as a research study in the modern age of IoT when every field of life is attempting to be smart by utilizing IoT technologies. A bespoke virtual data source/sender and server/sink (Emulator) is created to evaluate the scaling ability. Utilizing the Microsoft Transport datasets [28], [29], [30], a smart transport system for a varsity campus is simulated in this study. The dataset is in a comma-separated values (CSV) format and comprises 17621 records. Each record contains paths and contains geographical information including latitude, longitude, and altitude. Moreover, it has global positioning system (GPS) information, as well as, the date and time stamp collected at different time spans over four years. Using this information, Microsoft Visual Studio using C# (C-Sharp) is used to develop a customized simulating software with virtual data senders and a server.

Before designing the simulator, different classifiers are applied to the dataset to evaluate the performance of these classifiers. For this purpose, k nearest neighbor, Naïve Bayes, logistic regression, decision tree, and support vector machine is utilized. Table 2 presents the accuracy, precision, and recall of the above-mentioned classifiers. The statistics show that the decision tree outperforms the selected classifiers.

TABLE 2. Evaluation metrics of classifiers.

Classifier	Accuracy	Precision	Recall
Naïve Bayes	0.79	0.80	0.79
Logistic Regression	0.87	0.88	0.86
k Nearest Neighbor	0.84	0.83	0.84
Support Vector Machine	0.86	0.85	0.86
Decision Tree	0.93	0.94	0.93
Random Forest	0.92	0.92	0.92

The comparison of classifiers is also depicted in Figure 4. Here accuracy, precision, and recall of different classifiers are illustrated as bars. The accuracy, precision, and recall bars of the decision tree has more heights than others so its performance is the best. So decision tree is implemented in a custom-built simulator.

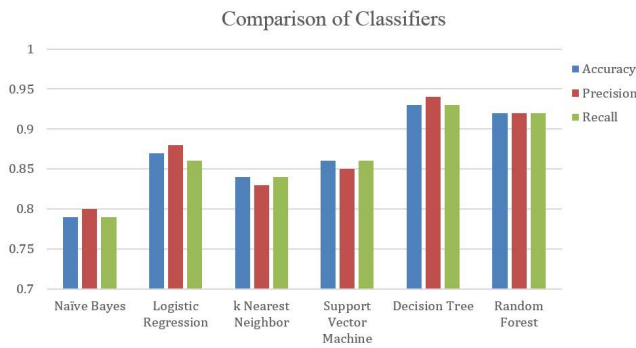


FIGURE 4. Comparison of classifiers.

The simulator’s major role is to deliver GPS data to the virtual IoT server in the form of virtual packets. These GPS data packets are created with the help of a dataset [28], [29], [30] and common-purpose GPS attributes accumulating in a CSV file. Latitude, longitude, and altitude, along with the time stamp are the most essential data items logged. The server administers the internal queue buffer to accommodate the incoming data. The IoT cloud server requires a bit of time to process all of the virtual GPS data packets, which implies that one executing cycle might consume t ms, where ms indicates milliseconds. The factor of delaying is simulated by computing the length L of the arrived virtual GPS data packet and utilizing that number L is the top limit of the delaying factor, with 10 ms as the lower limit. The delaying factor can now be written as

$$t_{packet} = rand(10, L) \tag{1}$$

where t_{packet} is the packet executing time, $rand()$ is the random function, L is the length of the packet, and the capacity limit of the virtual server’s buffer queue is 100 packets by default.

Virtual bus data are located in the source/sender buffer to mimic server workload handling, which delivers data at the pace indicated by the bus occurrence feature. The virtual IoT server/receiver continues to receive data in the arriving queue and executes packets based on the delaying factor for every queue GPS data packet. Consequently, the delay in one

executing cycle can be expressed as under

$$t_{cycle} = \sum_i^n t_{packet} \tag{2}$$

where n is the number of GPS data packets executed in a particular executing cycle.

The cycle delay uplift with the expansion of b buses as a result of greater data executing costs; the complete execution workload is expressed as under

$$t_{overall} = t_{cycle} \times b \tag{3}$$

where b is the counting of buses whose GPS data is delivered to the IoT receiver/server virtually.

The server’s average latency is now computed and written as follows

$$t_{average} = \frac{t_{overall}}{N} \tag{4}$$

The aggregate GPS data packets in the queuing buffer at the last of the execution cycle are represented by N .

On normal load circumstances, Figure 5 represents a graph of data execution time in ms at several time spans. It is found that execution time varies with time and peaks after a specific duration. When the load on the virtual IoT server is raised by adding additional buses, the time it takes to complete the task increases, resulting in a rising curve in Figure 6. Similarly, scaling up the IoT server diminishes processing time by reducing the least element of single GPS data packet delay, for instance, from 10 to 2 with five steps by decreasing 2 each time. In the random function, the decreasing fixed value widens the lowest and largest range for individual GPS data packet delay, effectively increasing the chance of minimal number choice. Figure 7 shows a falling curve.

Additionally, packet loss is another significant issue that degrades server efficiency. It happens when the IoT server is overloaded with packet processing and gains more time than the virtual IoT sender delivering GPS location packets. For instance, the queue will begin to enlarge, and its size will continue to rise till it extends to the highest capacity of 100 data packets. On this occasion, the IoT server will discard the virtual senders’ received packets, causing them to drop the packets.

A. PROPOSED ALGORITHM

The following four phases make up the primary algorithm for assessing vertical scalability. The algorithm’s flowchart is presented in Figure 8.

- **Step 1:** The virtualized transmitters send the busses’ position data (latitude, longitude, altitude) with date and time to the virtualized IoT receiver/server.
- **Step 2:** The virtualized IoT server executes all awaiting data packets from the virtualized IoT sources/senders while queued data packets reach the server’s highest ability.
- **Step 3:** Step 2 is iterated by rising the number of automobiles from the virtualized IoT senders to raise the

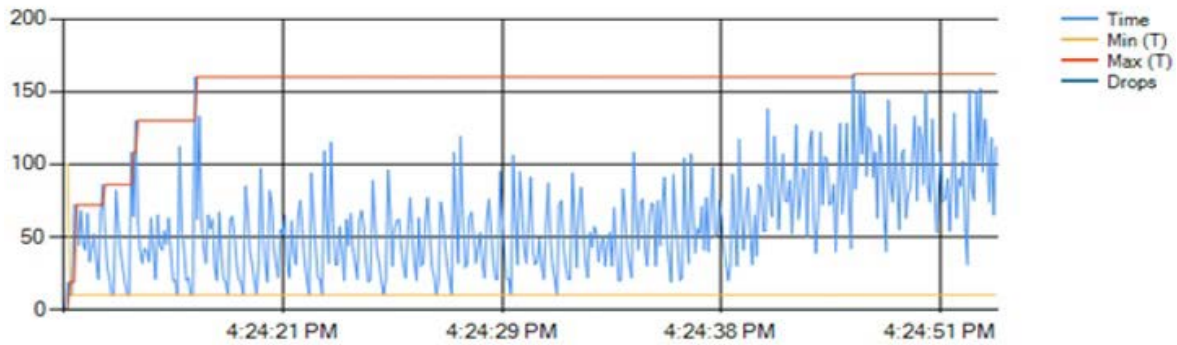


FIGURE 5. Graph illustrating the performance of a virtual IoT server under normal settings.

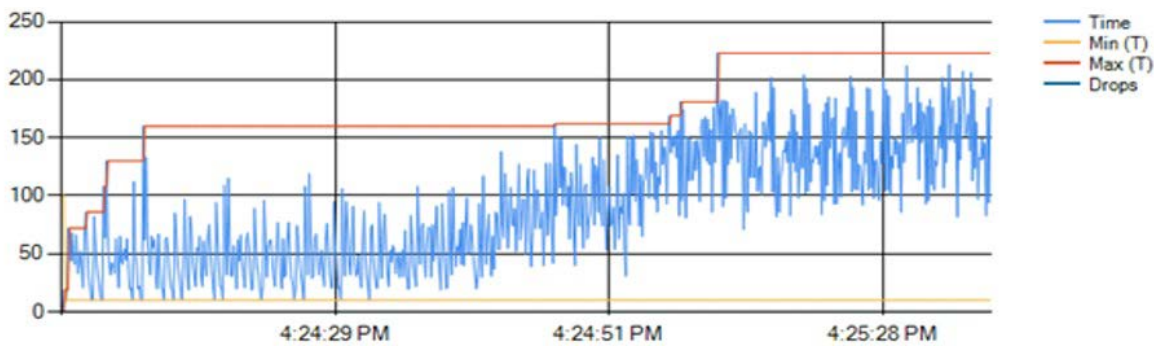


FIGURE 6. Performance graph of a virtual IoT server under stress.

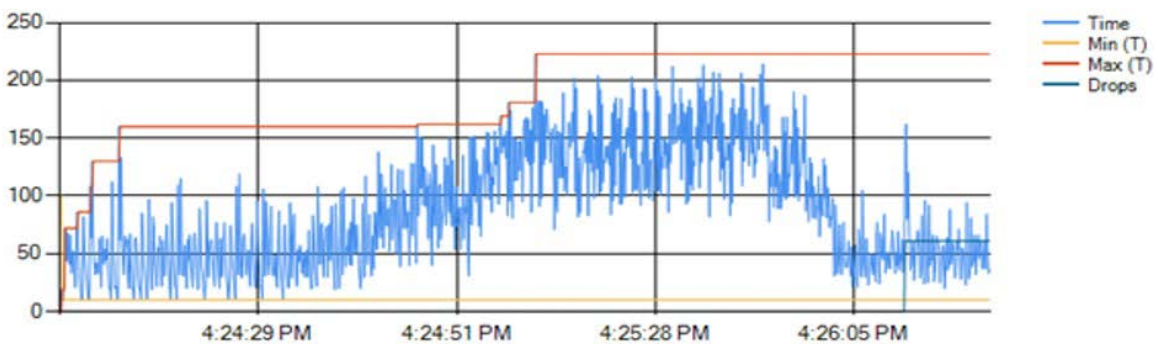


FIGURE 7. After scaling up, the performance of a virtual IoT server is shown.

receiver's workload until the server has become extra loaded and starts discarding arriving packets.

- **Step 4:** Vertical scalability is utilized to effectively manage more traffic / adjust extra buses by enlarging the execution power of the virtualized IoT server. It is done in this simulation by lessening the execution latency until it achieves a minimum definite level.
- **Step 5:** Then, we intend to apply horizontal scalability to the virtual server in the future, e.g. we will increase the number of worker threads that are emulating the server so that the performance will now increase again.

V. RESULTS AND DISCUSSIONS

The future flexibility or scaling ability is assessed utilizing three distinct sorts of workloads: light, average, and big. When a light workload is imposed, the simulation

effortlessly executes the GPS packets. Figure 5 represents a graph presenting standard operation, with the x -axis showing system time and y -axis representing processing time. When an average workload is introduced by expanding the number of buses, the simulation performs normally and gives a reasonable behavior of how the setup works. As soon as there is surging in packets caused by an increase in the number of busses in certain rush conditions, for example, admission process days or exam days, or just by an increase in the number of enrolled students, the simulator displayed a graph overburdening, as illustrated in Figure 6.

As seen in Figure 7, when scaling up or vertically scaling is utilized, the average execution time reduces again. As the number of enrolled students is rising, and smart varsity costs are also rising, as a result, the smart campus will expand admitting more students so the number of busses will also

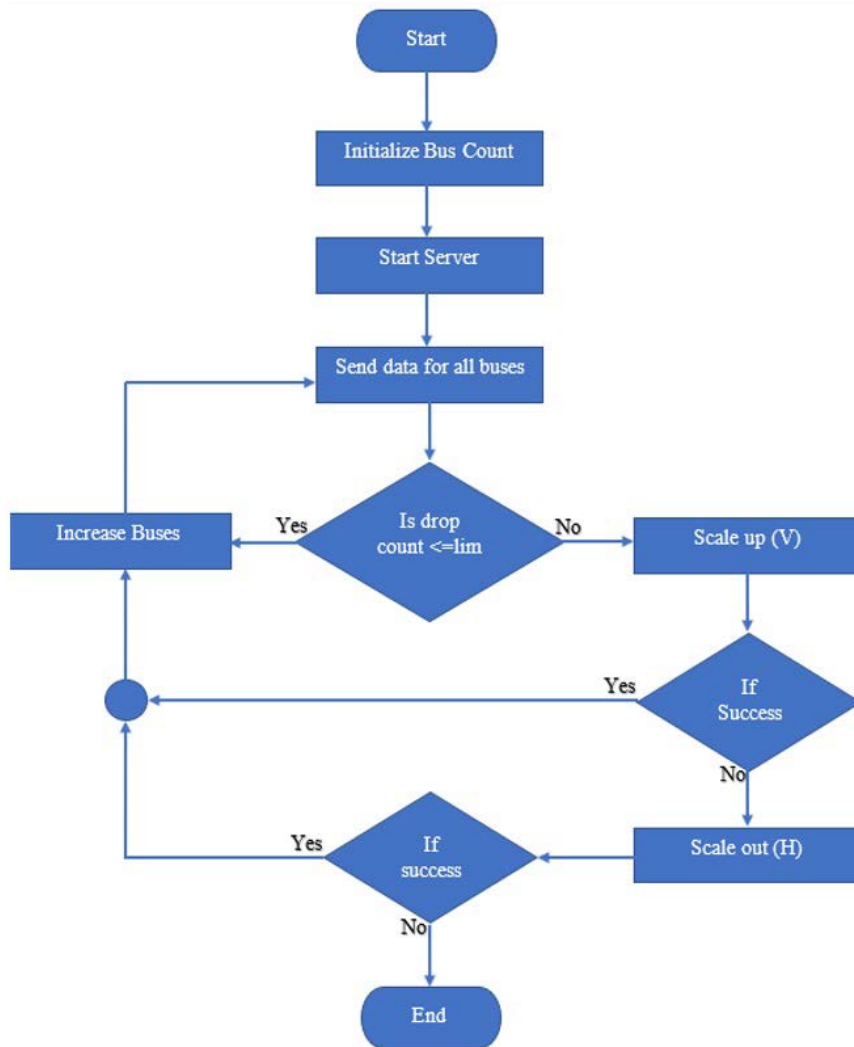


FIGURE 8. The scalability testing flowchart.

TABLE 3. Number of buses vs execution time statistics.

Buss count	Average execution time
6	34 ms
12	108 ms
21	785 ms
26	790 ms
33	827 ms

increase for picking up and dropping off admitted students for facilitating them for meeting high costs. As the number of buses grows, the average execution time rises as well, requiring horizontally scaling out in the future. Table 3 demonstrates the number of busses and the average packet processing response time in ms.

Figure 9 depicts the link between the average packet execution time and the number of buses. The average execution time is 34 ms with a load of 6 buses. The average execution time is increased for 33 buses to 827 ms. When the number of buses is extremely high to evaluate vertical scalability, the

results are not comparable, showing bottlenecks. Horizontal scalability can now be used in the future as mentioned in the flowchart.

Table 4 compares the assessment of smart campus transportation to prior studies. The load balancing of smart transportation utilizing vertical scaling assessment is explored, which is a completely new feature of the smart campus. Prior to this study, only the smart campus or smart transportation were studied separately, and in some cases, just architecture was offered, as in [22]. The algorithms are proposed along with statistical analyses, such as accuracy, precision, and recall, due to the more technical dive into the scenario.

Normally, in previous work, the debate was theoretical rather than technical. Because algorithms are provided with statistics, the work is completely new and unique in this regard. Table 4 displays entries marked as ND indicating that these parameters are not discussed. Several aspects are not covered by the existing literature, as shown in Table 4, like selected method, datasets, the context of the study, etc.

TABLE 4. Comparison of vertical scaling assessment with previous studies.

Citation	Method	Dataset (Instances/Features)	Evaluation parameters			Context
[21]	Decision Support	ND	ND	ND	ND	Smart Campus
[22]	SAAS, PAAS & IAAS	ND	ND	ND	ND	Smart Campus
[23]	LPWAN technologies	ND	ND	ND	ND	Smart Campus
[31]	PNN	ND	0.80	ND	ND	Intelligent Transport
[32]	GP & Regression	MAP DB	0.91	0.94	ND	Smart Campus
Proposed Method	Decision Tree	17621/4	0.93	0.94	0.93	Smart Campus

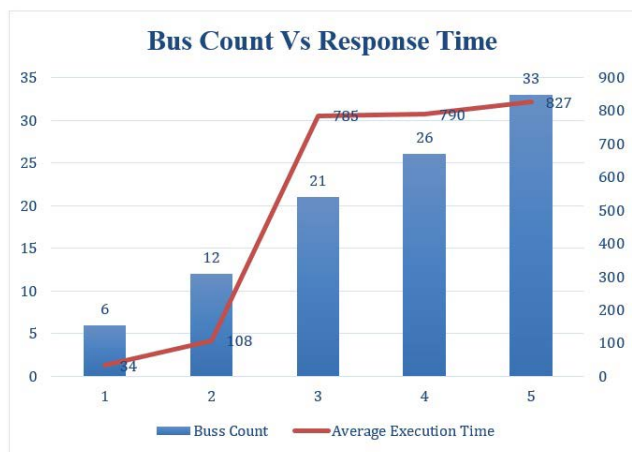


FIGURE 9. Plot showing response time vs the number of buses.

The GPS devices are installed in every bus, and the GPS devices periodically send GPS coordinates at random time intervals via mobile operator network to the smart campus IoT server. If the GPS data from buses increases due to the increase in the number of buses, then the IoT server will be overburdened. To overcome overburdening vertical scaling is applied to IoT servers by enhancing their processing power, storage capacity, etc. However, GPS coordinates have an issue of not exact positioning, so it opens new dimensions for researchers.

Almost every research work has some limitations. The limitations of conducted research work on smart transportation systems are presented here.

- The simulation is limited to the assessment of vertical scalability only.
- The buffer of the vertical server is limited to 100 packets, so more packets is being dropped.
- The scaling steps of the vertical server are limited to five steps.
- The open nature of smart transportation systems as wireless communication technology leads to many security and privacy challenges.

Smart applications such as smart transportation as well as smart parking, smart surveillance, smart lighting, etc. can also be accommodated by the IoT server because the IoT server is vertically scalable in this particular scenario in which additional requests can be handled by scaling up the IoT server. It will benefit the smart campus community and solve the issues of smart campus.

VI. CONCLUSION

The unique taxonomy explains scalability types in the case of vertical and horizontal scaling (IoT future flexibility) and device layer, communication layer, gateway layer, and server layer (IoT infrastructure). A custom-built simulator is utilized to test vertical scaling at the server layer. There are three sorts of loads: regular, medium, and large. The average execution time of the IoT server raises when the workload is high. After that vertical scalability is used until a specific point is reached, at which point the average execution time is reduced. When the workload on the virtual server is raised, the average execution time of the virtual IoT server also rises. The findings demonstrate that when the workload on the IoT server is high, the execution time of the IoT cloud server increases and becomes a bottleneck, necessitating horizontal scaling with many IoT cloud servers in the future. This study opens possibilities of how to use scaling while creating IoT systems at various layers, with appropriate vertical or horizontal types, to make the system adaptable for the future.

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MIRZA ABDUR RAZZAQ received the M.Sc. degree from The Islamia University of Bahawalpur, Bahawalpur, Pakistan, in 2002, the M.S. degree in computer science from the Virtual University of Pakistan, Lahore, Pakistan, in 2015, and the Ph.D. degree from Shah Abdul Latif University, Khairpur, Pakistan, in 2022. He is currently serving as an Assistant Professor of computer science and the Head of the Department of Computer Science, Government Associate College, Sadiqabad, Pakistan. His research interests include the Internet of Things, smart campus, the IoT security, and watermarking.



JAVED AHMAD MAHAR received the M.Sc. degree in computer science from Shah Abdul Latif University, Khairpur, Pakistan, in 1996, the M.S. degree in computer science from the Karachi Institute of Economics and Technology (PAF-KIET), Karachi, Pakistan, in 2007, and the Ph.D. degree from Hamdard University, Karachi, in 2012. He is currently a Professor with the Department of Computer Science, Shah Abdul Latif University. He has got more than 22 years of teaching experience. He has published several articles in national and international journals and peer-reviewed conference proceedings. His research interests include natural language processing, speech and image processing, big data analytics, software engineering, and programming paradigms.



ARIF MEHMOOD received the Ph.D. degree from the Department of Information and Communication Engineering, Yeungnam University, South Korea, in 2017. He is currently working as an Assistant Professor with the Department of Computer Science and Information Technology, The Islamia University of Bahawalpur, Pakistan. His recent research interests include data mining, mainly working on AI and deep learning-based text mining, and data science management technologies.



GYU SANG CHOI received the Ph.D. degree from the Department of Computer Science and Engineering, Pennsylvania State University, University Park, PA, USA, in 2005. He was a Research Staff Member of the Samsung Advanced Institute of Technology (SAIT), Samsung Electronics, from 2006 to 2009. Since 2009, he has been a Faculty Member of the Department of Information and Communication, Yeungnam University, South Korea. His research interests include non-volatile memory and storage systems.



IMRAN ASHRAF received the M.S. degree in computer science from the Blekinge Institute of Technology, Karlskrona, Sweden, in 2010, and the Ph.D. degree in information and communication engineering from Yeungnam University, Gyeongsan, South Korea, in 2018. He has worked as a Postdoctoral Fellow at Yeungnam University, where he is currently working as an Assistant Professor at the Department of Information and Communication Engineering. His research interests include indoor positioning and localization, advanced location-based services in wireless communication, smart sensors (LIDAR) for smart cars, and data mining.

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