

Performance Analysis of IoT Cloud-based Platforms using Quality of Service Metrics

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Abstract: There are several IoT platforms providing a variety of services for different applications. Finding the optimal fit between application and platform is challenging since it is hard to evaluate the effects of minor platform changes. Several websites offer reviews based on user ratings to guide potential users in their selection. Unfortunately, review data are subjective and sometimes conflicting – indicating that they are not objective enough for a fair judgment. Scientific papers are known to be the reliable sources of authentic information based on evidence-based research. However, literature revealed that though a lot of work has been done on theoretical comparative analysis of IoT platforms based on their features, functions, architectures, security, communication protocols, analytics, scalability, etc., empirical studies based on measurable metrics such as response time, throughput, and technical efficiency, that objectively characterize user experience seem to be lacking. In an attempt to fill this gap, this study used web analytic tools to gather data on the performance of some selected IoT cloud platforms. Descriptive and inferential statistical models were used to analyze the gathered data to provide a technical ground for the performance evaluation of the selected IoT platforms. Results showed that the platforms performed differently in the key performance metrics (KPM) used. No platform emerged best in all the KPMs. Users' choice will therefore be based on metrics that are most relevant to their applications. It is believed that this work will provide companies and other users with quantitative evidence to corroborate social media data and thereby give a better insight into the performance of IoT platforms. It will also help vendors to improve on their quality of service (QoS).

Index Terms: Performance analysis, IoT platform, response time, throughput, efficiency.

1. Introduction

The Internet of Things (IoT) is a technological revolution that allows devices to communicate with one another through the Internet. Basic objects (called Things) are becoming smart through IoT devices. As the number of IoT devices grows, so does the amount of data generated by these devices. It is estimated that by 2030, the number of IoT devices would outnumber human population on the planet [1]. These devices are conveniently managed via IoT platforms. The number of people who utilize the technology is likewise rising. Today, IoT users are emerging from a wide range of industries, including information technology services, higher education, agriculture, industrial automation, oil and gas, e-learning, marketing and advertising, and a host of others. This technology is being adopted and adapted in a variety of use-cases and applications, which includes smart cities, smart farming, smart healthcare systems, process automation, etc. It is basically used in system control, monitoring, and data generation for predictive and prescriptive analytics, etc.

The variety of IoT platforms is continually increasing as the number of users and use-cases grow. There is already a plethora of IoT platforms in the cyber market, which makes it challenging for businesses and other users to assess and choose the right IoT platform for their needs. Researchers have provided answers to questions such as which platform is appropriate for IoT applications using such criteria as: features, functionalities, architectures, security, communication protocols, analytics, scalability, etc. These evaluation criteria are good but they do not provide measurable metrics to assess the quality of experience (QoE) of the users. This is better assessed via the Quality of Service (QoS) provided by IoT platforms.

Currently, businesses and other users rely on online reviews based on user ratings from social media to judge the performance of IoT platforms. Unfortunately, such opinion polls garnered from social media is highly subjective and not a good basis for making critical business decisions. For example, one user may applaud a given platform while another expresses dissatisfaction with the same platform. Users may have used the same platform for different applications and may therefore have different experiences. What is needed is an empirical performance evidence to enable users make a better decision on the choice of IoT platforms to use.

This paper attempts to provide an objective performance measures for assessing IoT platforms by using statistical models to evaluate eight (8) popular IoT platforms. The selected platforms are Amazon Web Service (AWS), Microsoft Azure, Watson IBM, SAP, ThingSpeak, ThingsWorx, ThingsBoard, and Bolt IoT platforms. The platforms are selected based on their popularity – judged by number of users that patronize them. The Key Performance Metrics (KPMs) used for the evaluation are response time, throughput, and technical efficiency. It is believed that this performance evaluation based on QoS metrics will give more objective criteria for assessing the Quality of Experience (QoE) of IoT platforms, as these metrics directly impact user experience.

The rest of this paper is structured as follows: Section 2 examines related works, section 3 covers the method of data collection and the statistical models used in the data analysis, section 4 presents and discusses the findings, while section 5 concludes the paper.

2. Related Works

A number of descriptive and comparative surveys as well as performance evaluations of IoT cloud platforms have been conducted in literature to help users and developers in their selection of platforms that fit their purpose from the increasing number of platforms available. Muhammed and Ucuz [2] for example compared AWS, Microsoft Azure, and Google IoT systems based on hubs, analytics, and security limitations. They highlighted various features of the platforms and concluded that AWS is the preferred IoT cloud platform since it covers all customer needs for device connection, data analytics and security. This work is skewed towards availability of functional features of platforms but not how well a feature serves an application or user need. Sikarwar et al. [3] on the other hand surveyed several IoT-based cloud systems for their usability as well as their benefits and drawbacks. From their survey, they concluded that each cloud provider has its own unique features, but they can all be used to connect IoT devices and store data in a central server for additional processing and data analytics. Again, the conclusion from this work is opening ended, there is no metrics to guide a user in choosing a platform that will fit his purpose.

Babun et al. [4] carried out a performance analysis of popular IoT platforms. They devised an evaluation framework that takes into account seven criteria which are: topology design, programming languages, third-party support, extended protocol support, event handling, security, and privacy. The authors then utilized the framework to compare and contrast several IoT systems, focusing on their unique features in terms of communications, security, and privacy. They looked at how different IoT systems deal with security and privacy issues and outlined potential solutions that these platforms may apply to improve security and privacy in their systems. Security and privacy issues are very important features in any system, so this work is quite good in its own merit but it did solve the problem of using quantitative measures to assess QoE.

Asemanni et al. [5] presented various definitions of IoT platforms in literature and described the main characteristics and capabilities of IoT platforms. Agarwal et al.[1] grouped IoT platforms into four groups: publicly traded, open source, developer friendly, and end-to-end connectivity. The authors studied some platforms under each group based on

the generic IoT architecture and compared their features in terms of data collection, communication and application development. Senel et al. [6] presented a review of the reference framework for the Internet of Production. The authors looked through 212 IoT platforms on the market and then narrowed down to the finest solutions step by step. The chosen platforms were thoroughly discussed and contrasted in terms of features and functions. All of these works still provided open ended solutions, and did not really ease the task of choosing a suitable platform by a user.

The Security components of local IoT platforms in Korea were analyzed and compared with international ones by Yu and Kim [7] in order to achieve more secure domestic IoT growth. They observed that each IoT platform provides security solutions that are tailored to the platform's purpose and development environment. Their view was that a large majority of the presently existing platforms were created in silos, each with its own set of vulnerabilities, risks, and constraints when it comes to interacting with one another. As a result, they came to the conclusion that a universal IoT standard platform is required. They observed that it's also necessary to have a solution that can take into account the different platforms' weaknesses and threats. Yu and Kim [7] are obviously worried about interoperability of platforms, which is quite important in certain dispensations, however, the underlying QoS metrics must be considered. Hamza et al. [8] surveyed the performance metrics of program analysis (PA) and IoT Security issues and challenges and suggested future directions of PA in IoT Platforms.

Ullah and Smolander [9] tried to determine the most significant aspects of IoT platforms to consider before deciding on one. The author used the Delphi technique to verify 21 key features of IoT platforms listed in literature. Their effort was aimed at assisting businesses in selecting a suitable IoT platform from the vast array of options currently in the market. Hejazi et al. [10] offered an overview of IoT platforms, including architectures, principles of IoT building blocks, and interoperability protocols. The authors wanted to assist consumers and developers in selecting an appropriate IoT platform for their needs among the vast number and variety of platforms available. Again, these efforts at helping users did not consider the metrics that determine QoE of users, which is clearer to users in making choices.

A performance evaluation of the FIWARE IoT platform was carried out by Araujo et al. [11]. They simulated large-scale IoT installations on the FIWARE platform using emulated data via Constrained Application protocol (CoAP) and Message and Queuing Telemetry Transport (MQTT) protocols, which are critical for future smart cities. They tested the FIWARE platform in terms of vertical and horizontal scalability, and presented bottlenecks and limitations related to FIWARE components and cloud deployment. In conclusion the authors observed that, scaling vertically was not a cost-efficient technique at lower levels of demand, generally below 1000 requests per second for the tested setup. Similarly, scaling horizontally behind a load balancer did not result in a significant increase in the number of requests per second. This work focused on platform scalability using FIWARE as case study. Platform scalability is certainly important in many use-cases, however, it does not solve the problem of measurable user QoE.

Ullah et al. [12] used the characteristics of IoT platforms to distinguish AWS, Microsoft Azure, Google, IBM Watson and Oracle IoT platforms. They developed a methodology for selecting the best IoT platform for a certain firm by taking into account its individual needs and the capabilities offered by the various platforms. Again, in a smart lighting application, a performance assessment study of open source IoT management platforms employing Network Configuration Protocol (NETCONF) and Simple Network Management Protocol (SNMP) was conducted by Silva et al. [13]. The OpenDayLight (ODL) platform delivers the best results when using NETCONF based on the acquired data. Ref [12] tried a user-centric study, which is quite good but a generalized user-centric study with quantitative measures may be more helpful to users in making platform choices.

Nakhuva and Champaneria [14] discussed IoT platforms and compared some selected platforms based on their features. In comparison to the rest, they concluded that ThingWorx and Microsoft Azure are the most promising platforms for IoT solutions. Mahmud et al. [15] undertook a comprehensive review of a number of cutting-edge IoT systems in order to better grasp their underlying principles, similarities, and differences. Based on reviewed platforms, the authors introduced an IoT reference architecture. Each component was outlined, as well as the communication between them. The authors then compared their reference architecture to eight different platforms, four of which are open-source. They demonstrated that the components of their architecture correspond to those of current platforms, concluding that their IoT reference architecture may be used to compare and evaluate different platforms, as well as offer a common foundation for new IoT platform designs. These authors attempted to develop an architectural framework as a tool for comparative analysis of IoT platforms. This work makes a lot of sense to professionals but may not help many users in making informed platform choices.

From the foregoing review of current literature, it is obvious that a lot of work has been done on qualitative comparative analysis of IoT platforms based on features, functions, architecture, security, communication protocol, analytics, scalability etc, majority of which yield subjective results. However, it appears that little or nothing has been done on quantitative and more objective performance analysis based on metrics such as response time, throughput, and technical efficiency that underpins user experience. This work is an attempt to establish these measures.

3. Methodology

This section explains how data was gathered and analyzed during the course of the investigation.

3.1. Method of Data Collection

The data for the performance analysis of selected IoT cloud platforms were obtained via web monitoring and analytic tools [16]. The data collected are, response time, throughput, and traffic volume. The web analytic and diagnostic tools used were Site24*7 [17] and Similarweb [18]. Site24x7 delivers a comprehensive cloud monitoring solution for IT development and operations for small, and big companies. The service tracks real-world user interactions with webpages and applications through desktop and mobile devices. It provides deep monitoring features that allow IT development teams to keep tabs on and debug all aspects of an application's architecture, including servers, networks, and public clouds. End-user experience monitoring is conducted from over 100 sites worldwide and across many cellular providers [17]. Similarweb on the other hand is a platform that delivers online analytics services and provides users with data on web traffic [18]. Site24*7 was used to measure the response time and throughput while Similarweb was used for estimating the average number of visitors to the platforms. The data were collected for a period of 5 months (October 1 2021 to February 28 2022).

3.2. Data Analysis

Descriptive and inferential statistical models such as mean, coefficient of variation and Data Envelopment Analysis (DEA) were used for the performance analysis of the platforms. The systems were analyzed in terms of response time, throughput, and technical efficiency. Averaging and coefficient of variation techniques were used for the analysis of the response time and throughput while data envelopment analysis (DEA) was used for the analysis of the technical efficiency [19]. These terminologies are defined as follows:

i. Coefficient of Variation

The coefficient of variation is a measurement of how much a variable deviates from its mean or equilibrium position [20]. This coefficient can be used to assess a system's stability. An unstable system has a high coefficient of variation, whereas a stable system has a low value. Mathematically, coefficient of variation is given by (1)[20].

$$CV = \frac{\sigma}{\bar{x}} \quad \bar{x} = \frac{\sum_{i=1}^N x_i}{N} \quad \sigma = \sqrt{\frac{\sum_{i=1}^N |x - \bar{x}|^2}{N}} \quad (1)$$

Where \bar{x} is the mean of the dataset, x is the variable under study, N is the number of data in the dataset, σ is the standard deviation of the dataset and CV is the coefficient of variation

ii. Data Envelopment Analysis

In this study, Data Envelopment Analysis (DEA) approach is employed in the measurement of the efficiency of the platforms. DEA is a linear programming technique used in operations research to estimate the technical efficiency of a Decision-Making Unit (DMU). In technical efficiency analysis, the concern is how much of a given set of inputs is converted to output or how best has a given set of inputs been utilized. In DEA, three types of efficiencies are computed. The Overall Technical Efficiency (OTE), Pure Technical Efficiency (PTE) and scale efficiency.

OTE measures the overall success of a DMU in converting input to output given that the DMU is operating at a constant return to scale. It is thus also referred as Constant Return to Scale Technical Efficiency (CRSTE). OTE is evaluated using the Charnes, Cooper and Rhodes (CCR) model presented by the linear programming problem in (2) [21], while PTE is measured on the assumption that a variable return to scale exists between the input and output of a DMU. Similarly, it is also known as Variable Return to Scale Technical Efficiency (VRSTE). This implies that, a change in input does not produce a proportionate change in output. VRST is evaluated using the Banker, Charnes and Cooper (BCC) model given by the linear programming problem in (3) [21]. The scale efficiency is the ratio of CRSTE to VRSTE as shown in (4) [22]. It measures the amount of input that is successfully converted to output. It tells whether or not a DMU is operating at its optimum state. A scale efficiency of 100% shows that a DMU completely utilized its input while scale efficiency below 100% shows that not all the available input has been converted to output.

$$\eta_j(CCR) = \text{Max} \left(\frac{\sum_{r=1}^s v_r y_{jr}}{\sum_{i=1}^n u_i x_{ji}} \right) \quad \left| \left(\sum_{r=1}^s v_r y_{jr} - \sum_{i=1}^n u_i x_{ji} \right) \leq 1; u_1, \dots, u_n \wedge v_1, \dots, v_r \geq 1; \forall i \wedge j \right. \quad (2)$$

$$\eta_j(BCC) = \text{Max} \left(\frac{\sum_{r=1}^s v_r y_{jr}}{\sum_{i=1}^n u_i x_{ji}} - w \right) \quad \left| \left(\sum_{r=1}^s v_r y_{jr} - \sum_{i=1}^n u_i x_{ji} \right) \leq 1; u_1, \dots, u_n \wedge v_1, \dots, v_r \geq 1; \forall i \wedge j \right. \quad (3)$$

Where η_j is the technical efficiency of DMU_j , X_{ji} = Amount of input used by DMU_j , y_{jr} = Amount of output used by DMU_j , n = number of inputs used by DMUs, s = number of outputs used by DMUs, u_i = Weight of i input, v_r = Weight of r output and w is the constant of variation between the input and output

$$Scale.Efficiency = \frac{CRSTE}{VRSTE} \tag{4}$$

The data envelopment analysis of the collected data was performed using Data Envelopment Analysis Program (DEAP)[19]. The response time is the selected input variable, while the average number of connected users and throughput are the output variables. The application calculates the CRSTE, VRSTE, and scale efficiency of the DMUs (of IoT platforms) using the CCR and BCC models.

4. Result and Discussion

This section presents and discusses the findings of the performance evaluation of the selected IoT platforms, which was based on response time, throughput and technical efficiency analysis.

4.1. Analysis of Response Time

Response time is the length of time it takes a system to respond to a request for service. The response time of a system depends on the quality of the hardware and software infrastructures, volume of traffic to be served as well as the quality of the system design. It plays a significant role in the quality of user experience. The faster a system responds, the higher its performance is rated. A low response time is highly sought after in high precision decision making systems such as monitoring of health condition in intensive care unit (ICU), variables in oil and gas industry, smart manufacturing process etc. Alongside a low response, sensitive medical monitoring systems also require a high level of stability in a system’s response. This subsection presents an analysis of the mean response time of the IoT platforms under study as well as their response time stability for a 5-month period (October 1 2021 to February 28 2022).

i. Mean Response Time

The monthly mean response time of each of the IoT platforms and the amount of traffic served are presented in Fig. 1. Result shows that AWS, Microsoft Azure, Watson IBM, SAP, ThingsBoard, Microsoft Azure and ThingSpeak platforms offered the least response time of less than a second. AWS served the most traffic, between 59.2 and 64.6 million users, followed by Watson IBM, which served 25.4 to 28.4 million. ThingSpeak served the least amount of traffic, ranging from 278,000 to 310,000 users. ThingsWorx and Bolt platforms responded above a second except in January when they responded slightly below a second. ThingsWorx served 1.5 to 1.6 million users, whereas Bolt served 56,500 to 99,500 users.

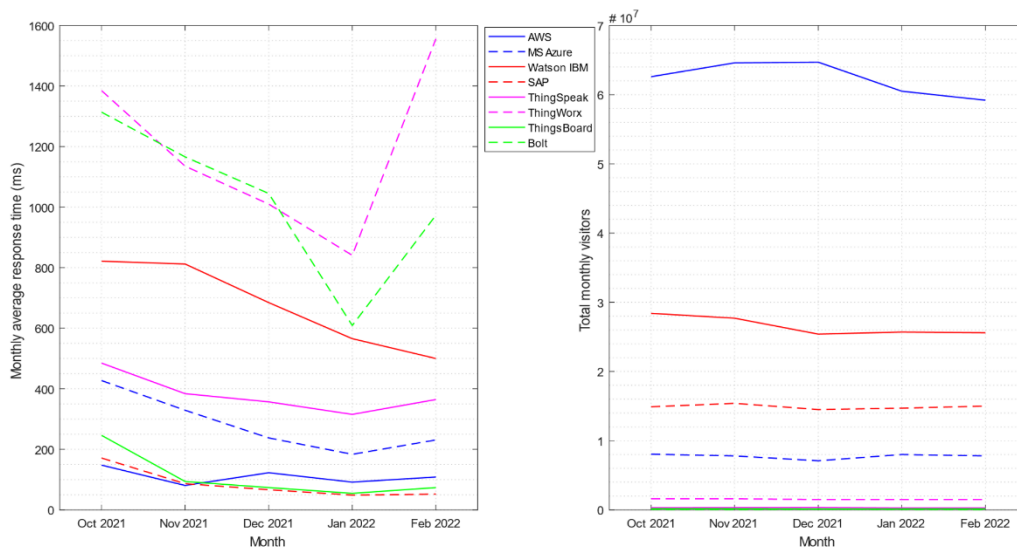


Fig. 1. Monthly meanresponse time/Total monthly visitors

The mean response time for the entire study period (see Fig. 2) showed that SAP had the lowest overall average response time (86ms), followed by ThingsBoard (109ms), AWS (111ms), Azure (282ms), ThingSpeak (381ms) and IBM (679ms) serving 13.9%, 0.14%, 54.85%, 6.82%, 0.27% and 23.38% respectively of the cumulative platforms' traffic. ThingsWorx on the other hand has the longest response time (1178ms) followed by Bolt (1021ms) serving only 1.36% and 0.07% respectively of the entire considered traffic.

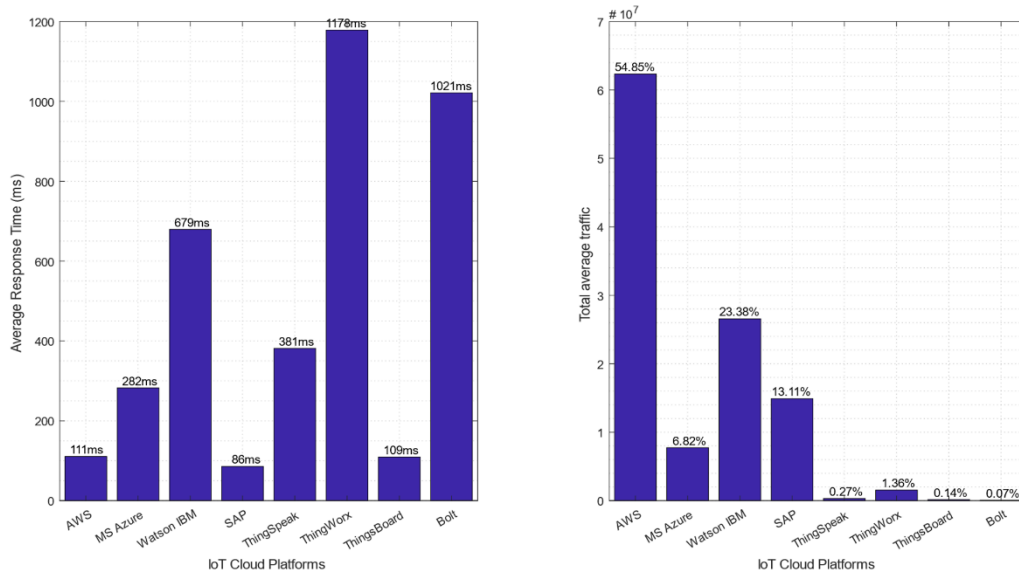


Fig. 2. Mean response time/Total traffic for the study period

ii. Response Time Stability

Beyond the response time of a system, the stability of a system's response time also plays a significant role in certain applications. For example, consider an ICU situation where a preterm baby's jaundice level is monitored via an IoT system at fixed intervals. If there is a high disparity in the system response, the study will be impacted negatively. A closer look at the response time data of the IoT cloud platforms shows that they also differ in terms of stability. Fig. 3 and 4 show the respond time characteristics of the IoT platforms for a period of 5 months.

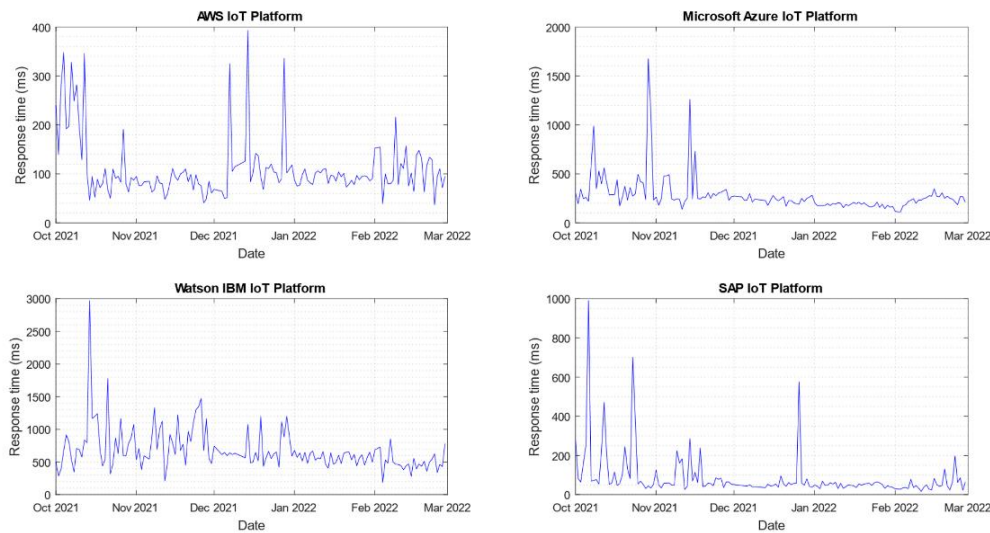


Fig. 3. Response Time Characteristics

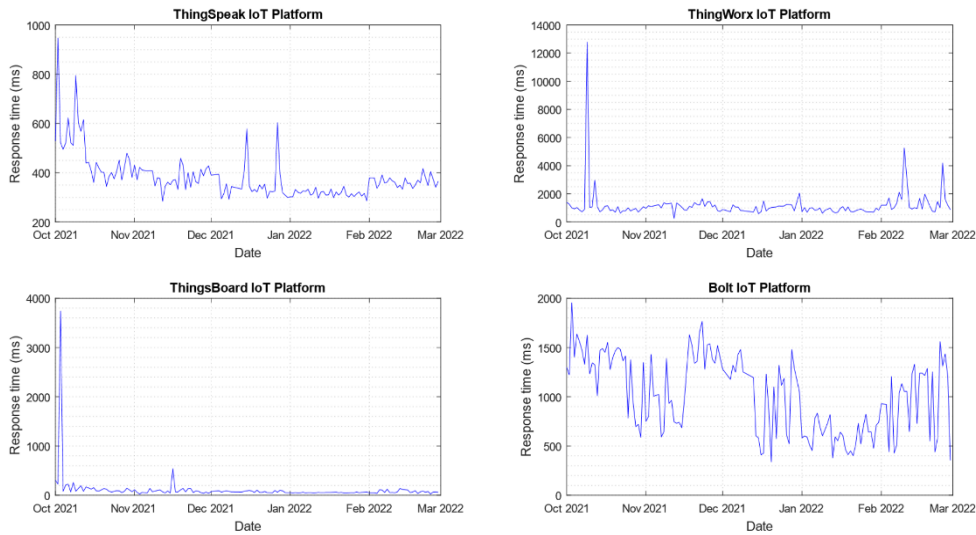


Fig. 4. Response Time Characteristics

By inspection, AWS, Watson IBM and Bolt IoT platforms show high variability in their response time characteristics. This is likely due to higher variability in carried traffic. However, a computational analysis of the variability of the gathered data will give a better judgment of the systems’ stability. This was estimated using coefficients of variation as given in (1). The computed coefficient of variation of each platform is normalized using (5) [23]

$$CV_N = \frac{CV - \min(CV)}{\max(CV) - \min(CV)} \tag{5}$$

Where CV_N is the normalized value of the coefficient of variation of a selected platform, CV is the coefficient of variation of the selected platform before normalization, $\min(CV)$ and $\max(CV)$ are the respective minimum and maximum coefficient of variation of all the platforms under study. The purpose of the normalization is to standardize the CV values between 0 and 1 in order to provide a relative judgement of their variation. Table 1 shows the coefficient of normalized variation CV_N of the platforms and consequently, the relative response time stability ($stability_{RT}$) is obtained from (6).

$$Stability_{RT} = 100 \times (1 - CV_N) \tag{6}$$

Table 1. Relative Response Time Stability

SN	IoT Platform	\bar{x}	σ	CV	CV_N	$Stability_{RT}(\%)$
1	AWS	110.55	63.11	0.5709	0.1326	86.74
2	MS Azure	282.42	190.59	0.6748	0.1736	82.64
3	Watson IBM	679.38	322.34	0.4745	0.0945	90.55
4	SAP	85.71	118.69	1.3847	0.4538	54.62
5	ThingSpeak	381.44	89.62	0.2349	0.0000	100.00
6	ThingWox	1178.35	1104.82	0.9376	0.2773	72.27
7	ThingsBoard	109.38	302.82	2.7685	1.0000	0.00
8	Bolt	1021.37	386.36	0.3783	0.0566	94.34

Results showed that ThingSpeak has the highest stability in response time (100%) followed by Bolt (94.34%), IBM (90.55%), AWS (86.74%) and Microsoft Azure (82.64%). ThingsBoard has the lowest response time stability (0%) relative to others. Fig. 5 shows a summary of the response time analysis of the various IoT platforms alongside the amount of traffic served.

According to the findings, AWS looks to be a relatively robust platform, with an average response time of less than one second and 86.74% stability while servicing 54.85% of total considered traffic volume. As a result, it is a likely candidate platform to consider in applications where response time is critical. However, appropriate platform maintenance is required to ensure that the platform's performance is maintained even when there is a larger amount of traffic. While handling large traffic volumes, IBM, Microsoft, and SAP all provided a fast response time with good stability. ThingSpeak managed 0.27 % traffic volume with a low mean response time of 381ms and 100% relative stability. As a result, it's an excellent platform to explore for low-latency applications where stability is critical, as long

as the vendors provide appropriate maintenance to handle increased traffic volume without sacrificing performance. Though ThingsBoard has a low response time, it has the lowest stability, despite only accounting for 0.14% of the total traffic volume. Though it is an excellent candidate for low-response-time applications, it is not ideal for applications where response time stability is critical.

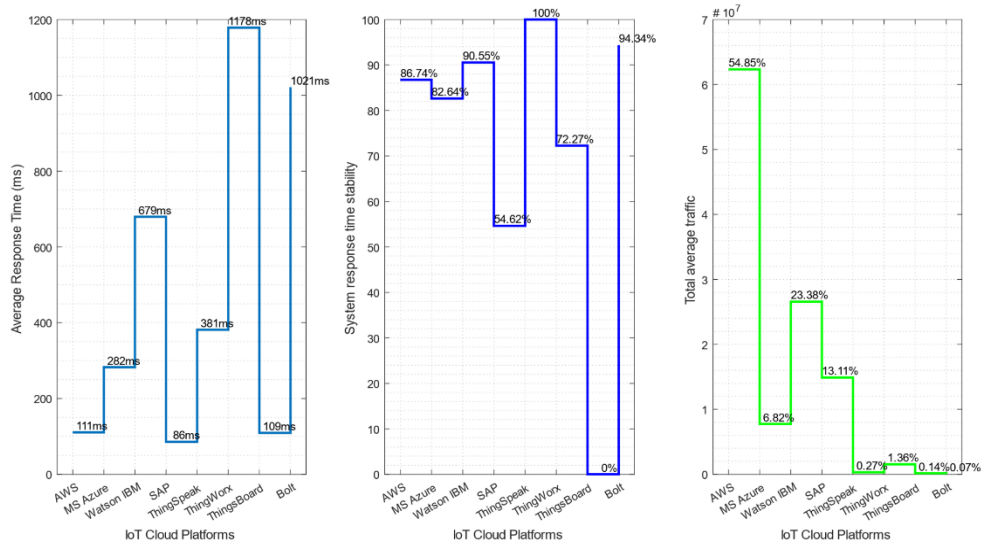


Fig. 5. Summary of Response Time Analysis

4.2. Analysis of Throughput

The amount of data successfully transmitted between a node or a user and a server during a specific period is referred to as throughput. It is determined by the server’s computing power and the number of concurrent users to be served. The findings of the throughput analysis of the platforms under study are presented in this section. The mean throughput as well as the stability of the throughput are investigated.

i. Mean Throughput

Fig. 6 depicts the monthly mean throughput provided by the platforms and the traffic volume served. The study's findings indicated that throughout the study period, Microsoft Azure and SAP platforms provided the highest level of throughput, supporting more than 10,000,000 users monthly. ThingsBoard was next with a throughput of approximately 1Mbps, followed by AWS with a throughput of between 472Kbps and 786Kbps and a monthly user base of more than 50,000,000 users. The lowest throughput was achieved by Watson IBM, ThingsWorx, Bolt, and ThingSpeak.

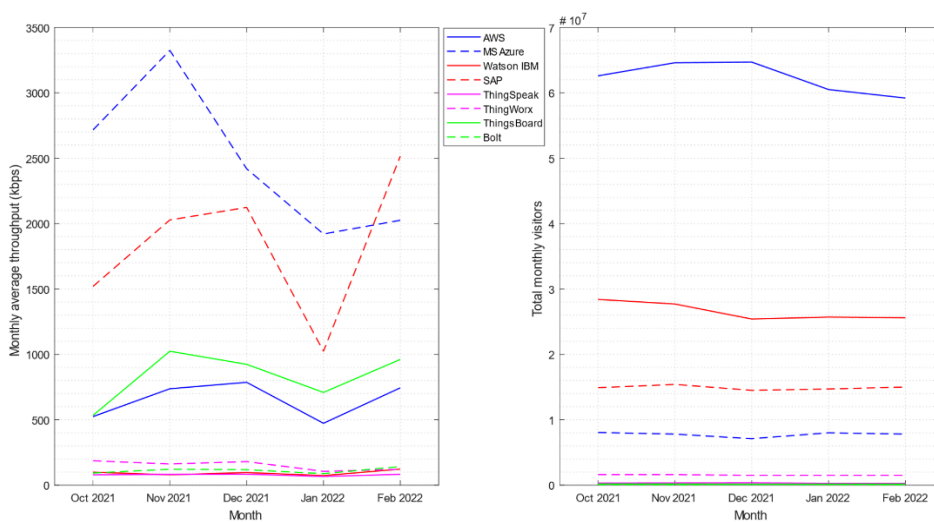


Fig. 6. Monthly mean throughput/Total number of visitors

As shown in Fig. 7, Microsoft Azure offered the highest throughput (2485kbps) followed by SAP (1827Kbps), then ThingsBoard (828Kbps) and AWS (650kbps). ThingSpeak had the lowest throughput of 79Kbps followed by Watson IBM (93.16Kbps) and Bolt (112Kbps).

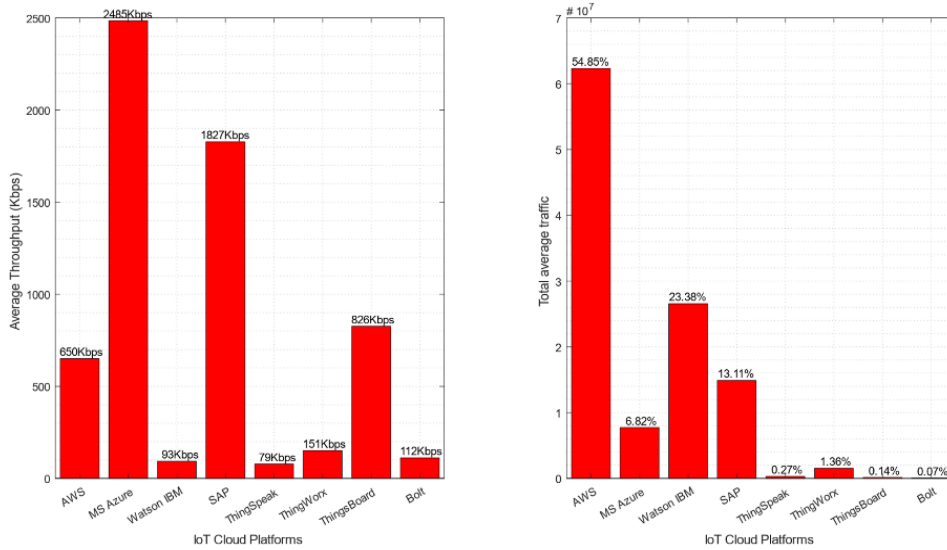


Fig. 7. Average throughput/Average traffic for the study period

ii. Throughput Stability

Fig. 8 and 9 depict the platforms' throughput characteristics over the period under consideration in order to assess the platforms' stability as a function of throughput. The figures show that ThingWorx and SAP platforms have a large disparity in throughput, despite the fact that their monthly traffic volume only vary slightly over the study period (see Fig. 6)

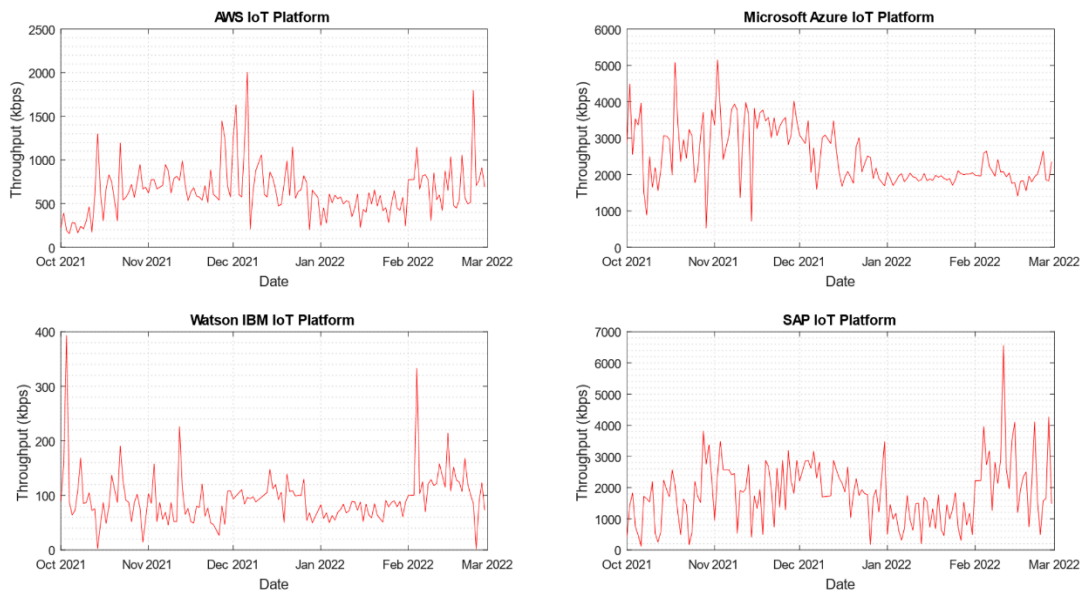


Fig. 8. Throughput Characteristics

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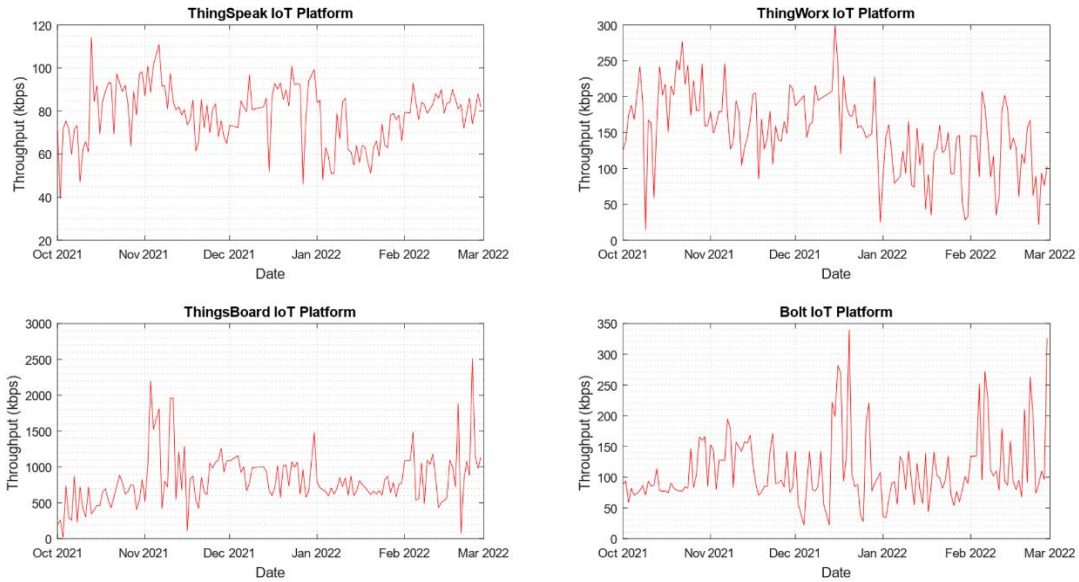


Fig. 9. Throughput Characteristics

To measure their relative throughput stability $Stability_{TP}$ (%) quantitatively, a coefficient of variation was computed on the throughput data gathered. Table 2 shows the result of the computation using (1), (5) and (6).

Table 2. Relative System Throughput Stability

SN	IoT Platform	\bar{x}	σ	CV	CV_N	$Stability_{RT}$ (%)
1	AWS	650.38	297.36	0.4572	0.7569	24.31
2	MS Azure	2484.61	813.36	0.3274	0.4115	58.85
3	Watson IBM	93.16	47.02	0.5047	0.8832	11.68
4	SAP	1827.22	1002.42	0.5486	1.0000	0.00
5	ThingSpeak	78.60	13.57	0.1727	0.0000	100.00
6	ThingWox	151.20	55.77	0.3689	0.5219	47.81
7	ThingsBoard	826.25	380.70	0.4607	0.7663	23.37
8	Bolt	111.66	56.91	0.5096	0.8963	10.37

According to Table 2, ThingSpeak platform is the most stable in terms of throughput, followed by Microsoft Azure at 58.85%. SAP was the least in comparison to the others, followed by Bolt and IBM Watson platforms. Fig 10. summarizes the platform's throughput analysis.

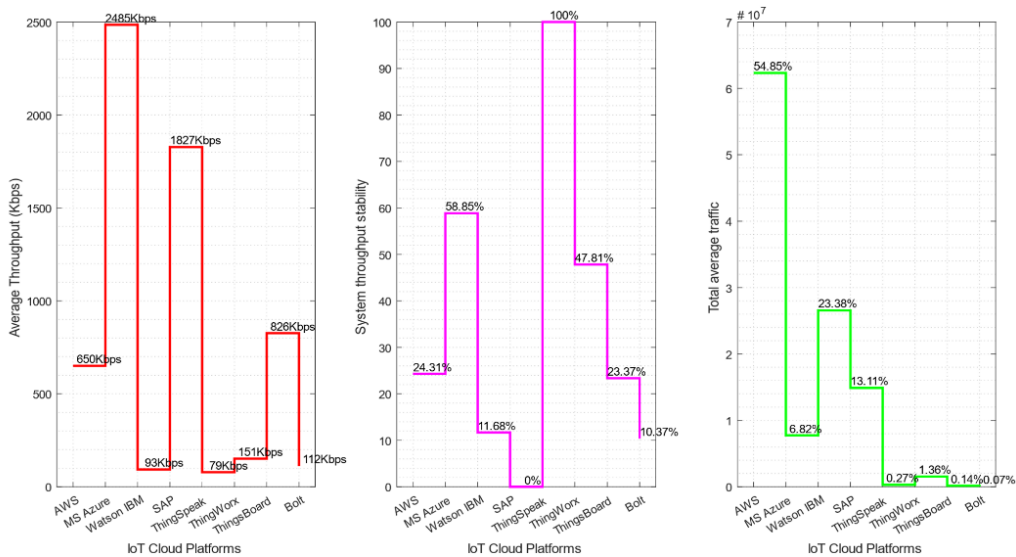


Fig. 10. Summary of Throughput Analysis

Results showed that Microsoft Azure platform has the highest average throughput with a relative stability of almost 60% under high traffic volume. As a result, it is ideal for high-throughput applications like telesurgery, where reliability is crucial. Though the SAP platform has a high throughput, as illustrated in Fig. 10, it has the highest level of throughput variability. As a result, it is ideal for high-throughput applications like computer vision, where throughput stability is not a major problem. ThingSpeak is the best in low throughput applications with high concern for stability. Though AWS has a relatively high throughput, its throughput stability is low possibly due to the massive volume of traffic on its servers. AWS and others with low throughput stability need to improve on their load balancing strategy in managing requests. ThingsBoard and Bolt platforms have low throughput stability eventhough they served the least volume of traffic. It is therefore needful for the vendors to improve on their hardware and software infrastructures.

4.3. Analysis of Technical Efficiency

The technical efficiencies of the platforms are computed using DEAP software program. The input (X) and output (Y) variables of the DMUs are given in Table 3. X_1 is the average response time in milliseconds (ms), Y_1 is the average throughput in Kbps while Y_2 is the average number of monthly visitors

Table 3. Input and output variables for the selected IoT Platforms

DMU (IoT Platform)	DMU ID	X_1	Y_1	Y_2
AWS	1	110.55	650.38	62320000
MS Azure	2	282.42	2484.61	7750000
Watson IBM	3	679.38	93.16	26560000
SAP	4	85.71	1827.22	14900000
ThingSpeak	5	381.44	78.60	309340
ThingWox	6	1178.35	151.20	1540000
ThingsBoard	7	109.38	826.25	158300
Bolt	8	1021.37	111.66	76000

The summary of efficiency metric of the data envelopment analysis result using DEAP software is given in Fig. 11

DMU	crste	vrste	scale	
1	1.000	1.000	1.000	-
2	0.413	1.000	0.413	drs
3	0.069	0.135	0.513	irs
4	1.000	1.000	1.000	-
5	0.010	0.225	0.043	irs
6	0.006	0.073	0.088	irs
7	0.354	0.784	0.452	irs
8	0.005	0.084	0.061	irs

Fig. 11. DEAP Efficiency Result

Fig. 12 illustrates the platforms' efficiencies in percentage. IRS means increasing return to scale. This implies that when there is an increase in input, the output increased with a greater proportion. DRS on the other hand means decreasing return to scale, which implies that the percentage increase in output is less than that of the input. The data envelopment analysis revealed that both the AWS and SAP platforms are performing at their optimal levels of overall, pure, and scale technical efficiency. Watson IBM came in second place with a scale efficiency of 51.3%. ThingsBoard took 3rd position (45.2%), followed by Microsoft Azure. While Microsoft Azure has a pure technical efficiency of 100%, its overall technical efficiency is 41.3%. As a result, it has a scale efficiency of 41.3%. This` reveals that the Azure platform's inputs are not being fully exploited. ThingsWorx was ranked fifth, followed by Bolt and ThingSpeak. Due to ThingSpeak's low technical efficiency, it has a high potential for growth if properly maintained.

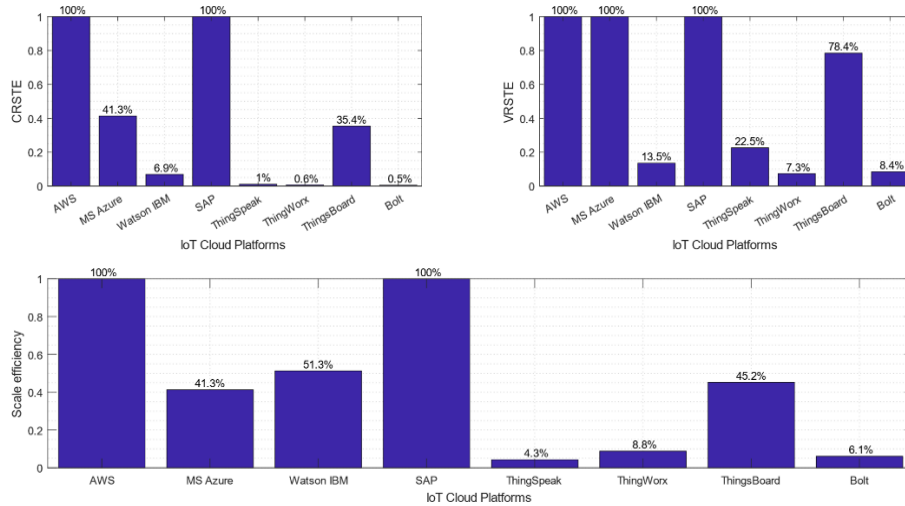


Fig. 12. Technical Efficiency Summary

5. Conclusion

This study attempted to provide an empirical evidence for assessing performance of IoT platforms rather than relying on social media data generated from users’ opinion polls, and which are usually very subjective. Analysis of data gathered from October 2021 to February 2022, revealed that SAP IoT platform is the best option for high precision decision making systems that require a very short response time. However, in applications where a reliable system response is essential, such as monitoring a critical medical condition or a sensitive variable in an oil and gas system, the ThingSpeak platform outperformed others. In high throughput applications such as image processing applications, surveillance systems, telesurgery etc Microsoft Azure platform is the best. However, in low throughput application where stability is paramount, ThingSpeak platform is the best. AWS is the most robust and resilient IoT platform, serving the largest volume of traffic with low response time (111ms) and relatively high throughput (650Kbps). AWS and SAP platforms are performing optimally, as can be seen from the technical efficiency result of Fig. 12. The capacities of the other platforms however are not being fully utilized. Adequate maintenance is therefore needed to boost their technical efficiencies.

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References

- [1] M. Agarwal, Pretti; Alam, “IoT Cloud Platforms : an Application Development Perspective Investigating IoT Middleware Platforms for Smart Application Development The advancement in sensor , actuator , computing and storage technologies has given,” *Sel. Proc. ICSC 2019*, no. October, pp. 231–244, 2018.
- [2] A. S. Muhammed and D. Ucuz, “Comparison of the IoT Platform Vendors, Microsoft Azure, Amazon Web Services, and Google Cloud, from Users’ Perspectives,” *8th Int. Symp. Digit. Forensics Secur. ISDFS 2020*, pp. 19–22, 2020, doi: 10.1109/ISDFS49300.2020.9116254.
- [3] R. Sikarwar, P. Yadav, and A. Dubey, “A survey on IOT enabled cloud platforms,” *Proc. - 2020 IEEE 9th Int. Conf. Commun. Syst. Netw. Technol. CSNT 2020*, pp. 120–124, 2020, doi: 10.1109/CSNT48778.2020.9115735.
- [4] L. Babun, K. Denney, Z. B. Celik, P. McDaniel, and A. S. Uluagac, “A survey on IoT platforms: Communication, security, and privacy perspectives,” *Comput. Networks*, vol. 192, no. March, p. 108040, 2021, doi: 10.1016/j.comnet.2021.108040.
- [5] M. Asemani, F. Abdollahei, and F. Jabbari, “Understanding IoT Platforms,” *2019 5th Int. Conf. Web Res.*, pp. 172–177, 2019.
- [6] J. B. Hoffmann, P. Heimes, and S. Senel, “IoT platforms for the internet of production,” *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4098–4105, 2019, doi: 10.1109/JIOT.2018.2875594.
- [7] J. Yu and Y. Kim, “2016 International Conference on Platform Technology and Service, PlatCon 2016 - Proceedings,” *2016 Int. Conf. Platf. Technol. Serv. PlatCon 2016 - Proc.*, pp. 1–5, 2016.
- [8] A. A. Hamza, I. T. Abdel-Halim, M. A. Sobh, and A. M. Bahaa-Eldin, “A survey and taxonomy of program analysis for IoT platforms,” *Ain Shams Eng. J.*, vol. 12, no. 4, pp. 3725–3736, 2021, doi: 10.1016/j.asej.2021.03.026.
- [9] M. Ullah and K. Smolander, “Highlighting the key factors of an IoT platform,” *2019 42nd Int. Conv. Inf. Commun. Technol. Electron. Microelectron. MIPRO 2019 - Proc.*, pp. 901–906, 2019, doi: 10.23919/MIPRO.2019.8756748.
- [10] H. Hejazi, H. Rajab, T. Cinkler, and L. Lengyel, “Survey of platforms for massive IoT,” in *2018 IEEE International Conference on Future IoT Technologies, Future IoT 2018*, 2018, vol. 2018-Janua, pp. 1–8, doi: 10.1109/FIOT.2018.8325598.

- [11] V. Araujo, K. Mitra, S. Saguna, and C. Åhlund, "Performance evaluation of FIWARE: A cloud-based IoT platform for smart cities," *J. Parallel Distrib. Comput.*, vol. 132, pp. 250–261, 2019, doi: 10.1016/j.jpdc.2018.12.010.
- [12] M. Ullah, P. H. J. Nardelli, A. Wolff, and K. Smolander, "Twenty-One Key Factors to Choose an IoT Platform: Theoretical Framework and Its Applications," *IEEE Internet Things J.*, vol. 7, no. 10, pp. 10111–10119, 2020, doi: 10.1109/JIOT.2020.3000056.
- [13] J. De C. Silva, P. H. M. Pereira, L. L. De Souza, C. N. M. Marins, G. A. B. Marcondes, and J. J. P. C. Rodrigues, "Performance Evaluation of IoT Network Management Platforms," *2018 Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2018*, pp. 259–265, 2018, doi: 10.1109/ICACCI.2018.8554364.
- [14] B. Nakhuva and T. Champaneria, "Study of Various Internet of Things Platforms," *Int. J. Comput. Sci. Eng. Surv.*, vol. 6, no. 6, pp. 61–74, 2015, doi: 10.5121/ijcses.2015.6605.
- [15] R. Mahmud, R. Kotagiri, and R. Buyya, "Fog Computing: A taxonomy, survey and future directions," *Internet of Things*, vol. 0, no. 9789811058608, pp. 103–130, 2018, doi: 10.1007/978-981-10-5861-5_5.
- [16] K. O. Shakerkhan and E. T. Abilmazhinov, "Development of a Method for Choosing Cloud Computing on the Platform of Paas for Servicing the State Agencies," *Int. J. Mod. Educ. Comput. Sci.*, vol. 11, no. 9, pp. 14–25, 2019, doi: 10.5815/ijmecs.2019.09.02.
- [17] "Website Monitoring, Website Monitoring Service, Server Monitoring: Site24x7." [Online]. Available: <https://www.site24x7.com/>. [Accessed: 25-Mar-2022].
- [18] Similarweb, "Website Traffic," 2021. [Online]. Available: <https://www.similarweb.com/>. [Accessed: 25-Mar-2022].
- [19] M. Sahai, P. Agarwal, V. Mishra, M. Bag, and V. Singh, "Supplier Selection through Application of DEA," *Int. J. Eng. Manuf.*, vol. 4, no. 1, pp. 1–9, 2014, doi: 10.5815/ijem.2014.01.01.
- [20] C. Stępniaik, "Coefficient of Variation," *Int. Encycl. Stat. Sci.*, pp. 267–267, 2011, doi: 10.1007/978-3-642-04898-2_177.
- [21] Y. Gökşen, O. Doğan, and B. Özkarakacak, "A Data Envelopment Analysis Application for Measuring Efficiency of University Departments," *Procedia Econ. Financ.*, vol. 19, no. 15, pp. 226–237, 2015, doi: 10.1016/s2212-5671(15)00024-6.
- [22] L. S. Zaremba and W. H. Smoleński, "Optimal portfolio choice under a liability constraint," *Ann. Oper. Res.*, vol. 97, no. 1–4, pp. 131–141, 2000, doi: 10.1023/A.
- [23] B. Bolstad, "Data Normalization and Standardization," *Bmbolstad.Com*, no. 1, pp. 1–3, 2012, doi: 10.13140/RG.2.2.28948.04489.

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