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Article

Event-triggered reinforcement learning-based internet data bandwidth allocation technique as a metric for balanced QoS and QoE

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Abstract: This research work studies the performance and management of the internet services of institutions of higher learning in Nigeria. Data were collated from a federal, state, and private university designated as FEDERAL1, STATE1, and PRIVATE1, respectively, in this research study. The reinforcement learning-based internet data bandwidth allocation model was developed for bandwidth allocation and prediction to enhance balanced quality of service (QoS) and quality of experience (QoE) of the users. The linear Lagrange's method of interpolation, the LILARINT model, was developed and implemented to predict and allocate effective internet data bandwidth for the significantly increasing number of internet users in each of the institutions. The problem of inability to predict and allocate acceptable internet data bandwidth with the corresponding number of internet users was solved by the LILARINT model. The Allen's PRESS regression, R^2 of the LILARINT models, was very close to unity, which is an indication that the models developed stood at the very best fit. In this research work, it is clear that PRESS regressions, R^2 for the selected institutions, were better than the regression, R^2 obtained from Nielsen's institution. Using the measured and simulated results, we found out that PRESS regression, R^2 has significantly performed best in the LILARINT model developed. In the overall comparative analysis, the FEDERAL1 LILARINT model emerged as the most reliable model developed and implemented. The model has a regression, R^2 of 0.9999, mean squared error (MSE) of 1.455, mean absolute deviation (MAD) of 122.6920, Standard Deviation (σ) of 8.2975, and mean absolute percentage error (MAPE) of 0.6274%.

Keywords: reinforcement learning-based; quality of service (QoS); quality of experience (QoE); internet data bandwidth; allocation; prediction; linear Lagrange's interpolation model

1. Introduction

The Internet has already made a tremendous impact in many countries all over the world, but it is only the beginning. The internet will dominate as the resource for sharing data within devices and networks of the communities, hotels, campuses, corporate organizations, and exotic homes that become more powerful and robust. There are many aspects of active seamless Internet of Things communications systems, which include Radio Frequency Identification (RFIDs), Wireless Sensor Networks (WSNs), Mobile Ad-Hoc Networks (MANETs), and Vehicular Ad-Hoc Networks (VANETs). Today, internet connectivity and reliability are the heart of every business operation. The campus environment is even of more paramount importance than any other establishment. Corporate organizations rely on it to run mission-critical business applications that drive productivity and profits. Campuses rely on it to promote academic knowledge, research, and intellectualism. Actually, internet access is no longer a luxury but a critical component of the overall network infrastructure that must be highly reliable and always available [1–10].

ICT-based institutions are facing a lot of challenges, which include poor internet data bandwidth optimization, prediction, and allocation. In this research work, the problem of ineffective Internet bandwidth optimization and allocation, which has resulted in a high level of service downtime in the availability of Internet access, was sufficiently addressed. The problem of poor Internet bandwidth optimization, which has resulted in a high level of service downtime in the availability of Internet access, was equally addressed. One of the greatest problems affecting the ICT-based institution is the inability to predict or allocate.

The required acceptable internet data bandwidth with the corresponding number of internet users was addressed. However, the problem of poor quality of service (QoS) and quality of experience (QoE) among internet bandwidth users was proffered solutions [11–17].

The concept of event-triggered reinforcement learning-based internet data bandwidth prediction, allocation, and control basically involves the following:

a. The change in the limit of bandwidth reservation in the Windows operating system, which could enhance internet data bandwidth speed [18].
b. The control or limit of internet bandwidth speed of individual users by the administrator [19].
c. The installation and management of Employee Bandwidth Management and Bandwidth Control Applications [20].
d. The act of limiting the speed of internet data bandwidth using software programs [21,22].
e. The means of linking internet data bandwidth with SONICWALL Bandwidth Management using Firewalls [23–25].
f. The management and prediction of average number of users and acceptable internet data bandwidth [26].

This paper is organized as follows: Section 2 broadly enumerated the recently reviewed related works and research gaps. Section 3 clearly discusses the research considerations on internet data bandwidth prediction methodology. Section 4 discusses the results of internet bandwidth measurement in a federal, state, and private university designated as FEDERAL1, STATE1, and PRIVATE1, respectively. The various sustainable comparative statistical performance evaluation analyses were fully enumerated in Section 5. Finally, we conclude this paper in Section 6.

2. Recent reviewed related works and research gaps

The recent reviewed related works and research gaps are shown in **Table 1**.

Table 1. Recent reviewed related works and research gaps.

Publication	Work Done	Results Obtained	Research Gap
[27]	Discussed and classified the literature on ML-enabled IoT upon three perspectives: Application, data, and industry.	No specific result was obtained in IoT ML- and DL-based environments.	It was just a survey without suggestion(s) for challenge(s) and solution(s).
[28]	Proposed a dynamic algorithm for internet bandwidth allocation. In addition, used a neural network to predict and improve the polling mechanism.	The bandwidth allocation was adequate and efficient.	The simulation infrastructure for the Virtual Passive Optical Network (VPON) was inaccurate.
[29]	Proposed a technique to reduce the energy consumption for IoT nodes and increase the network efficiency to route adjustment schemes.	There was no specific result obtained through this technique.	The simulation infrastructure was inaccurate due to the missing important specifications of IoT devices.
[30]	Presented an optimal control system that minimizes the closed loop of the physical system and reduces the data bandwidth cost.	This special optimal control system did not produce appreciable results.	The work neglected most IoT specifications.
[31]	Introduced a bandwidth trading framework to utilize blockchain software-defined networks.	This special bandwidth trading framework did not produce appreciable results.	There was limited implementation infrastructure, which affects the accuracy of results.
[32]	Proposed a novel concept based on statistical detection and monitoring of sensing signals.	There was no provable and verifiable result obtained.	There was limited implementation infrastructure.
[33]	Presented a novel quality of service (QoS) scheduling system to undertake the semi-automatic bandwidth slicing for processing of critical traffic in edge or cloud environments.	There were provable results on the edge/cloud servers.	It only applied to edge/cloud servers.
[34]	Presented the results that highlighted the strengths and weaknesses in the DL and ML techniques that were related to IoT technology.	There was no verifiable result obtained.	It was just a survey without suggestion(s) for challenge(s) and solution(s).
[35]	Predicted the network performance in the IoT systems by applying the LSTM algorithm.	There was no provable and verifiable result obtained.	It used long short-term memory (LSTM) without considering the IoT nature and specifications.
[36]	Surveyed and summarized the major efforts that were achieved in the field of DL for IoT technology.	There was no verifiable result obtained.	It was just a survey without suggestion(s) for challenge(s) and solution(s).
[37]	Proposed a bandwidth prediction methodology to enhance the quality of experience (QoE) in 4G and 5G networks.	The results obtained were not provable and verifiable.	Many performance metrics, such as energy consumption, were not considered.
[38]	Designed an antenna to enhance the bandwidth and communication in numerous wireless body area networks (WBAN).	There were appreciable results in the wireless body area network (WBANs).	The solution is proposed for wireless body area networks (WBANs) only.
[39]	Proposed a bandwidth adjustment technique that considered the sensitivity of applications using a queuing system in fog/cloud environments.	There were no provable and verifiable results on the queuing system in a fog/cloud environment.	The proof research claim was inaccurate.
[40]	Designed a new voltage regulator called Low Drop-Out (LDO). The regulator was used to enhance bandwidth in IoT applications.	There were appreciable results in the IoT applications.	The model used a special communication circuit.
[41]	Presented and proposed a mechanism to predict the bandwidth and connectivity between mobile devices.	The data bandwidth prediction was successful only among mobile devices.	The implementation infrastructure comprised only mobile devices.
[42]	Proposed a mechanism to maximize the number of tasks for the IoT-based 5G network environments.	The results obtained were not provable and verifiable.	The technique may struggle to reduce the computing tasks when data enters the coverage of 4G networks.

Table 1. (*Continued*).

Publication	Work Done	Results Obtained	Research Gap
[43]	Proposed a method to predict the bandwidth that was available for video streaming over HTTP.	The DL- and ML-based system could not achieve the video streaming over HTTP.	He did not consider different varieties of video size and type in addition to other data types.
[44]	Presented and proposed a method for predicting bandwidth in network links.	There was no provable and verifiable result obtained.	There was missing important data in the result evaluation process.
[45]	Predicted and allocated the bandwidth in mobile broadband networks.	There were no provable results due to the complexity of the networks.	It has a very high complexity.
[46]	Proposed a scheme to achieve real-time routing of traffic that is time-sensitive.	There were provable results obtained on the optical networks only.	There was utilization of optical networks only.
[48]	Proposed a learning methodology for software agents to control the sending rate of internet video calls.	There were no provable results due to the complexity of the methodology.	The structure of the agent increased the complexity of the proposed methodology.
[49]	Investigated a survey about resource allocation algorithms and methods in the IoT environments.	There was no provable and verifiable result obtained.	It was just a survey without suggestion(s) for challenge(s) and solution(s).
[50]	Analyzed bottleneck performance in a cloud rendering system.	There was no provable and verifiable result obtained.	He did not guarantee the required bandwidth for data transmission.
[51]	Proposed a multi-objective approach to guide the routing process in mixed IoT traffic.	There were provable results obtained in the health and care scenario.	The approach was tested using only an elderly health and care scenario.
[52]	Proposed a data communication trial to enhance the bandwidth for IoT-based applications.	There were provable results obtained in the bandwidth enhancement.	The trial was achieved only from a communication perspective.

3. Research considerations on internet data bandwidth prediction methodology

The research method for Internet data bandwidth prediction and allocation is a metric for evaluating effective internet data bandwidth management and quality of service (QoS) in higher institutions of learning [53–57]. In this research, the University of Lagos, Lagos State, Nigeria; Lagos State University of Science and Technology; and Covenant University were selected as the case studies for federal, state, and private universities, respectively. The concept of internet data bandwidth allocation and prediction is simply availability of data for users to enhance effective quality of experience (QoE) [58–63]. A careful study of ICT infrastructures which support the development and implementation of the Internet of Things and 5G broadband networks provided the basis of the assumptions utilized in this research work [64–66]. All internet users were all expected to be on 5G broadband technology in order to adequately utilize the allocated data bandwidth.

There are certain unique and classic precautions that were made in the process of collation of data in FEDERAL1, STATE1, and PRIVATE1. The case study of this research work, which includes the categorization of Internet users, is as follows:

a. Staff that stay On-line (SSO1);
b. Staff that live On-line (SLO1);

c. Students that stay On-line (SSO2);
d. Students that live On-line (SLO2).

This methodology employed in this study is the mathematical analysis of the linear Lagrange's interpolation for predicting and allocating the annual total number of internet users and corresponding acceptable internet data bandwidth [67–71].

The FEDERAL1, STATE1, and PRIVATE1 as the case study of this research work have the following data shown in **Tables 2–10**. This is the most recent numerical data of the total number of Internet users on the campus. **Figures 1–18** clearly show the distribution of the total number of internet users in 2021, 2022, and 2023. In the process of evaluating and estimating the internet data bandwidth for individual users, it was equally presumed that all users possessed 5G devices to ensure sustainable long-term optimization, prediction and allocation [72–76].

Table 2. FEDERAL1 internet bandwidth usage in 2021.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	95	450	23	568	5.7867
February	102	470	29	601	4.0067
March	98	515	22	635	4.2333
April	90	1651	27	1,768	11.7867
May	117	410	22	549	3.6600
June	99	640	19	758	5.0533
July	111	505	21	637	4.4067
August	80	409	22	511	3.4067
September	107	1440	35	1,582	10.5467
October	106	450	23	579	3.8600
November	101	460	30	591	3.9400
December	94	100	27	221	1.4733
TOTAL	1200	7500	300	9000	60.0020

Table 3. State1 internet bandwidth usage in 2021.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	20	20	7	47	0.8488
February	21	15	8	44	0.7946
March	40	252	8	300	5.4182
April	50	750	10	810	14.6292
May	22	36	41	112	2.20228
June	60	33	15	108	1.9505
July	66	38	11	115	2.0769
August	71	39	13	123	2.2214
September	60	36	15	111	2.0047
October	51	40	14	105	1.8963
November	67	36	13	116	2.0950
December	2	5	2	9	0.1625
TOTAL	530	1300	170	2000	36.1209

Table 4. PRIVATE1 internet bandwidth usage in 2021.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	16	133	11	160	1.14286
February	18	130	15	163	1.16428
March	15	126	13	154	1.10000
April	16	975	11	1,002	7.15714
May	19	135	10	164	1.17142
June	17	139	16	172	1.22857
July	12	137	14	163	1.16428
August	15	140	14	169	1.20714
September	20	855	18	893	6.37857
October	16	126	15	157	1.12142
November	16	134	17	167	1.19286
December	10	120	6	136	0.97143
TOTAL	190	3150	160	3500	24.99997

Table 5. FEDERAL1 internet bandwidth usage in 2022.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	102	735	27	864	5.7597
February	101	733	31	865	5.7665
March	97	634	22	753	5.0198
April	110	2,650	33	2,793	18.6193
May	101	635	28	764	5.0932
June	98	737	28	863	5.7531
July	113	836	27	976	6.5064
August	83	839	30	952	6.3464
September	118	2,450	31	2,599	17.3260
October	104	733	32	869	5.7931
November	102	748	21	871	5.8065
December	101	710	20	831	5.5398
TOTAL	1230	12,440	330	14,000	93.3329

Table 6. State1 internet bandwidth usage in 2022.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	27	29	15	71	1.3002
February	25	21	18	64	1.1720
March	56	270	3	329	6.0496
April	55	900	2	957	17.5255
May	46	52	12	110	2.0144
June	66	53	16	135	2.4612
July	56	51	14	121	2.2128

Table 6. (*Continued*).

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
August	68	55	10	133	2.4356
September	57	51	12	120	2.1905
October	53	52	13	118	2.1609
November	50	56	11	117	2.1426
December	11	10	4	25	0.4578
TOTAL	570	1,600	130	2,300	42.1231

Table 7. PRIVATE1 internet bandwidth usage in 2022.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	17	186	10	213	1.52129
February	18	190	16	224	1.59985
March	19	180	14	213	1.52129
April	21	900	15	1.246	8.89921
May	16	1210	17	218	1.55700
June	17	200	14	231	1.64985
July	18	180	16	214	1.52844
August	19	187	18	224	1.59985
September	20	1050	17	1,087	7.76359
October	16	189	18	223	1.59271
November	19	198	10	227	1.62128
December	10	160	10	180	1.28560
TOTAL	210	4115	175	4500	32.13996

Table 8. FEDERAL1 internet bandwidth usage in 2023.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	110	1010	29	1149	7.66020
February	117	1025	32	1174	7.82687
March	98	995	25	1118	7.45352
April	112	3750	37	3899	25.99401
May	107	1028	30	1165	7.76687
June	101	970	29	1100	7.33352
July	120	989	28	1137	7.58019
August	103	1020	32	1155	7.70020
September	121	3635	30	3786	25.24066
October	108	997	33	1138	7.58686
November	98	1081	24	11,203	8.02021
December	55	900	21	976	6.50683
TOTAL	1250	17,400	350	19,000	126.66994

Table 9. State1 internet bandwidth usage in 2023.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	32	35	17	84	1.5546
February	30	31	20	81	1.4990
March	58	290	4	352	6.5145
April	58	1100	3	1161	21.4870
May	54	60	12	126	2.3320
June	58	74	9	141	2.6095
July	59	41	10	110	2.0357
August	56	60	14	130	2.4090
September	58	64	12	134	2.4800
October	59	61	8	128	2.3690
November	49	61	10	120	2.2210
December	14	13	6	33	0.6107
TOTAL	585	1890	125	2600	48.1221

Table 10. PRIVATE1 internet bandwidth usage in 2023.

Month	Number of Staff	Number of Student	Number of Visitor	Sub-total of Internet Users	Internet Data Bandwidth (Terabytes)
January	20	198	16	234	1.67118
February	18	200	14	232	1.65900
March	15	196	15	226	1.61405
April	24	1,650	18	1692	12.08396
May	19	197	15	231	1.64976
June	17	202	11	230	1.64262
July	20	190	20	230	1.64262
August	18	208	14	240	1.71404
September	20	1,450	21	1491	10.64845
October	17	199	18	234	1.67118
November	19	200	16	231	1.64976
December	18	195	12	225	1.60691
TOTAL	225	5,085	190	5500	39.28067

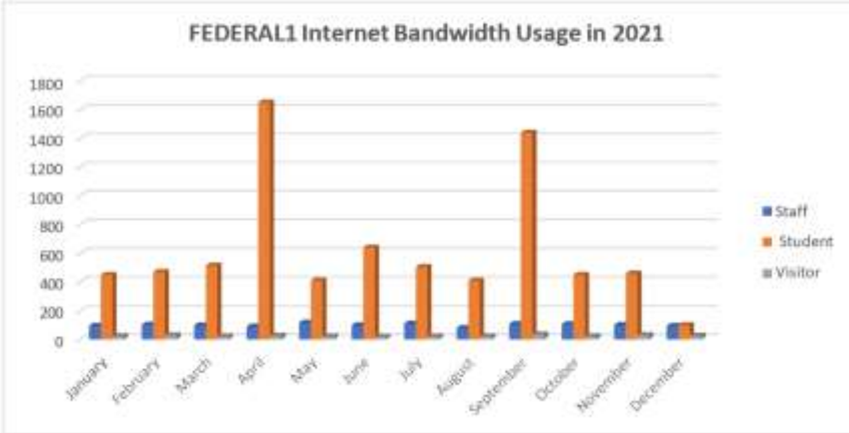

Figure 1. FEDERAL1 internet data bandwidth users in 2021—Bar chart.

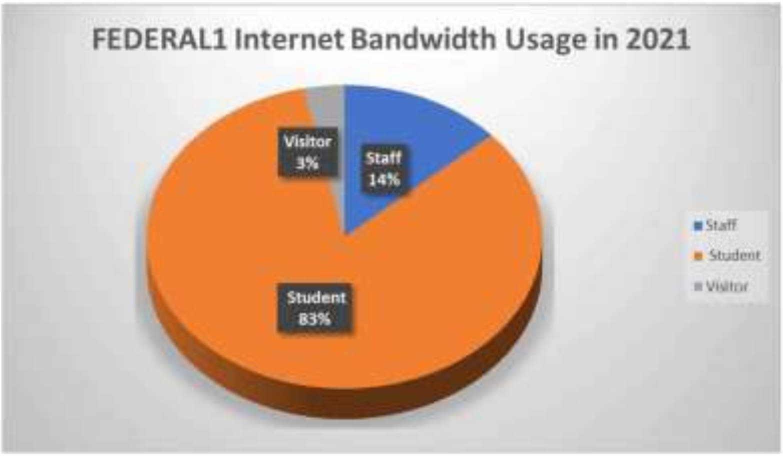

Figure 2. FEDERAL1 internet data bandwidth users in 2021—Pie chart.

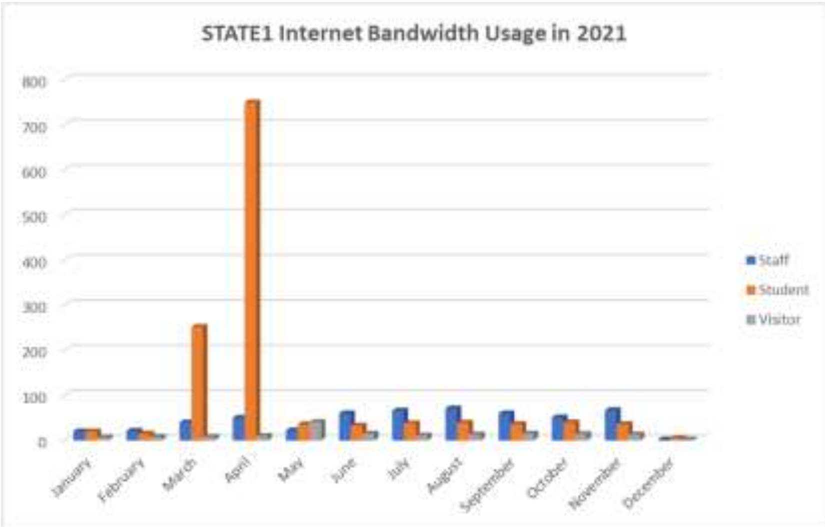

Figure 3. State1 internet data bandwidth users in 2021—Bar chart.

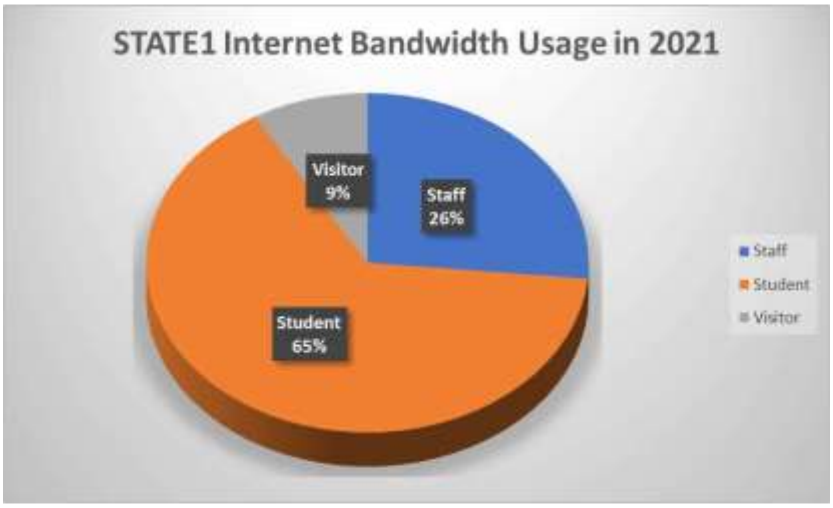

Figure 4. State1 internet data bandwidth users in 2021—Pie chart.

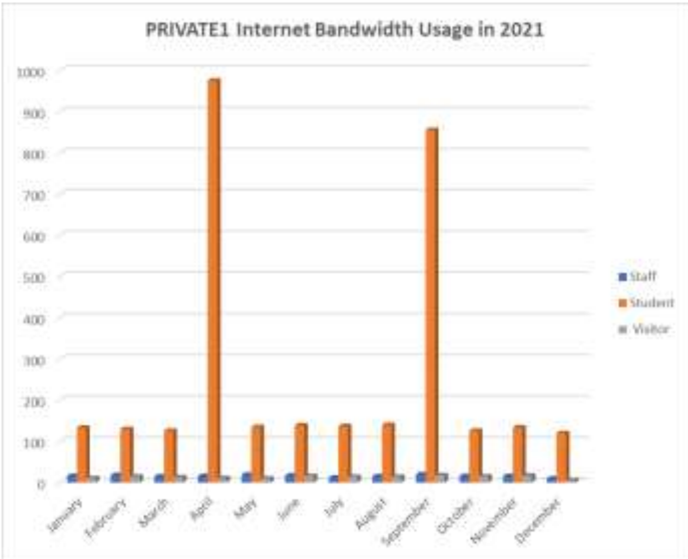

Figure 5. PRIVATE1 internet data bandwidth users in 2021—Bar chart.

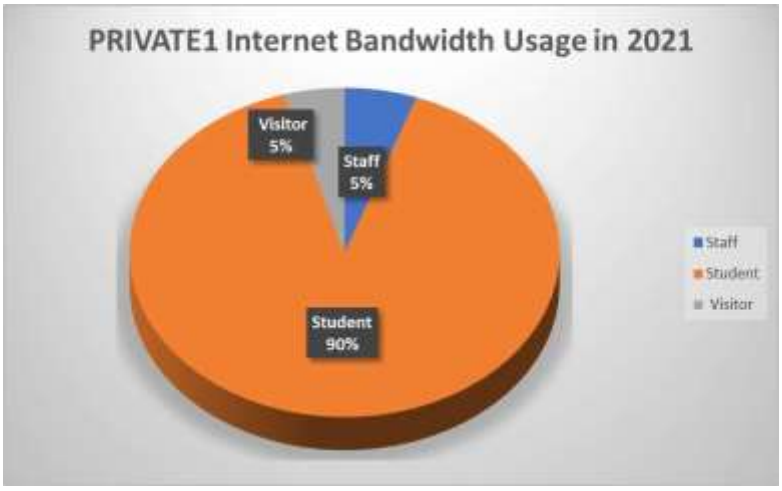

Figure 6. PRIVATE1 internet data bandwidth users in 2021—Pie chart.

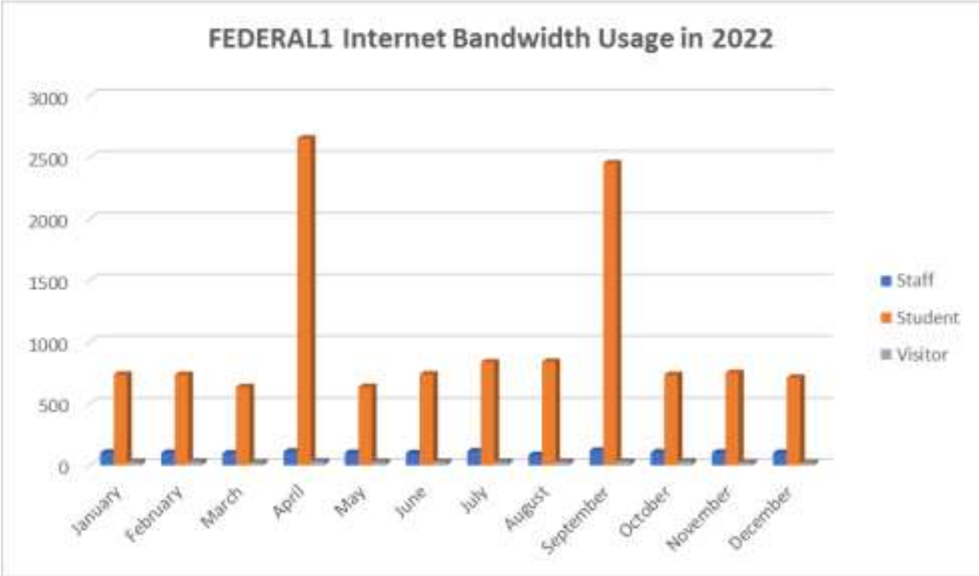

Figure 7. FEDERAL1 internet data bandwidth users in 2022—Bar chart.

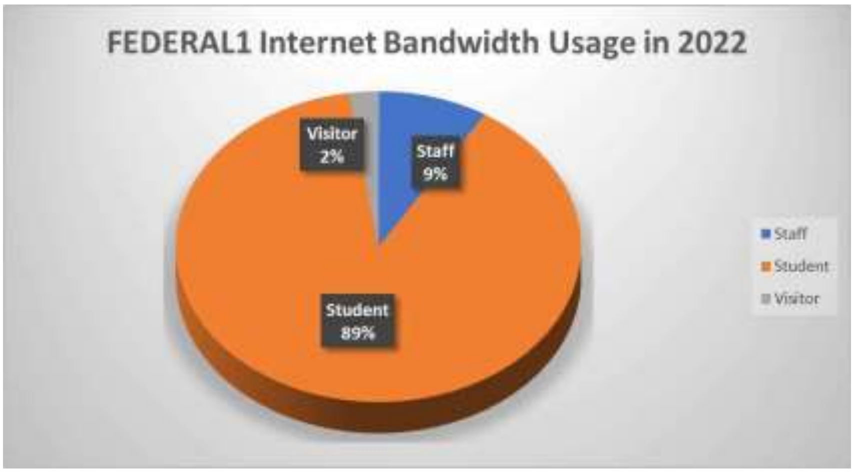

Figure 8. FEDERAL1 internet data bandwidth users in 2022—Pie chart.

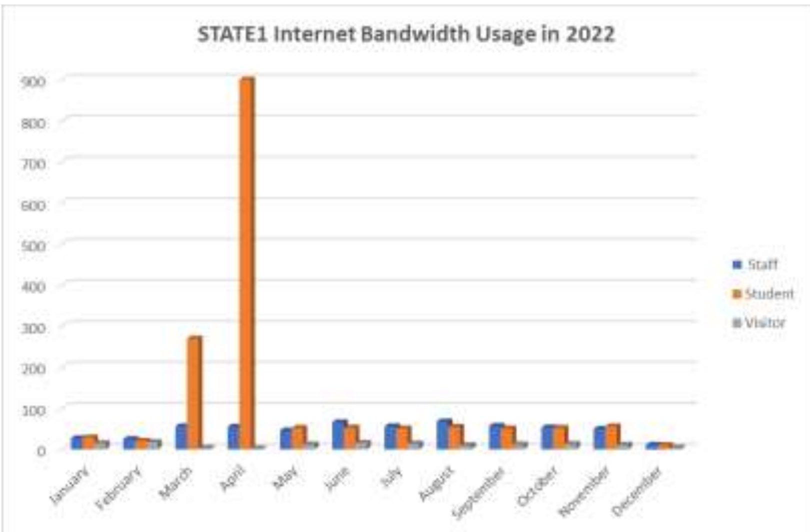

Figure 9. State1 internet data bandwidth users in 2022—Bar chart.

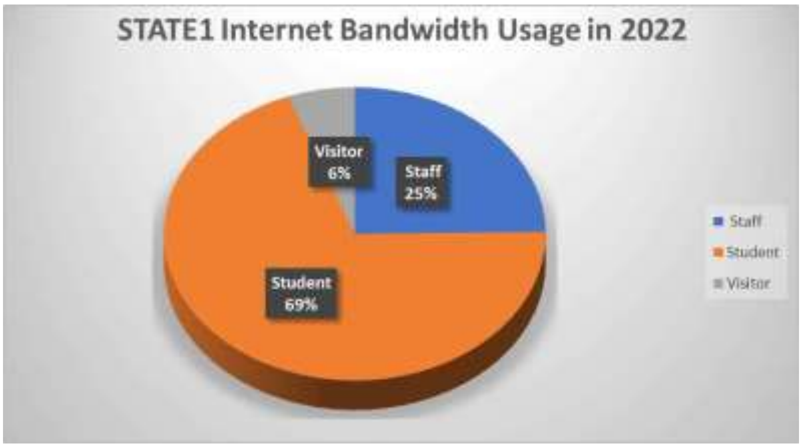

Figure 10. State1 internet data bandwidth users in 2022—Pie chart.

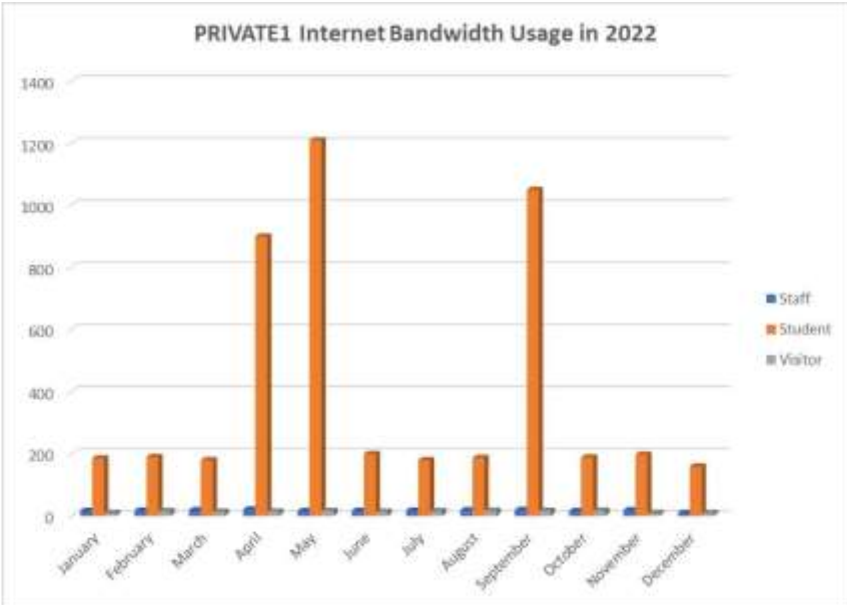

Figure 11. PRIVATE1 internet data bandwidth users in 2022—Bar chart.

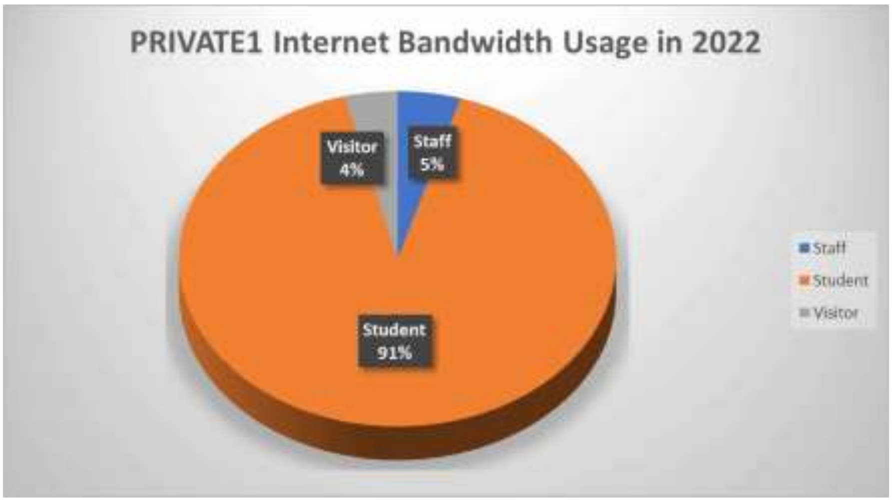

Figure 12. PRIVATE1 internet data bandwidth users in 2022—Pie chart.

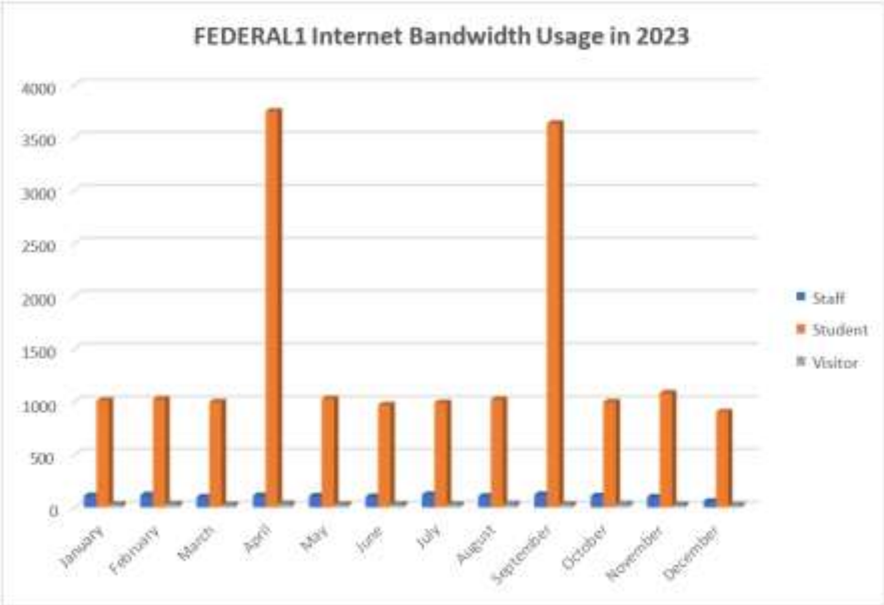

Figure 13. FEDERAL1 internet data bandwidth users in 2023—Bar chart.

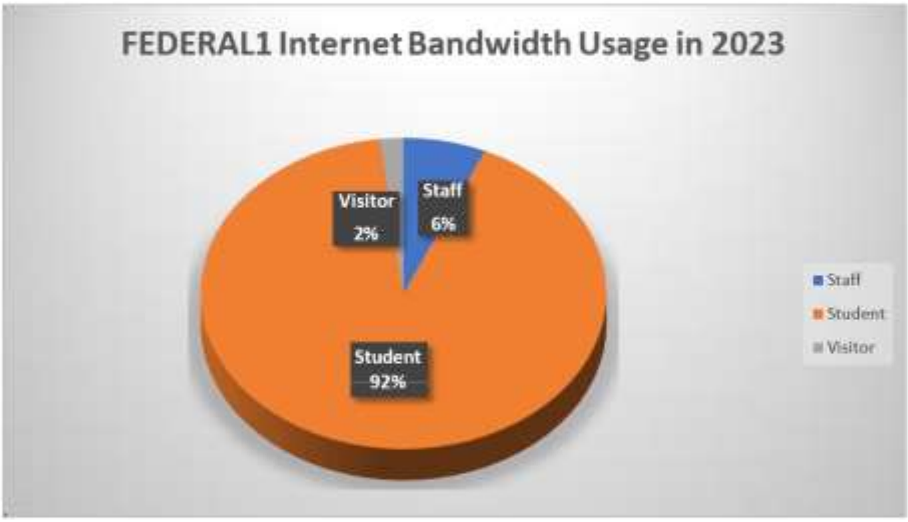

Figure 14. FEDERAL1 internet data bandwidth users in 2023—Pie chart.

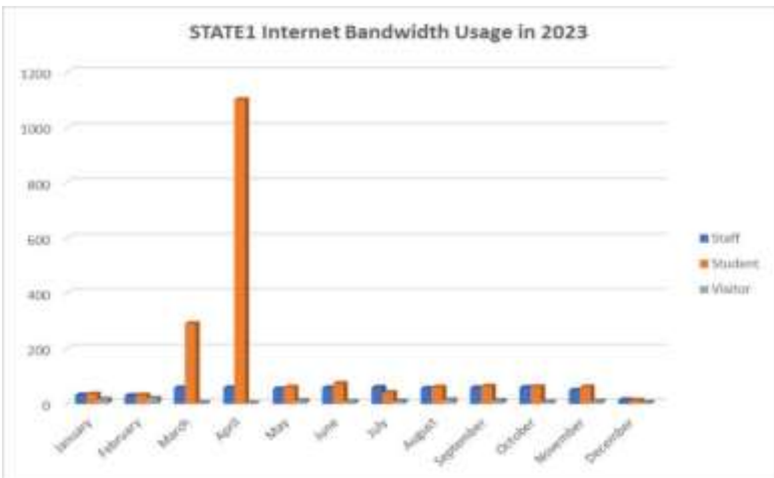

Figure 15. State1 internet data bandwidth users in 2023—Bar chart.

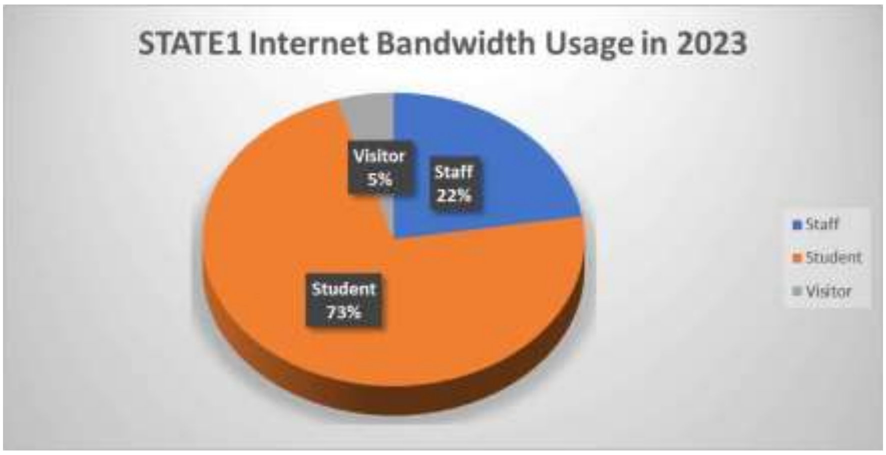

Figure 16. State1 internet data bandwidth users in 2023—Pie chart.

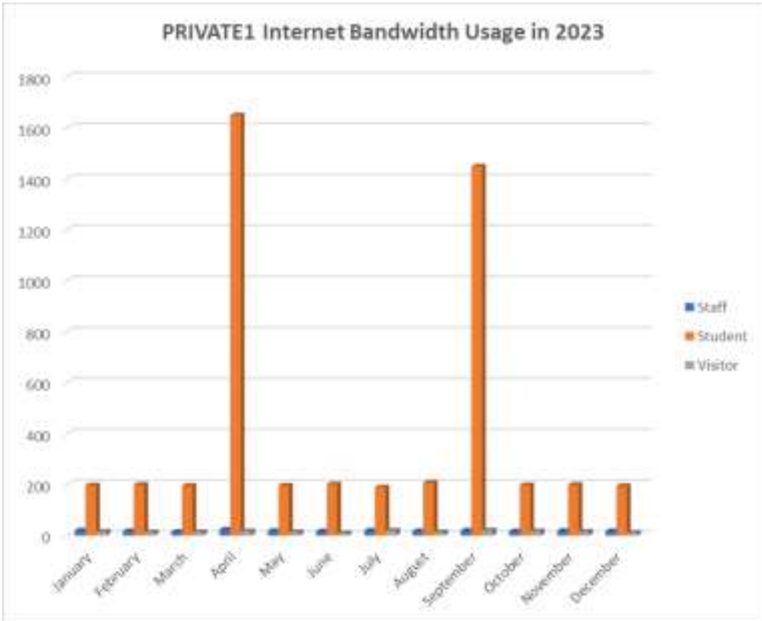

Figure 17. PRIVATE1 internet data bandwidth users in 2023—Bar chart.

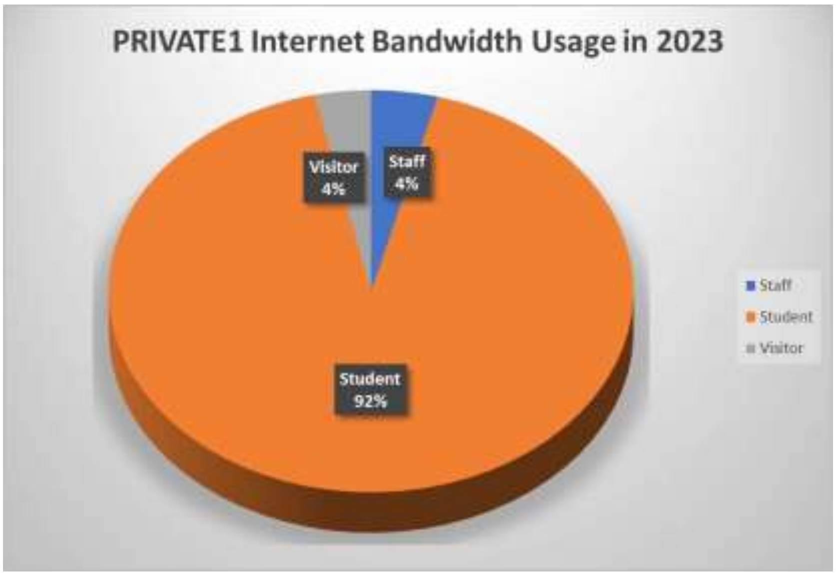

Figure 18. PRIVATE1 internet data bandwidth users in 2023—Pie chart.

A section of the data tables above was obtained from the Network Administrator's Users Record attached to the office of the Director of ICT in FEDERAL1, at which the overall ISPs Internet Data Bandwidth measured is 60.00 Terabytes in the year 2021, 93.33 Terabytes in the year 2022, and 126.67 Terabytes in the year 2023. Another section of these tables showed that the records from the Director of ICT in STATE1 measured 36.1209 Terabytes in the year 2021, 42.1231 Terabytes in the year 2022, and 48.1221 Terabytes in the year 2023. The last section of these tables showed that the record attached to the office of the Director of ICT in PRIVATE1is 25.0000 Terabytes in the year 2021, 32.1400 Terabytes in the year 2022 and 39.2800 Terabytes the year 2023. The measurements were based on total annual internet data bandwidth usage from the SNMP and Solaris Bandwidth Manager Program installed on the Internet Server [77–94]. The research also showed that FEDERAL1, STATE1, and PRIVATE1 have the following measured annual Internet data bandwidth in the tables hereunder.

In the last three years, we have three measured and estimated data points that can be interpolated so as to predict the effective internet data bandwidth and the acceptable number of internet users for the Internet access in the entire campus community. For better analysis, we used the following representations hereunder:

x_i: Represents the Average Number of Internet users ('000)

F(x_i): Represents the effective annual internet data bandwidth (Terabytes). The measured and estimated data points are tabulated in **Tables 11–13**.

Table 11. Acceptable internet data bandwidth with annual total number of internet users for FEDERAL1.

x_i ('000)	F(x_i) (Terabytes)
9.00	60.00
14.00	93.33
19.00	126.67

Table 12. Acceptable internet data bandwidth with annual total number of internet users in state1.

x_i ('000)	F(x_i) (Terabytes)
2.00	36.12
2.30	42.12
2.60	48.12

Table 13. Acceptable internet data bandwidth with annual total number of internet users for PRIVATE1.

x_i ('000)	F(x_i) (Terabytes)
3.500	25.00
4.500	32.14
5.500	39.28

Using the first three data points, we can apply Lagrange's interpolation for the prediction. The Linear Lagrange's interpolation (LILARINT) model is a polynomial that represented the internet data bandwidth [95–100]. The LILARINT model is a mathematical model generated from the three data points measured and estimated in the tables above. The LILARINT model polynomial is as follows:

$$P_n(x) = L_0(x_0) + L_1(x_1)f(x_1) + L_2(x_2)f(x_2) \tag{1}$$

where:

$$L_0(x_0) = \frac{(x - x_1)(x - x_2)}{(x_0 - x_1)(x_0 - x_2)} \tag{2}$$

$$L_1(x_1) = \frac{(x - x_0)(x - x_2)}{(x_1 - x_0)(x_1 - x_2)} \tag{3}$$

$$L_2(x_2) = \frac{(x - x_0)(x - x_1)}{(x_2 - x_0)(x_2 - x_1)} \tag{4}$$

From the available data points,

$$L_0(x_0) = \frac{(x - 14)(x - 19)}{(9 - 14)(9 - 19)} \tag{5}$$

$$L_1(x_1) = \frac{(x - 9)(x - 19)}{(14 - 9)(14 - 19)} \tag{6}$$

$$L_2(x_2) = \frac{(x - 14)(x - 14)}{(19 - 9)(19 - 14)} \tag{7}$$

In the case of FEDERAL1, we can now obtain values for the expected number of internet users and the corresponding effective internet data bandwidth. For 20,000 internet users, the corresponding effective internet bandwidth will be calculated as follows:

$$P_n(20) = L_0(x_0) + L_1(x_1)f(x_1) + L_2(x_2)f(x_2)$$

$$P_n(20) = \frac{(20 - 14)(20 - 19)(60)}{(9 - 14)(9 - 19)} + \frac{(20 - 9)(20 - 19)(93.33)}{(14 - 9)(14 - 19)} + \frac{(20 - 9)(20 - 14)(126.67)}{(19 - 9)(19 - 14)}$$
$$= \frac{(6)(1)(60)}{(-5)(-10)} + \frac{(11)(1)(93.33)}{(5)(-5)} + \frac{(11)(6)(126.67)}{(10)(5)} = 7.2 - 44.0652 + 167.2044$$

$P_n(20)$ = 133.33 Terabytes

For 25,000 Internet users, the corresponding effective internet data bandwidth will be evaluated as follows:

$$P_n(25) = \frac{(25 - 14)(25 - 19)(60)}{(9 - 14)(9 - 19)} + \frac{(25 - 9)(25 - 19)(93.33)}{(14 - 9)(14 - 19)} + \frac{(25 - 9)(25 - 14)(126.67)}{(19 - 9)(19 - 14)}$$
$$= \frac{(11)(6)(60)}{50} - \frac{(16)(6)(93.33)}{25} + \frac{(16)(11)(126.67)}{50}$$
$$= (1.32)(60) - (3.84)(93.33) + 3.52(126.67) = 79.2 - 358.3872 + 445.8784$$

$P_n(25)$ = 166.67 Terabytes

Further calculations show that:

$P_n(30) = 200.01$ Terabytes, $P_n(35)= 233.35$ Terabytes, $P_n(40) = 266.70$ Terabytes, $P_n(45) = 300.04$ Terabytes, $P_n(50) = 333.38$ Terabytes, $P_n(55) = 366.72$ Terabytes, $P_n(60) = 400.06$ Terabytes, $P_n(65) = 433.40$ Terabytes, $P_n(70) = 466.74$ Terabytes, $P_n(75) = 500.08$ Terabytes, $P_n(80) = 533.42$ Terabytes and $P_n (85) = 566.76$ Terabytes.

In the case of STATE1, we have the followings:

$P_n(2.75) = 51.12$ Terabytes, $P_n(2.90) = 54.12$ Terabytes, $P_n(3.05) = 57.12$ Terabytes, $P_n(3.20) = 60.12$ Terabytes, $P_n(3.275) = 61.62$ Terabytes, $P_n(3.350)= 63.12$ Terabytes, $P_n(3.425) = 64.62$ Terabytes, $P_n(3.500) = 66.12$ Terabytes, $P_n(3.575) = 67.62$ Terabytes, $P_n(3.650) = 69.12$ Terabytes, $P_n(3.725) = 70.62$ Terabytes, $P_n(3.8) = 72.12$ Terabytes, $P_n(3.875) = 73.62$ Terabytes, $P_n(3.950) = 75.12$ Terabytes, and $P_n(4.025) = 76.62$ Terabytes.

In the case of PRIVATE1, we have the followings:

$P_n (6.5) = 46.42$ Terabytes, $P_n(7.5) = 53.56$ Terabytes, $P_n(8.5) = 60.70$ Terabytes, $P_n(9.5)= 67.84$ Terabytes, $P_n(10.5) = 74.98$ Terabytes, $P_n(11.5) = 82.12$ Terabytes, $P_n(12.5) = 89.26$ Terabytes, $P_n(13.5) = 96.40$ Terabytes, $P_n(14.5) = 103.54$ Terabytes, $P_n(15.5) = 110.68$ Terabytes, $P_n(16.5) = 117.82$ Terabytes, $P_n(17.5) = 124.96$ Terabytes and $P_n(18.5) = 132.10$ Terabytes.

4. Results of internet bandwidth measurement in FEDERAL1, state1 and PRIVATE1

The Linear Lagrange's Interpolation (LILARINT) model was used on the three data points measured from the ICT department of FEDERAL1, STATE1, and PRIVATE1. The simulated or predicted result of the MATLAB program developed for the FEDERAL1, STATE1, and PRIVATE1 LILARINT models is found in **Figures 19–24**. The table of the measured internet bandwidth versus the acceptable number of users in FEDERAL1, STATE1, and PRIVATE1 is found in **Tables 14–16**, respectively. The graph of the measured internet bandwidth versus the acceptable number of users is found in **Figures 25–27**, respectively. The table of the measured and simulated internet bandwidth versus acceptable users is also found in **Tables 17–19**, respectively. The graph of the measured and simulated data bandwidth and acceptable users is found in **Figures 28–30**, respectively.

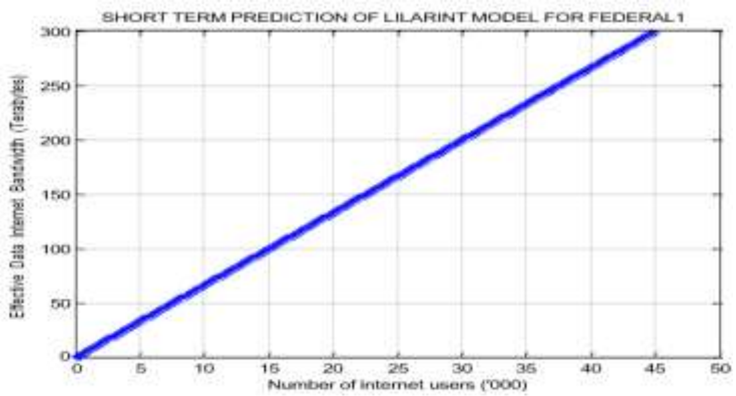

Figure 19. Simulated internet data bandwidth versus number of internet users for short-term prediction for FEDERAL1.

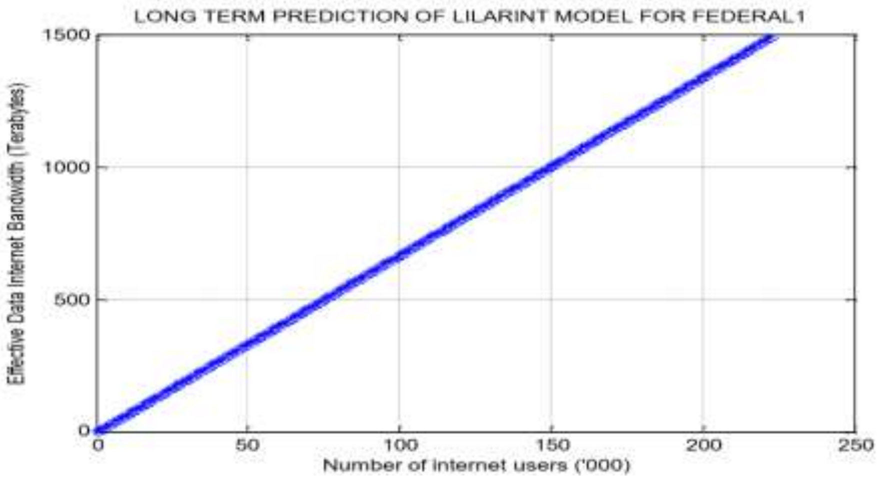

Figure 20. Simulated internet data bandwidth versus number of internet users for long-term prediction for FEDERAL1.

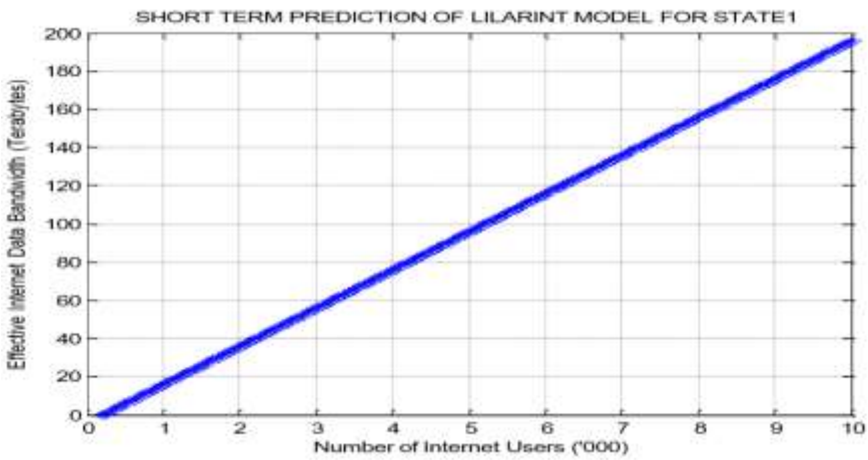

Figure 21. Simulated internet data bandwidth versus number of internet users for short-term prediction for state1.

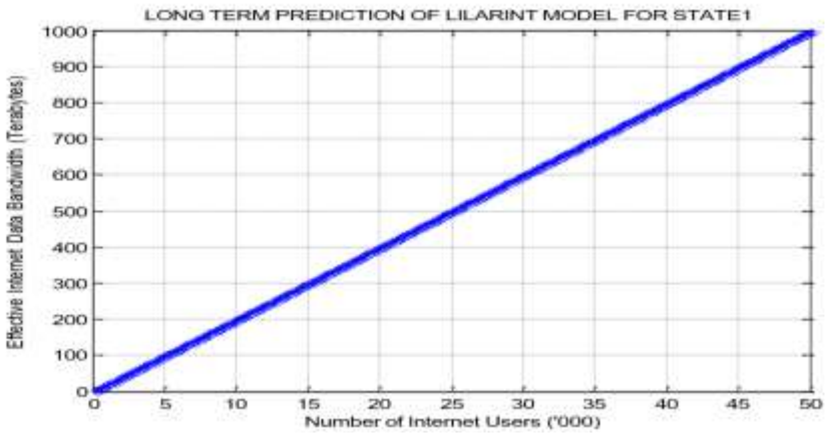

Figure 22. Simulated internet data bandwidth versus number of internet users for long-term prediction for state1.

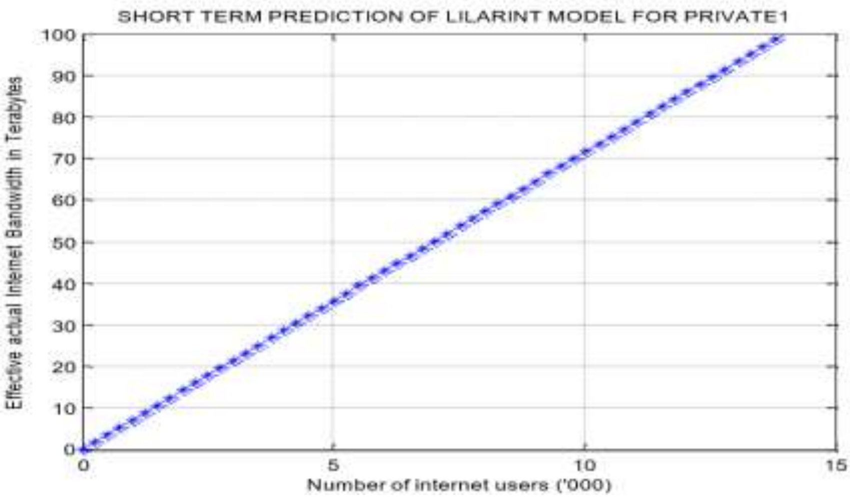

Figure 23. Simulated internet data bandwidth versus number of internet users for short-term prediction for PRIVATE1.

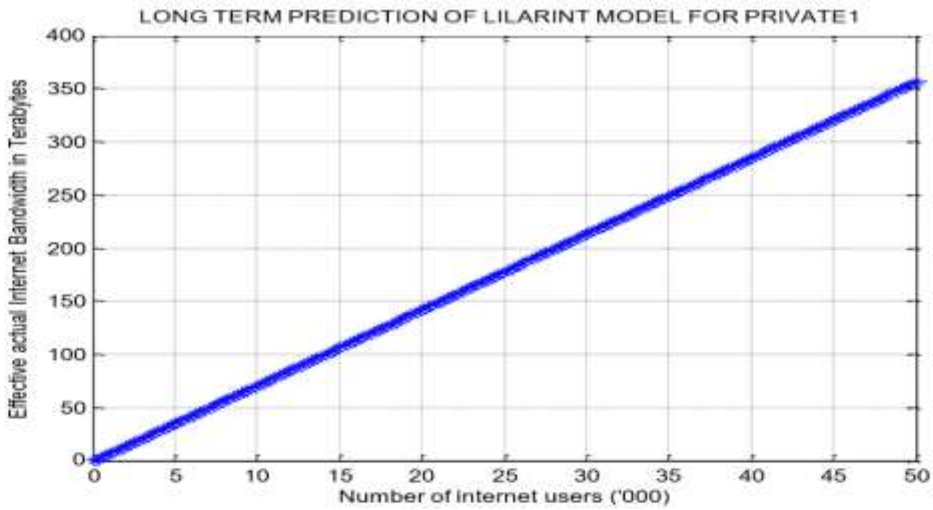

Figure 24. Simulated internet data bandwidth versus number of internet users for long-term prediction for PRIVATE1.

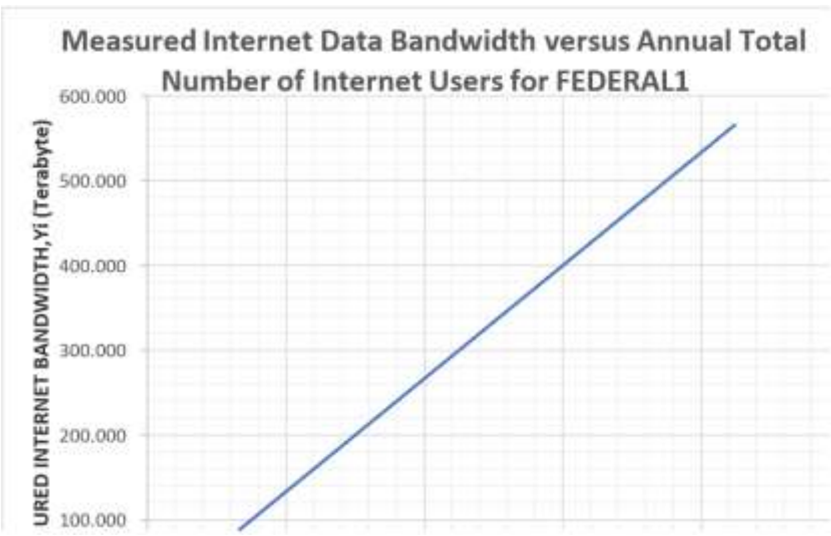

Figure 25. Measured internet data bandwidth versus number of internet users for FEDERAL1.

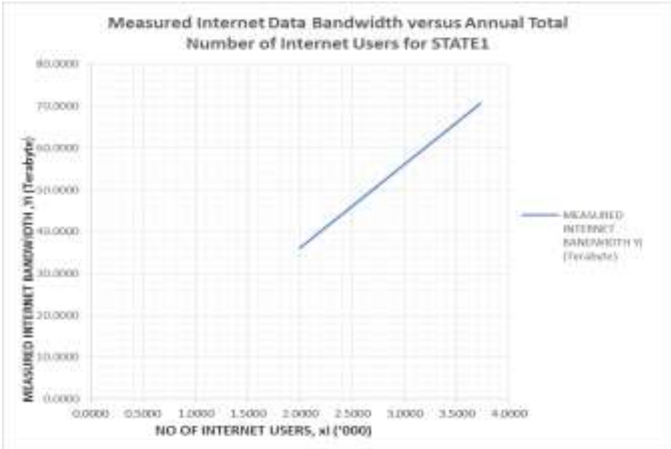

Figure 26. Measured internet data bandwidth versus number of internet users for state1.

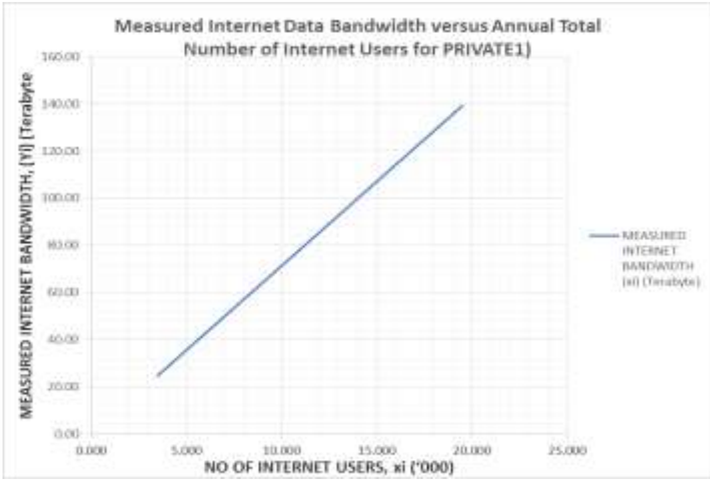

Figure 27. Measured internet data bandwidth versus number of internet users for PRIVATE1.

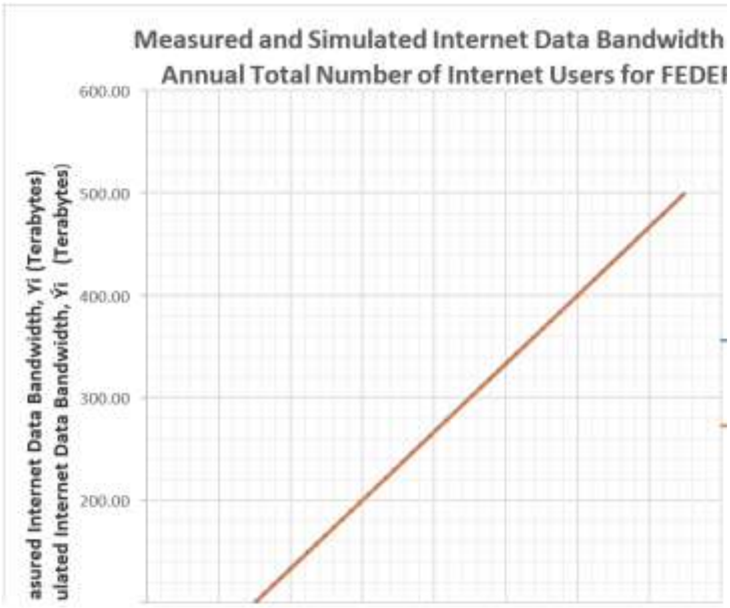

Figure 28. Measured and simulated internet data bandwidth versus number of internet users for FEDERAL1.

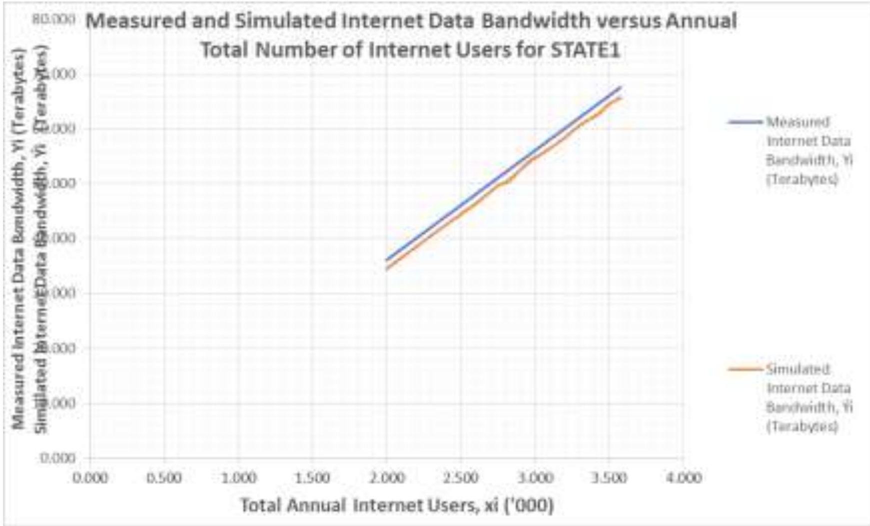

Figure 29. Measured and simulated internet data bandwidth versus number of internet users for state1.

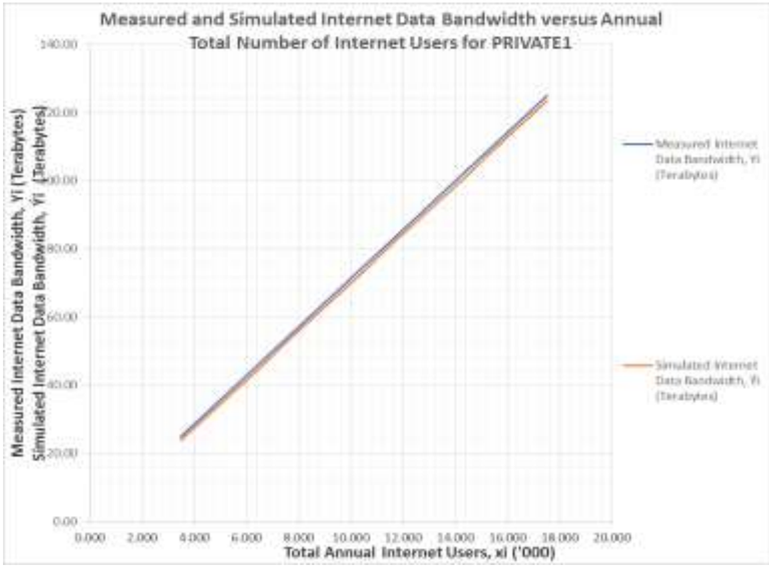

Figure 30. Measured and simulated internet data bandwidth versus number of internet users for PRIVATE1.

Table 14. Measured internet data bandwidth versus annual total number of internet users for FEDERAL1.

x_i (‘000)	F(x_i) (Terabyte)
9.0000	60.00
14.0000	93.33
19.0000	126.67
20.0000	133.33
25.0000	166.67
30.0000	200.01
35.0000	233.35
40.0000	266.70
45.0000	300.04

Table 14. (*Continued*).

x_i (‘000)	F(x_i) (Terabyte)
50.0000	333.38
55.0000	366.72
60.0000	400.06
65.0000	433.40
70.0000	466.74
75.0000	500.08
80.0000	533.42
85.0000	566.76

Table 15. Measured internet data bandwidth versus annual total number of internet users for state1.

x_i (‘000)	F(x_i) (Terabyte)
2.0000	36.1200
2.3000	42.1200
2.6000	48.1200
2.7500	51.1200
2.8250	52.6200
2.9000	54.1200
2.9750	55.6200
3.0500	57.1200
3.1250	58.6200
3.2000	60.1200
3.2750	61.6200
3.3500	63.1200
3.4250	64.6200
3.5000	66.1200
3.5750	67.6200
3.6500	69.1200
3.7250	70.6200

Table 16. Measured internet data bandwidth versus annual total number of internet users for PRIVATE1.

x_i (‘000)	F(x_i) (Terabyte)
3.5000	25.00
4.5000	32.14
5.5000	39.28
6.5000	46.42
7.5000	53.56
8.5000	60.70
9.5000	67.84
10.5000	74.98

Table 16. (*Continued*).

x_i ('000)	F(x_i) (Terabyte)
11.5000	82.12
12.5000	89.26
13.5000	96.40
14.5000	103.54
15.5000	110.68
16.5000	117.82
17.5000	124.96
18.5000	132.10
19.5000	139.24

Table 17. Measured and simulated internet data bandwidth versus annual total number of internet users for FEDERAL1.

Total Annual Internet Users, x_i ('000)	Measured Internet Data Bandwidth, Y_i (Terabytes)	Simulated Internet Data Bandwidth, $\acute{Y}_i$ (Terabytes)
9.00	60.00	59.00
14.00	93.33	92.00
19.00	126.67	125,50
20.00	133.33	132.00
25.00	166.67	165.50
30.00	200.01	199.00
35.00	233.35	232.00
40.00	266.70	265.50
45.00	300.04	299.00
50.00	333.38	332.00
55.00	366.72	365.50
60.00	400.06	399.00
65.00	433.40	432.00
70.00	466.74	465.50
75.00	500.08	499.00

Table 18. Measured and simulated internet data bandwidth versus annual total number of internet users for state1.

Total Annual Internet Users, x_i ('000)	Measured Internet Data Bandwidth, Y_i (Terabytes)	Simulated Internet Data Bandwidth, $\acute{Y}_i$ (Terabytes)
2.000	36.12	34.50
2.300	42.12	40.60
2.600	48.12	46.40
2.750	51.12	49.70
2.825	52.62	50.50
2.900	54.12	52.60
2.975	55.62	54.45
3.050	57.12	55.60

Table 18. (*Continued*).

Total Annual Internet Users, x_i (‘000)	**Measured Internet Data Bandwidth, Y_i (Terabytes)**	**Simulated Internet Data Bandwidth, $\acute{Y}_i$ (Terabytes)**
3.125	58.62	57.00
3.200	60.12	58.40
3.275	61.62	60.20
3.350	63.12	61.55
3.425	64.62	62.70
3.500	66.12	64.65
3.575	67.62	65.65

Table 19. Measured and simulated internet data bandwidth versus annual total number of internet users for PRIVATE1.

Total Annual Internet Users, x_i (‘000)	**Measured Internet Data Bandwidth, Y_i (Terabytes)**	**Simulated Internet Data Bandwidth, $\acute{Y}_i$ (Terabytes)**
3.50	25.00	24.00
4.50	32.14	31.00
5.50	39.28	38.00
6.50	46.42	45.00
7.50	53.56	52.50
8.50	60.70	59.50
9.50	67.84	66.50
10.50	74.98	73.50
11.50	82.12	81.00
12.50	89.26	88.00
13.50	96.40	95.00
14.50	103.54	102.00
15.50	110.68	109.50
16.50	117.82	116.50
17.50	124.96	123.50

4.1. Reinforcement Learning-based system

The reinforcement learning-based system is quite a unique programming system that handles simulation of mathematical functions and variables. This is the popular MATLAB application. It accepts data and provides a robust mathematical analysis which includes prediction. The source codes of the reinforcement learning used in this research work are highlighted hereunder.

4.1.1. MATLAB program of linear Lagrange’s interpolation (LILARINT) model for FEDERAL1 short term prediction

```
clc clear
x=linspace(0,50,200);
A=60.*(x-14.0).*(x-19.0)./(50.0);
B=93.33.*(x-9.0).*(x-19.0)./(-25);
C=126.67.*(x-9.0).*(x-14.0)./(50.0); P=A+B+C;
```

```
figure, plot(x,P,'*-'),axis([0,50,0,300]);
xlabel('Number of internet users("000)');
ylabel('Effective Data Internet Bandwidth (Terabytes)');
title('SHORT TERM PREDICTION OF LILARINT MODEL FOR FEDERAL1')
grid on
```

4.1.2. MATLAB program of linear Lagrange's interpolation (LILARINT) model for FEDERAL1 long term prediction

```
clc
clear
x=linspace(0,1500,1000);
A=60.*(x-14.0).*(x-19.0)./(50.0);
B=93.33.*(x-9.0).*(x-19.0)./(-25);
C=126.67.*(x-9.0).*(x-14.0)./(50.0);
P=A+B+C;
figure, plot(x,P,'*-'),axis([0,250,0,1500]);
xlabel('Number of internet users("000)');
ylabel('Effective Data Internet Bandwidth (Terabytes)');
title('LONG TERM PREDICTION OF LILARINT MODEL FOR FEDERAL1');
grid on
```

4.1.3. MATLAB program of linear Lagrange's interpolation (LILARINT) model for state1 short term prediction

```
clc clear
x=linspace(0,10.0,200);
A=36.12.*(x-2.30).*(x-2.60)./(0.18);
B=42.12.*(x-2.00).*(x-2.60)./(-0.09);
C=48.12.*(x-2.00).*(x-2.30)./(0.18); P=A+B+C;
figure, plot(x,P,'*-'),axis([0,10.0,0,200]);
xlabel('Number of Internet Users("000)');
ylabel('Effective Internet Data Bandwidth (Terabytes)');
title('SHORT TERM PREDICTION OF LILARINT MODEL FOR STATE1')
grid on
```

4.1.4. MATLAB program of linear Lagrange's interpolation (LILARINT) model for state1 long term prediction

```
clc clear
x=linspace(0,50.0,200);
A=36.12.*(x-2.30).*(x-2.60)./(0.18);
B=42.12.*(x-2.00).*(x-2.60)./(-0.09);
C=48.12.*(x-2.00).*(x-2.30)./(0.18); P=A+B+C;
figure, plot(x,P,'*-'),axis([0,50.0,0,1000]);
xlabel('Number of Internet Users("000)');
ylabel('Effective Internet Data Bandwidth (Terabytes)');
title('LONG TERM PREDICTION OF LILARINT MODEL FOR STATE1');
```

```
grid on
```

4.1.5. MATLAB program of linear Lagrange's interpolation (LILARINT) model for PRIVATE1 short term prediction

```
clc clear
x=linspace(0,50,200); A=25.*(x-4.5).*(x-5.5)./(2);
B=32.14.*(x-3.5).*(x-5.5)./(-1);
C=39.28.*(x-3.5).*(x-4.5)./(2); P=A+B+C;
figure, plot(x,P,'*-'),axis([0,15,0,100]);
xlabel('Number of internet users("000)');
ylabel('Effective actual Internet Bandwidth in Terabytes');
title('SHORT TERM PREDICTION OF LILARINT MODEL FOR PRIVATE1');
grid on
```

4.1.6. MATLAB program of linear Lagrange's interpolation (LILARINT) model for PRIVATE1 long term prediction

```
clc clear
x=linspace(0,50,200); A=25.*(x-4.5).*(x-5.5)./(2);
B=32.14.*(x-3.5).*(x-5.5)./(-1);
C=39.28.*(x-3.5).*(x-4.5)./(2); P=A+B+C;
figure, plot(x,P,'*-'),axis([0,50,0,400]); xlabel('Number of internet users("000)');
ylabel('Effective actual Internet Bandwidth in Terabytes'); title('LONG TERM PREDICTION OF LILARINT MODEL FOR PRIVATE1');
grid on
```

4.2. Comparative measured and simulated internet data bandwidth with total annual internet users for FEDERAL1

The table of the comparative of both measured and simulated internet data bandwidth with total annual internet users for FEDERAL1, STATE1, and PRIVATE1 is also found in **Tables 17–19**, respectively. The graph of both measured and simulated data bandwidth and acceptable users is found in **Figures 28–30**, respectively.

5. Discussion on internet data bandwidth optimization and prediction for FEDERAL1

The analysis of Linear Lagrange's Interpolation (LILARINT) model is one of the parameterization metrics for evaluating the efficiency, quality of service (QoS), and quality of experience (QoE) of ICT-based institutions. A MATLAB program was developed for this crucial objective of this research. We represent Effective Internet Data Bandwidth (Terabyte) as B and the Annual Total Number of Internet Users ('000) as U.

Mathematically, we can deduce the relation governing the two parameters. The relation is given as: $B = \mathrm{m}U + C_0$

where: m = Gradient of the straight line and C_0 = Constant of the linear equation. Collating data from **Figures 7** and **8**, the gradient can be evaluated as follows.

Therefore, $m = \Delta B/\Delta U = (166.67 - 126.67)/(25.00 - 20.00) = 40.00/5.00 = 8$. Now, $m = 8$.

$B = 8U + C_0$. From the graph in **Figures 7** and **8**, when $B = 0$, $U = 0$. Therefore, $C_0 = 0$, the final relation could be written as:

$$B = 8U \tag{8}$$

The Equation (8) governs the relationship between the effective internet data bandwidth (B) and annual total number of internet users (U) in FEDERAL1 as the case study of this research.

In the case of STATE1, the equation is deduced as:

$$B = 20U - 5 \tag{9}$$

In the case of PRIVATE1, the equation is deduced as:

$$B = 7.14U \tag{10}$$

5.1. Validation of internet data bandwidth prediction model using Nielsen's law for FEDERAL1, state1 and PRIVATE1

The Equation (8) that governs the relationship between the effective internet data bandwidth and the annual total number of users in FEDERAL1 is expected to agree with Nielsen's law of internet bandwidth prediction at a global level. It is the law mostly used for internet data bandwidth globally because Edholm's law did not provide adequate information to authenticate its validity.

According to Nielsen's law, expressed in a simplified approach that clearly states that there will always be a few super-users who have advanced equipment that runs really fast. This confirms the present availability of Internet of Things technology. Nielsen's law addresses the more normal high-end users who are willing to pay a premium but still want well-tested equipment that can be bought in a regular shop. This is the kind of user that he may have had on an ISDN line in 1998. In 2010, another upgrade was made, which stands at 31 Mbps data bandwidth. This new data point also fits the prediction of 1998. In 2013, the line was upgraded to deliver 58 Mbps of internet bandwidth without the need for a new cable modem. This upgrade was a bit below the predicted trend, so we certainly hope for better next time. In 2014, the line was upgraded to 120 Mbps. The differential between 2013 and 2014 is somewhat better than the law predicted, so some of the catch-up we called for last year did in fact happen. In 2016, the line was upgraded to 240 Mbps. It was almost exactly on the trend. In 2018, it was upgraded to 300 Mbps, which was slightly below the prediction. In 2019, it was now 325 Mbps. The regression line has R^2 = 0.9900, meaning that Nielsen's law explains 99% of the variability in the data. Beyond any form of ambiguity, one small change is that when he first wrote about this in 1998, the best-fit growth rate from 1984 to 1998 data was 53%, which can be rounded up to 50%, whereas the best-fit growth rate for the larger data set of 1984 to 2019 was 49% per year, which still rounds up to 50%. In 2023, the line was upgraded to 1120 Mbps. This is a little lower than the predicted, but still very close to the regression line as shown in the Nielsen's law exponential growth diagram. The conclusion is that Nielsen's law has held true throughout a 40-year period.

In 2024, in order to validate the LILARINT model in the ICT unit of FEDERAL1, the unit used this model to subscribe for 190 Terabytes of annual data bandwidth for 29,500 total internet users. In 2023, the measured data bandwidth was 126 Terabytes to 19,000 total internet users. The annual internet data bandwidth increase was 49.99%, which can be rounded up to 50%. There was no significant complaint of insufficient internet data bandwidth throughout this year. This expressly shows that this prediction really agrees with Nielsen's law.

In 2024, in order to validate the LILARINT model in the ICT unit of STATE1, the unit used this model to subscribe for 72 Terabytes of annual data bandwidth for 3850 total internet users. In 2023, the estimated data bandwidth was 48.12 Terabytes for 2600 total internet users. The annual internet data bandwidth increase was 49.68%, which can be rounded up to 50%. In this case, there was no significant complaint of insufficient internet data bandwidth for the whole year. This equally shows that this prediction completely agrees with Nielsen's law.

In 2024, in order to validate the LILARINT model in the ICT unit of PRIVATE1, the unit used this model to subscribe for 59.12 Terabytes of annual data bandwidth for 6600 total number of internet users. In 2023, the estimated data bandwidth was 39.28 Terabytes to 5500 total internet users. The annual internet data bandwidth increase was 50.50%, which can be rounded up to 50%. There was no significant complaint of insufficient internet data bandwidth throughout this year. This also shows that this prediction really agrees with Nielsen's law [101–112].

With this information, it is clear that the LILARINT model is 100% reliable and efficient in its internet data bandwidth prediction. Corresponding results from the empirical data analysis from the Linear Lagrange's Interpolation (LILARINT) predictor model showed that it was well defined and modeled. The detailed results were comprehensively enumerated in the **Tables 20–29**.

Table 20. Effective internet data bandwidth with annual total number of internet users for FEDERAL1.

Year	Annual Total Number of Internet users	Effective Internet Data Bandwidth (Terabytes)
2021	9000	60.00
2022	14,000	93.33
2023	19,000	126.67
2024	29,500	190.00

Table 21. Effective internet data bandwidth with annual total number of internet users for state1.

Year	Annual Total Number of Internet users	Effective Internet Data Bandwidth (Terabytes)
2021	2000	36.12
2022	2300	42.12
2023	2600	48.12
2024	3850	72.00

Table 22. Effective internet data bandwidth with annual total number of internet users for PRIVATE1.

Year	Annual Total Number of Internet users	Effective Internet Data Bandwidth (Terabytes)
2021	3500	25.00
2022	4500	32.14
2023	5500	39.28
2024	6600	59.12

Table 23. PRESS regression data table for FEDERAL1 LILARINT model.

x_i (‘000)	Y_i	$Ý_i$	$(Y_i – Y)$	$(Y_i – Y)^2$	$[Y_i − Ý_i]/Y_i$	$(Y_i − Ý_i)$	$(Y_i − Ý_i)^2$
9.00	60.00	59.00	−212.032	44,957.56	0.0166666	1.0000	1.0000
14.00	93.33	92.00	−178.702	31,934.40	0.0142505	1.3300	1.7689
19.00	126.67	125,50	−145.362	21,130.11	0.0093600	1.1700	1.3589
20.00	133.33	132.00	−138.702	19,238.24	0.0099752	1.3300	1.7689
25.00	166.67	165.50	−105.362	11,101.15	0.0070198	1.1700	1.3689
30,00	200.01	199.00	−72.022	5187.17	0.0050497	1.0100	1.0201
35.00	233.35	232.00	−38.682	1496.30	0.0057850	1.3500	1.8225
40.00	266.70	265.50	−53.32	28.43	0.0044994	1.2000	1.4400
45.00	300.04	299.00	28.008	784.45	0.0034662	1.0400	1.0816
50.00	333.38	332.00	61.348	3763.58	0.0041394	1.3800	1.9044
55.00	366.72	365.50	94.688	8965.82	0.0033267	1.2200	1.4884
60.00	400.06	399.00	128.028	16,391.17	0.0026496	1.0600	1.1236
65.00	433.40	432.00	161.368	26,039.63	0.0032303	1.4000	1.9600
70.00	466.74	465.50	194.708	37,911.20	0.0026567	1.2400	1.5376
75.00	500.08	499.00	228.048	52,005.89	0.0021596	1.0800	1.1664
Total	4080.48	4060.50	1840.38	280,935.10		17.9800	21.8202

Table 24. PRESS regression data table for state1 LILARINT model.

x_i (‘000)	Y_i	$Ý_i$	$(Y_i – Y)$	$(Y_i – Y)^2$	$[Y_i − Ý_i]/Y_i$	$(Y_i − Ý_i)$	$(Y_i − Ý_i)^2$
2.000	36.12	34.50	−19.80	39,204.00	0.0448505	1.6200	2.6244
2.300	42.12	40.60	−13.80	190.44	0.0360874	1.5200	2.3104
2.600	48.12	46.40	−7.80	60.84	0.0357439	1.7200	2.9584
2.750	51.12	49.70	−4.80	23.04	0.0277778	1.4200	2.0164
2.825	52.62	50.50	−3.30	10.89	0.0402889	2.1200	4.4944
2.900	54.12	52.60	−1.80	3.24	0.0280857	1.5200	2.3104
2.975	55.62	54.45	−0.30	0.09	0.0210356	1.1700	1.3689
3.050	57.12	55.60	1.20	1.44	0.0266106	1.5200	2.3104
3.125	58.62	57.00	2.70	7.29	0.0276356	1.6200	2.6244
3.200	60.12	58.40	4.20	17.64	0.0286094	1.7200	2.9584
3.275	61.62	60.20	5.70	32.49	0.0230447	1.4200	2.0164
3.350	63.12	61.55	7.20	51.84	0.0248733	1.5700	2.4649
3.425	64.62	62.70	8.70	75.69	0.0219746	1.4200	2.0164
3.500	66.12	64.65	10.20	104.04	0.0222232	1.4700	2.1609
3.575	67.62	65.65	11.70	136.89	0.0291334	1.9700	3.8809
Total	838.80	814.50	103.20	39,919.86		23.8000	38.5160

Table 25. PRESS regression data table for PRIVATE1 LILARINT model.

x_i ('000)	Y_i	$Ý_i$	$(Y_i – Y)$	$(Y_i – Y)^2$	$[Y_i − Ý_i] /Y_i$	$(Y_i − Ý_i)$	$(Y_i − Ý_i)^2$
3.50	25.00	24.00	−50.015	2,501.53	0.040000	1.0000	1.000
4.50	32.14	31.00	−43.015	1,838.29	0.035470	1.1400	1.2996
5.50	39.28	38,00	−35.735	1,277.01	0.032587	1.2800	1.6384
6.50	46.42	45.00	−28.595	817.69	0.030590	1.4200	2.0164
7.50	53.56	52.50	−21.455	460.33	0.019791	1.0600	1.1236
8.50	60.70	59.50	−14.315	208.89	0.019769	1.2000	1.4400
9.50	67.84	66.50	−7.175	51.48	0.019752	1.3400	1.7956
10.50	74.98	73.50	−0.035	0.00146	0.019739	1.4800	2.1904
11.50	82.12	81.00	7.105	50.48	0.013639	1.1200	1.2544
12.50	89.26	88.00	14.245	202.91	0.014116	1.2600	1.5876
13.50	96.40	95.00	21.385	457.30	0.014523	1.4000	1.9600
14.50	103.54	102.00	28.525	813.66	0.014873	1.5400	2.3716
15.50	110.68	109.50	35.805	1271.97	0.010661	1.1800	1.3924
16.50	117.82	116.50	42.805	1832.24	0.011204	1.3200	1.7424
17.50	124.96	123.50	49.945	2494.47	0.011684	1.4600	2.1316
Total	1125.23	1105.50	400.155	14,278.25		19.2000	23.9440

Table 26. Mean absolute percentage error (MAPE) data table for FEDERAL1 LILARINT model.

x_i ('000)	Y_i Actual	$Ý_i$ Predicted	$(Y_i – Ý_i)$ Difference	$\%(Y_i − Ý_i)$ % Difference	$[Y_i − Ý_i]$ Absolute Difference	$(Y_i − Ý_i)/Y_i$
9.00	60.00	59.00	1.0000	1.666666667	1.0000	0.01666666
14.00	93.33	92.00	1.3300	1.425050895	1.3300	0.01425051
19.00	126.67	125.50	1.1700	0.923659903	1.1700	0.00923660
20.00	133.33	132.00	1.3300	0.997524938	1.3300	0.00997525
25.00	166.67	165.50	1.1700	0.701985960	1.1700	0.00701986
30,00	200.01	199.00	1.0100	0.504974751	1.0100	0.00504975
35.00	233.35	232.00	1.3500	0.578530105	1.3500	0.00578530
40.00	266.70	265.50	1.2000	0.449937570	1.2000	0.00449943
45.00	300.04	299.00	1.0400	0.346620450	1.0400	0.00346620
50.00	333.38	332.00	1.3800	0.413942048	1.3800	0.00413942
55.00	366.72	365.50	1.2200	0.332678883	1.2200	0.00332679
60.00	400.06	399.00	1.0600	0.264960256	1.0600	0.00264960
65.00	433.40	432.00	1.4000	0.323027226	1.4000	0.00323027
70.00	466.74	465.50	1.2400	0.265672537	1.2400	0.00265673
75.00	500.08	499.00	1.0800	0.215965445	1.0800	0.00215965
Total	4080.48	4060.50	17.9800		17.9800	0.09411201

Table 27. Mean absolute percentage error (MAPE) data table for STATE1 LILARINT model.

x_i ('000)	Y_i Actual	$\acute{Y}_i$ Predicted	$(Y_i - \acute{Y}_i)$ Difference	$\%(Y_i - \acute{Y}_i)$ % Difference	$[Y_i - \acute{Y}_i]$ Absolute Difference	$(Y_i - \acute{Y}_i)/Y_i$
2.000	36.12	34.50	1.6200	4.48505	1.6200	0.0448505
2.300	42.12	40.60	1.5200	3.60873	1.5200	0.0360874
2.600	48.12	46.40	1.7200	3.57440	1.7200	0.0357440
2.750	51.12	49.70	1.4200	2.77778	1.4200	0.0277778
2.825	52.62	50.50	2.1200	4.02889	2.1200	0.0402889
2.900	54.12	52.60	1.5200	2.80857	1.5200	0.0280857
2.975	55.62	54.45	1.1700	2.10356	1.1700	0.0210356
3.050	57.12	55.60	1.5200	2.66106	1.5200	0.0266106
3.125	58.62	57.00	1.6200	2.76356	1.6200	0.0276356
3.200	60.12	58.40	1.7200	2.86094	1.7200	0.0286094
3.275	61.62	60.20	1.4200	2.30445	1.4200	0.0230445
3.350	63.12	61.55	1.5700	2.48733	1.5700	0.0248733
3.425	64.62	62.70	1.4200	2.19746	1.4200	0.0219746
3.500	66.12	64.65	1.4700	2.22323	1.4700	0.0222323
3.575	67.62	65.65	1.9700	2.91334	1.9700	0.0291334
Total	838.80	814.50	23.8000		23.8000	0.4379836

Table 28. Mean absolute percentage error (MAPE) data table for PRIVATE1 LILARINT model.

x_i ('000)	Y_i Actual	$\acute{Y}_i$ Predicted	$(Y_i - \acute{Y}_i)$ Difference	$\%(Y_i - \acute{Y}_i)$ % Difference	$[Y_i - \acute{Y}_i]$ Absolute Difference	$(Y_i - \acute{Y}_i)/Y_i$
3.50	25.00	24.00	1.0000	4.00000	1.0000	0.040000
4.50	32.14	31.00	1.1400	3.54670	1.1400	0.035470
5.50	39.28	38,00	1.2800	3.25867	1.2800	0.032587
6.50	46.42	45.00	1.4200	3.05903	1.4200	0.030590
7.50	53.56	52.50	1.0600	1.97912	1.0600	0.019791
8.50	60.70	59.50	1.2000	1.97683	1.2000	0.019769
9.50	67.84	66.50	1.3400	1.97524	1.3400	0.019752
10.50	74.98	73.50	1.4800	1.97390	1.4800	0.019739
11.50	82.12	81.00	1.1200	1.36393	1.1200	0.013639
12.50	89.26	88.00	1.2600	1.41163	1.2600	0.014116
13.50	96.40	95.00	1.4000	1.45234	1.4000	0.014523
14.50	103.54	102.00	1.5400	1.48732	1.5400	0.014873
15.50	110.68	109.50	1.1800	1.06614	1.1800	0.010661
16.50	117.82	116.50	1.3200	1.12042	1.3200	0.011204
17.50	124.96	123.50	1.4600	1.16843	1.4600	0.011684
Total	1125.23	1105.50	19.2000		19.2000	0.409303

Table 29. Comparative statistical performance evaluation analysis.

UNIVERSITY	Regression, (R^2)	MSE	MAD	Standard Deviation (σ)	MAPE (%)
FEDERAL1	0.9999	1.455	122.6920	8.2975	0.6274
STATE1	0.9990	2.567	6.8800	6.8987	2.9199
PRIVATE1	0.9983	1.596	26.6770	3.5622	2.7287

5.2. Performance evaluation analysis using Allen's press for FEDERAL1, state1 and PRIVATE1 LILARINT model

The detail about the statistical data analysis is found in **Table 23**. The PRESS regression is given as:

$$R^2 = 1 - \frac{SSE}{SST} \quad (11)$$

where: SSE = Sum of the squared differences between the actual or measured internet data bandwidth, Y_i and predicted or simulated internet data bandwidth value $\acute{Y}_{i.}$

$$SSE = \Sigma\,(Y_i - \acute{Y}_i)^2 \quad (12)$$

where: i = 1, 2, 3, …, 15.

SST = Sum of squared differences between actual or measured internet data bandwidth, Y_i and the average of Y_i values.

$$SST = \Sigma\,(Y_i - Y)^2 \quad (13)$$

where: i = 1, 2, 3, …, 15.

$R^2 < 1$; R^2 must be less than UNITY.

From **Table 23**, we have the following representations:

Y_i = Actual or measured Internet data bandwidth. $\acute{Y}_i$ = Predicted or simulated Internet data bandwidth

Y = Average actual or measured Internet data bandwidth.

From Equations (12) and (13), we have the following representations:

SSE = The sum of the squared differences between the actual or measured Internet data bandwidth, Y_i and the predicted or simulated Internet data bandwidth, $\acute{Y}_i$

SST = The sum of the squared differences between the actual or measured Internet data bandwidth, Y_i and the average actual measured Internet data bandwidth, Y.

From **Table 23**, the average empirical actual or measured internet data bandwidth is computed as:

Y = (60.00 + 93.33 + 126.67 + 133.33 + 166.67 + 200.01 + 233.35 + 266.70 + 300.04 + 333.74 + 366.72 + 400.06 + 433.40 +466.74 + 500.08)/15
= (580 + 1000.10 + 1533.56 + 966.82)/15
= (4080.48)/15
Y = 272.032

Using **Table 23** and Equation (13), we have:

SST = (44,957.56 + 31,934.40 + 21,130.11 + 19,238.24 + 11,101.15 + 5,187.17 + 1496.30 + 28.43 + 785.45 + 3763.58 + 8965.82 + 16,391.17 + 26,039.63 + 37,911.20 + 52,005.89)
= 98,022.07 + 37,022.86 + 13,542.28 + 132,347.89
SST = 280,935.10

Using **Table 23** and Equation (12), we have:

SSE = (1.0000 + 1.7689 + 1.3689 + 1.7689 + 1.3689 + 1.0201 + 1.8225 + 1.4400 + 1.0816 + 1.4884 + 1.1236 + 1.9600 + 1.5376 + 1.1664)
= 7.2756 + 7.2686 + 7.276
SSE = 21.8202

The PRESS Regression, R^2 of FEDERAL1 LILARINT model can be computed as follows. Using **Table 23,** we have:

PRESS R^2 = 1 – (21.8202)/(280,935.10)
= 1 − 0.00007669896
R^2 = 0.9999

In the case of STATE1, Using **Table 24**, R^2 = 0.9990
In the case of PRIVATE1, Using **Table 25**, R^2 = 0.9983
Recall, the Nielsen's Regression, R^2 = 0.9900.
It is obvious that the statistical performance regression of the LILARINT model in FEDERAL1, STATE1, and PRIVATE1 is better than that of Nielsen's.

5.3. Performance evaluation analysis using mean squared error (MSE) for FEDERAL1 LILARINT model

From **Table 23**, the mean squared error (MSE) can be computed as follows:

MSE = (21.8202)/(15)
MSE = 1.455

The MSE for the FEDERAL1 LILARINT model is 1.455.
From **Table 24**, the MSE for the STATE1 LILARINT model is 2.567 From **Table 25**, the MSE for the PRIVATE1 LILARINT model is 1.596.

5.4. Performance evaluation analysis using mean absolute deviation (MAD) for FEDERAL1 LILARINT model

From **Table 23**, the mean absolute deviation (MAD) can be computed as follows:

MAD = (212.032 + 178.702 + 145.362 + 138.702 + 105.362 + 72.022 + 38.682 + 53.32 + 28.008 + 61.348 + 94.688 + 128.028 + 161.368 + 194.708 + 228.048)/15
= (780.16 + 253.58 + 806.84)/15
= (1840.38)/15
MAD = 122.692

The MAD for the FEDERAL1 LILARINT model is 122.692.
From **Table 24**, the MAD for the STATE1 LILARINT model is 6.8800. From **Table 25**, the MAD for the PRIVATE1 LILARINT model is 26.6770.

5.5. Performance evaluation analysis using Standard Deviation (σ) for FEDERAL1 LILARINT model

From **Table 23**, the mean Standard Deviation (σ) can be computed as follows: Standard Deviation,

$\sigma = \sqrt{(280{,}935.10)/(4080.48)}$
$= \sqrt{68.8485}$
$\sigma = 8.2975$

The Standard Deviation, σ for the FEDERAL1 LILARINT model is 8.2975.

From **Table 24**, the Standard Deviation, σ for the STATE1 LILARINT model is 6.8987. From **Table 25**, the Standard Deviation, σ for the PRIVATE1 LILARINT model is 3.5622.

5.6. Performance evaluation analysis using mean absolute percentage error (MAPE) for FEDERAL1 LILARINT model

We considered **Table 26** for the computation of mean absolute percentage error (MAPE) for FEDERAL1 LILARINT model.

From **Table 26**, the mean absolute percentage error can be computed as follows:

MAPE= (0.09411201)/15
= 0.006274 (100)
MAPE = 0.6274%

The mean absolute percentage error (MAPE) for FEDERAL1 LILARINT model is 0.6274%.

From **Table 27**, the mean absolute percentage error (MAPE) for STATE1 LILARINT model is 2.9199%.

From **Table 28**, the mean absolute percentage error (MAPE) for PRIVATE1 LILARINT model is 2.7287%.

6. Conclusion

In this paper, the reinforcement learning-based platform was considered; the Linear Lagrange's Interpolation (LILARINT) model was well-designed and implemented. The potential limitation of this model is that a very huge surge in the number of internet users within a year could weaken the predictability and allocation of data bandwidth. In other words, an astronomical increase in the number of internet users could become a brick wall against the performance of the model. Whenever this scenario occurs, it is recommended that the model has to be redesigned. In this analysis, the FEDERAL1 LILARINT model happened to be much better than other models and that of Nielsen's. The model has a regression R^2 of 0.9999, mean square error (MSE) of 1.455, mean absolute deviation (MAD) of 122.6920, Standard Deviation (σ) of 8.2975, and a minimum mean absolute percentage error (MAPE) of 0.6274%. Since the regression R^2 of FEDERAL1, STATE1 and PRIVATE1 is very close to unity, it implies that the model is highly reliable and it is in its best fit. With this information, it is clear that the LILARINT models are 100% reliable and efficient in their internet data bandwidth prediction and allocation.

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