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Forecasting Power Consumption in the DSL Access Network System based on Network Activities by using Machine Learning

Dang Fillatina Hashim[1], Fauziahanim Che Seman[1,2,*], Siti Amely Jumaat[1,2], Ahmad Fateh Mohamad Nor[1], Ansar Jamil[1], Hamza Ahmad[3]

[1] Fakulti Kejuruteraan Elektrik dan Elektronik, Universiti Tun Hussein Onn Malaysia, Parit Raja, 86400 Batu Pahat, Johor, Malaysia
[2] Research Centre for Applied Electromagnetics, Institute of Integrated Engineering, Universiti Tun Hussein Onn Malaysia, Parit Raja, 86400 Batu Pahat, Johor, Malaysia
[3] Department of Electrical Engineering, University of Engineering & Technology Mardan, 23200 Mardan, Pakistan

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ABSTRACT

The widespread telecommunication networks and Internet services like Digital Subscriber Line (DSL) access has contributed to the growing demand of electricity. With environmental consciousness arising from non-renewable energy sources, coupled with rising demand, industries need to implement green strategies. This research focuses on predicting power consumption in DSL access networks using machine learning approaches. With an emphasis on Very High Bit Rate Digital Subscriber Line 2 (VDSL2) technology, the study investigates DSL modem's power usage under an ideal and a bridge tap faulty conditions of copper cable along distances ranging from 100 to 1000 meters. The different levels of network activities are generated by IxChariot software and Pearson's correlation techniques are used to analyse the relationship between power consumption and network activities. Combining the Train-Valid-Test and Random Forest algorithms, a predictive Machine Learning model is developed to forecast the power consumption based on relevant variables. The results show that power consumption tends to increase as the network activities are heavier and the proposed model presents a low minimum absolute error as a good model to forecast the power. It may aid Internet service providers to predict the optimum power limit in the network systems and pursue further investigation on how to reduce electricity use in the telecommunication field.

1. Introduction

In today's digital age, the global expansion of the Internet and the use of telecom networks have played significant roles in the Information and Communication Technology (ICT) [1]. Internet usage serves millions of users with multiple purposes such as social media, educational activities or business [2]. Malaysia is not excluded from experiencing Internet penetration [3]. In addition to the innovation of digital devices and the evolution of websites and social media, the drastic growth of Internet use

* *Corresponding author.*
E-mail address: fauziahs@uthm.edu.my

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is also affected by how the Internet can now be accessed easily almost anywhere either in urban or rural areas. Based on the Internet Users Survey 2020 by the Malaysian Communication and Multimedia Commission (MCMC), the number of Internet users has increased to 88.7% with 75.6% is in urban areas and 24.4% in rural areas [4].

This growth of human activities on the Internet contributes to the consumption of electricity that approximately reaches 1% of total power consumption in broadband-enabled countries [5]. Malaysia faces the rise of electricity supply every year as it is seen that the number of customers of Tenaga Nasional Berhad (TNB), Sabah Electricity Sdn Bhd (SESB) and Sarawak Energy Berhad (SEB) is increasing especially in the domestic sector [6]. Due to this, the excessive of electricity use results in issues occur when generating non-renewable natural resources which have negative environmental impacts such as climate change, greenhouse and carbon dioxide emission. Ministry of Energy, Science Technology and Climate Change in Malaysia had been established to manage matters related to energy, environment, climate change and green technology [7].

When the knowledge of sustainable environments and Green ICT expands, industries or corporations like Telco to reduce the energy consumption for a future-generation of ICTs network that mitigates the climate change and emission of carbon [8]. It has become imperative to analyse energy usage in telecommunication networks, particularly at the side of customer premises equipment (CPE). As Internet demand and higher bandwidth services increase, Internet traffic continues to increase which leads to growth of quantity, capacity and energy consumption of transmission and switching equipment [9].

Digital Subscriber Line (DSL) technologies or copper-loop access technologies are widely used for delivering broadband speed over a specific distance up to several megahertz [10]. Over the years, the maximum available bit rate has continuously been improved over phone lines using modems by taking advantage of low-cost digital signal processors [11]. Even though mobile broadband and fibre speed connections are beginning to increase significantly, DSL technology remains the dominant form of broadband nowadays due to its use of existing copper home phone lines which are available in most of the areas that also make it easier to be installed. In Malaysia, the number of active subscribers of DSL technology is high compared to other technologies such as GPON technology. Furthermore, DSL technology’s ability allows data transmission from hundreds (Kbps) to millions of bits per second (Mbps), contingent on several factors like distance. The highest-speed DSL variant is very-high bit rate (VDSL) technology, reaches tens of Mbps supporting performance such as Internet access, video conferencing, provision of digital videos and distance learning [12]. VDSL excels in delivering higher speeds with a wider frequency spectrum than older DSL technologies, accommodating both asymmetric and symmetric configurations. In this research, VDSL technology is examined under ideal and faulty condition, where impairments such as attenuation, bridged tap and crosstalk are introduced [13].

Based on power consumption analysis by Ramli *et al.,* [1], ADSL technology consumed 72% of total power and VDSL had 16% of total power consumption in a year compared to GPON technology. Accessing power in relation to total bandwidth reveals that ADSL and VDSL achieve 3.58 W/Mbps and 0.83 W/Mbps respectively. On the CPE side, the DSL modem is a critical component installed in customers’ premises to deliver the service, connects directly to the Digital Subscriber Line Access Multiplexer (DSLAM) enhancing DSL availability especially for customers distant from the central office (CO). As in studies by Khan *et al.,* [14], the power usage varies with active components of the modem and the experiment involved with various kinds of routers. Meanwhile, based on the studies by Shapi, Ramli and Awalin [15], the correlation of electricity consumption and the Internet is related to the rapid growth of networks and data centres as well as the demand for data traffic. Furthermore, based on the studies by Mosavi and Bahmani [16], VDSL is reported to consume 3-5W/Subs which is slightly higher than ADSL equipment that consumes only 1-2 W/Subs.

Machine learning (ML) is described as a field of study whereby computer software that relies upon different algorithm and enables it to self-learn the data from measured results based on the experimental performed tasks [17]. Hence, this paper uses ML concept to develop software capable of learning the energy consumption patterns in DSL modems based on the network activities by users. The Artificial Neural Network, machine learning model is created for future use in forecasting the power consumption and data traffic in telecommunication systems [18,19]. Train-Valid-Test optimizes the performance and accuracy of forecasting model in practice by splitting data into training set, validating set and testing set. Random Forest Regressor, ensemble learning and decision trees techniques is utilized to train a predictive model based on the relationship between input variables and the target data for making predictions.

In this project, the power consumed by broadband network equipment at the CPE side is measured with network configurations under VDSL family technologies with different distance of copper cable. Moreover, this paper investigates the correlation between power consumption at the customer premises and requirements for high data demand and high-quality services.

2. Methodology

The overall experiment starts with a DSL access network that imitates the actual Telekom Malaysia (TM) infrastructure using VDSL2 technology connect DSLAM to DSL modem (CPE) [20]. The Traffic Simulator (IxChariot) simulates network activities and a multimetre measures DSL modem current under several cable conditions and lengths. The analysis identifies correlations and the machine learning model is developed for future prediction. Figure 1 shows the general block diagram of the experiment's flow.

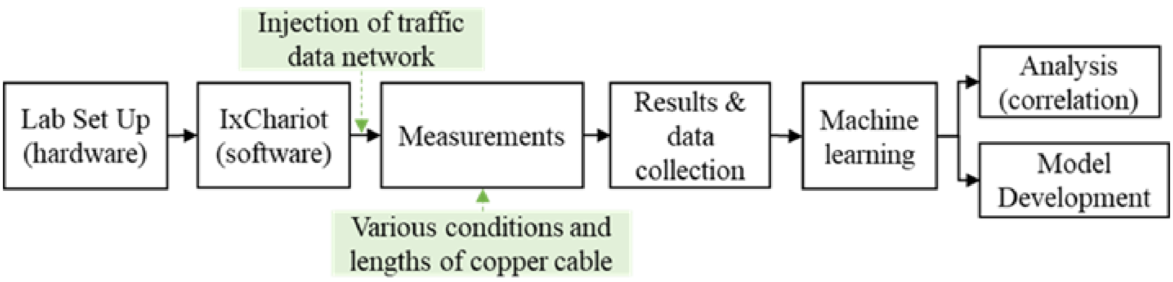


Fig. 1. General block diagram of the research flow

2.1 Data Acquisition

A DSL network setup includes the main equipment, DSLAM MA5616 for VDSL2 17a profile Internet access technology and acts as a node to serve other equipment such as the traffic simulator (IxChariot), tag block and network switch.

The ideal copper cable condition means data transmissions have no issues or undesired effects. However, some impairments may occur in DSL technologies such as crosstalk, attenuation and bridged tap [16]. Bridge tap is a limitation due to dangling unterminated cable in the communication line that may cause impedance mismatches throughout transmission data. Thus, two cable condition, ideal and bridge tap fault, are investigated at three lengths (100m, 500m and 1000m). DSL modem HG655m is a CPE device that measures output parameter under varied network activities simulated by IxChariot.

2.2 Correlation Analysis Strategy

Power is calculated from measured current and constant voltage using a fundamental formula of power as Eq. (1). Pearson's correlation is used to access the correlation analysis between power consumption and throughput with the help of Python codes to come out with the *r* correlation coefficient as a strength of the relationship with the graphical representations.

$$P = IV \tag{1}$$

2.3 Machine Learning Plan

Machine learning predicts the pattern of DSL modem power consumption based on the network activities. In achieving this, the Train-Valid-Test split with ratio of 80-10-10 and random forest algorithm are employed. During this process, a random forest regressor is used to forecast real-valued output power, considering factors like cable conditions, length and level of throughput (Mbps). The overall process of developing machine learning is shown in Figure 2.

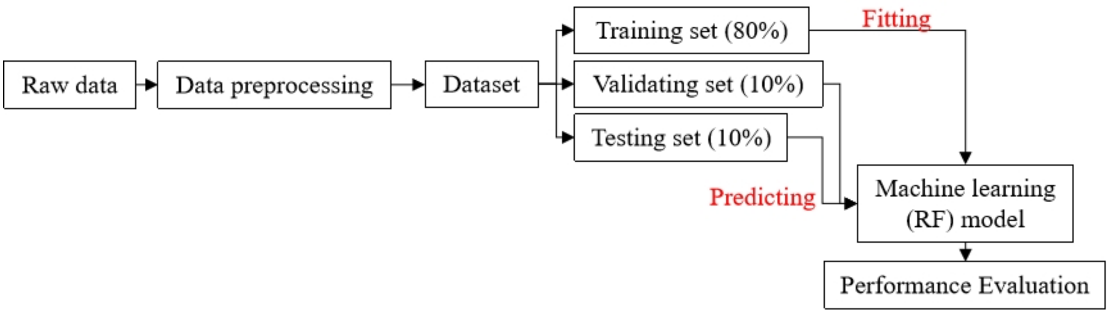
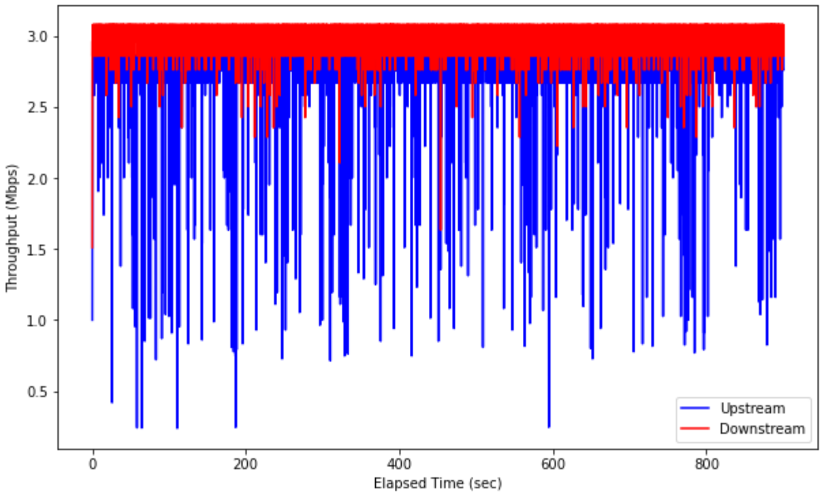


Fig. 2. Flowchart of machine learning development process

3. Results

3.1 Data Observation on Throughput of Network Activities

In this project, data observation on throughput of network activities, imitated by IxChariot parameters were divided into downstream which refers to the data flow from DLSAM (network) to CPE (end-user) and upstream for vice versa. Figure 3, Figure 4 and Figure 5 below illustrate the time-series line graphs of throughput for varying distances and network activities including the upstream and downstream. The elapsed time on the horizontal axis shows the actual time as per set for every measuring process which was 15 minutes. It could also be observed that downstream throughput exceeds upstream throughput. Note that the characteristics of IxChariot parameters here were divided into two, upstream (US) and downstream (DS) considering the data flow's directions as well. In this project, downstream refers to the data flow from the MSAN (network) to the modem (end-user) and the opposite data flow is called upstream. These graphs display the stationary time plot which means the consistent values over time. However, higher network activities show reduced amounts of data.



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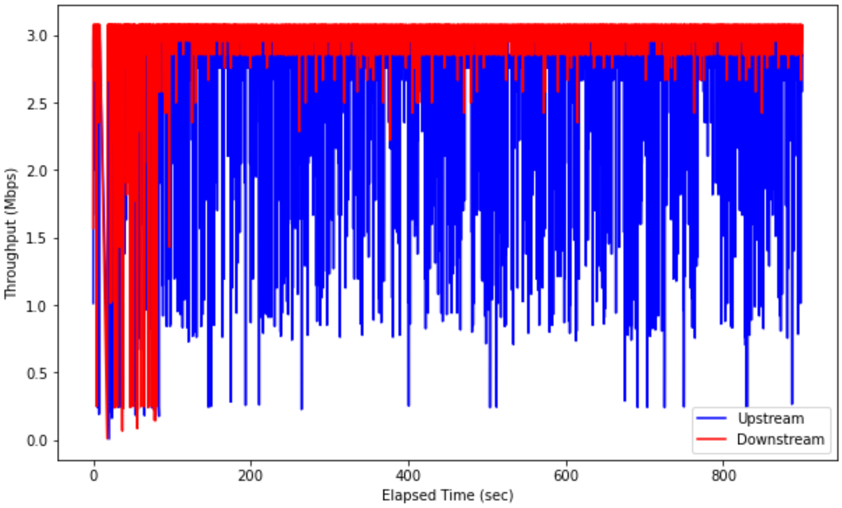

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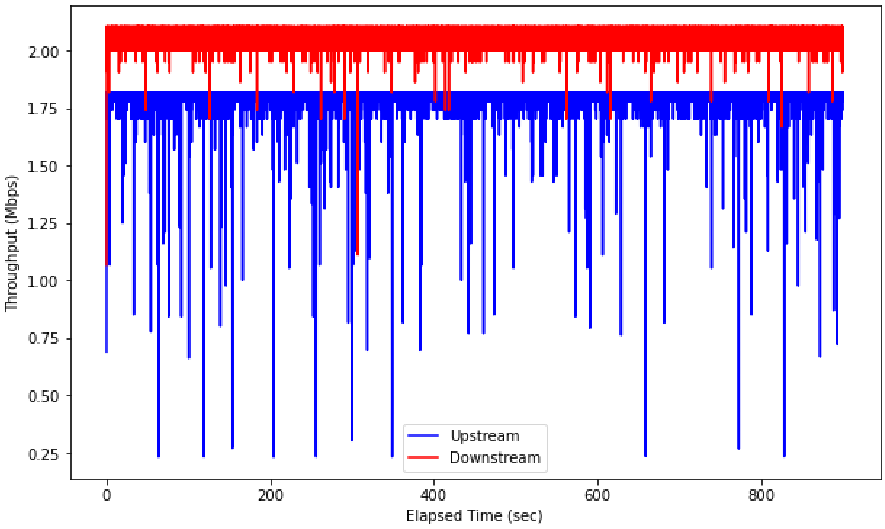

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Fig. 3. Time series line graphs of throughput for low network activity in distances of (a) 100m (b) 500m (c) 1000m

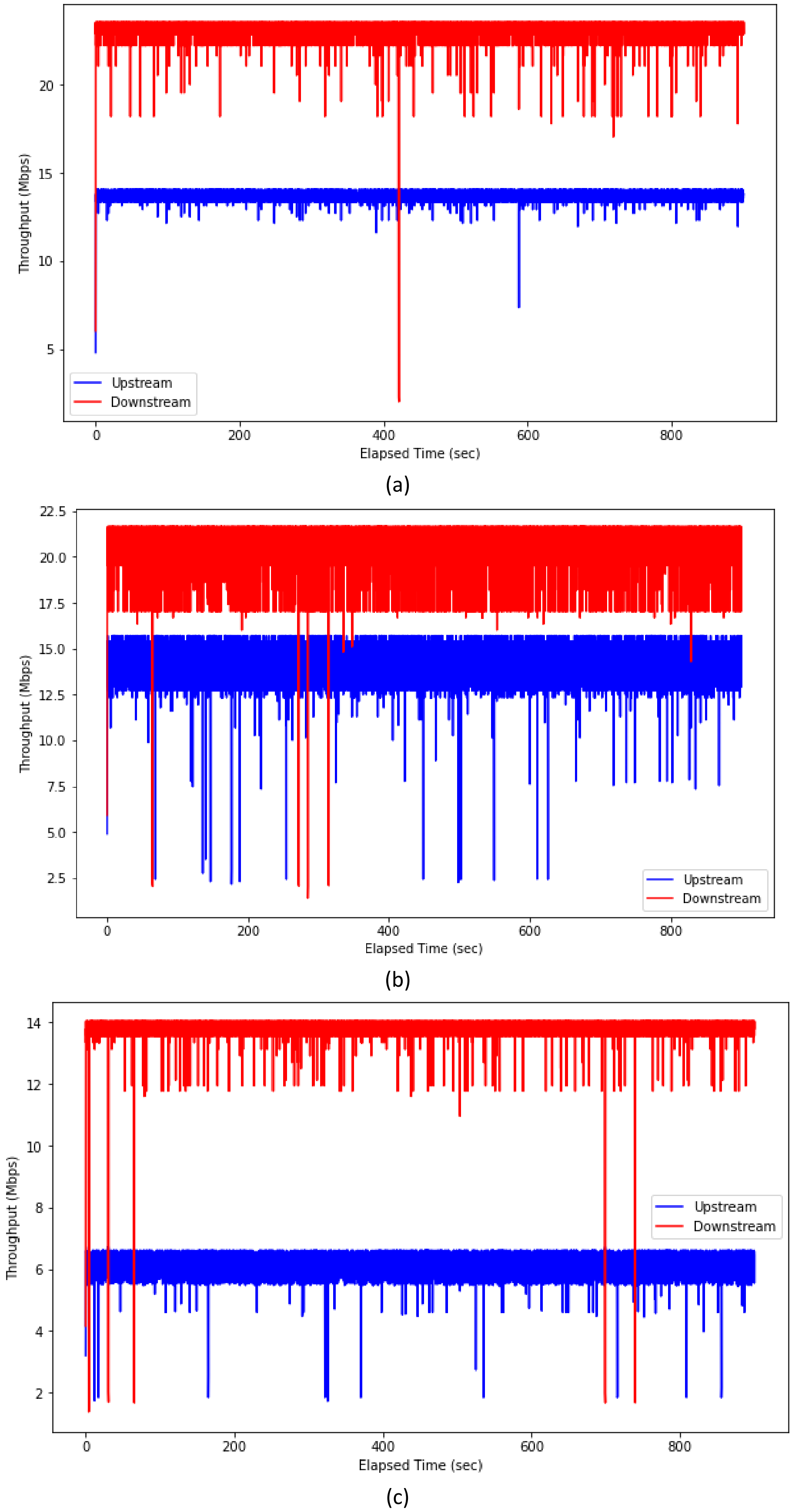
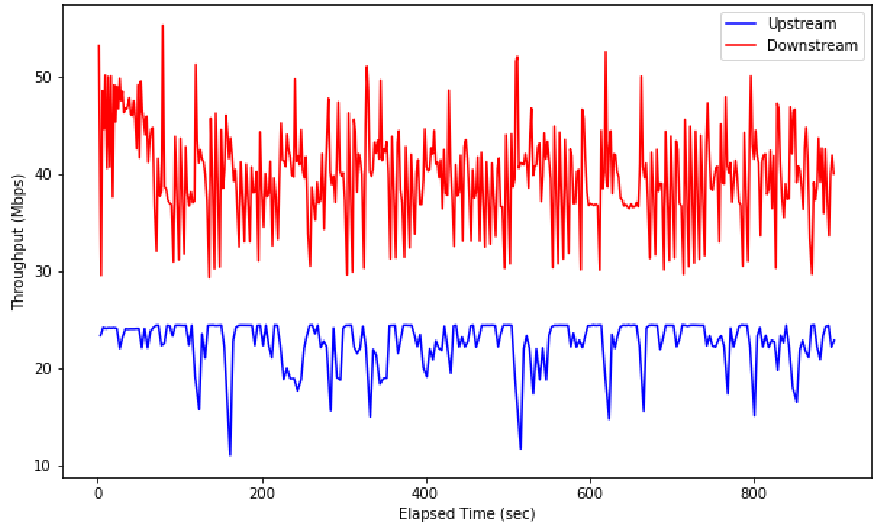


Fig. 4. Time series line graphs of throughput for medium network activity in distances of (a) 100m (b) 500m (c) 1000m



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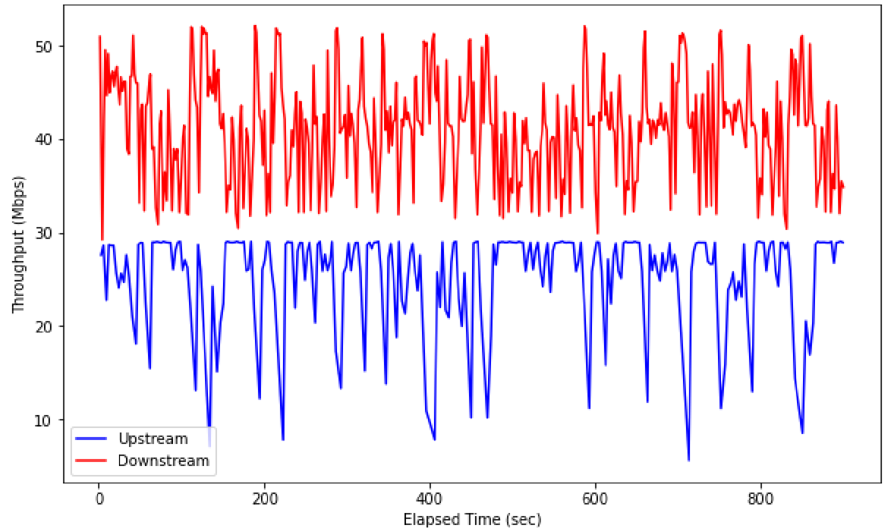

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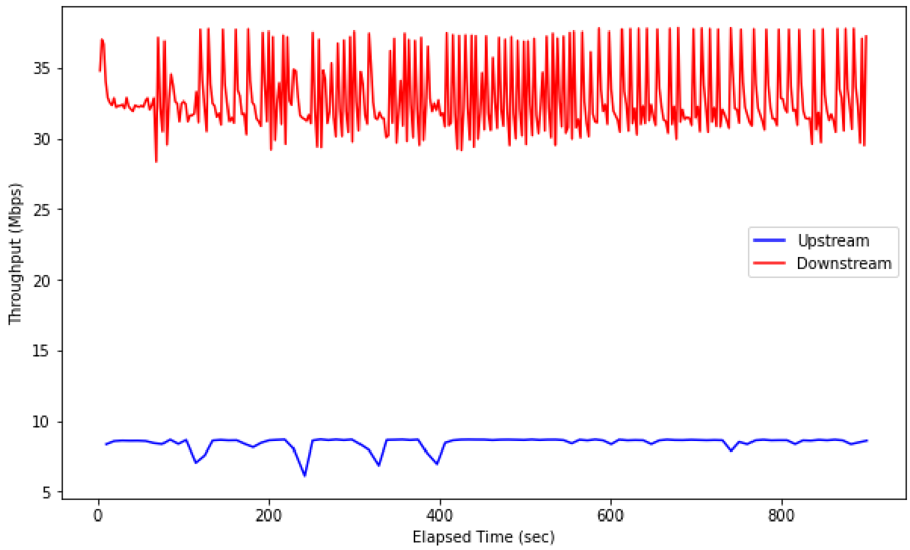


(c)

Fig. 5. Time series line graphs of throughput for high network activity in distances of (a) 100m (b) 500m (c) 1000m

Table 1 presents the statistical description of the mean and range values of throughput rates, summarizing the whole collected IxChariot data in both upstream and downstream directions. This is essential to convey the data and the throughput variations for different levels of network activities. Overall mean values, the throughput for downstream exceeds upstream in every distance and network activity. The low network activity, the range of throughput was between 0 Mbps to 2 Mbps for upstream and 0 Mbps to 4 Mbps for downstream. Meanwhile, the throughput between 1 Mbps to 16 Mbps was injected in the upstream direction and 1 Mbps to 24 Mbps downstream for the medium level of throughput. For the high network activity, the generated throughput in upstream and downstream flowed at the range between 5 Mbps to 30 Mbps and 28 Mbps to 56 Mbps, respectively. From this observation, it was summarized that the higher network activities served the higher range of throughput for the traffic generated by IxChariot. This difference was crucial to be used in correlation analysis.

Table 1
List of statistical descriptions of throughput (Mbps)

Network activities	Distance	Data direction	Mean (Mbps)	Min (Mbps)	Max (Mbps)
Lowy	100	US	2.760508	0.493940	2.857000
		DS	2.969436	1.510000	3.077000
	500	US	2.830754	0.007000	2.963000
		DS	2.985002	0.009000	3.077000
	1000	US	1.789900	0.231000	1.818000
		DS	2.051363	1.067000	2.105000
Medium	100	US	13.714042	4.790000	14.035000
		DS	23.064747	2.005000	23.530000
	500	US	14.454697	2.168000	15.686000
		DS	20.919686	1.401000	21.622000
	1000	US	6.367436	1.720000	6.723000
		DS	13.791349	1.372000	14.035000
High	100	US	22.752028	11.012000	24.420000
		DS	40.061262	29.283000	55.249000
	500	US	25.747642	5.633000	29.059000
		DS	41.506013	29.218000	52.117000
	1000	US	8.471537	6.112000	8.693000
		DS	32.941976	28.339000	37.825000

3.2 Correlation between Power Consumption and Network Activities

This project was appropriate to use numerical data as variables such as elapsed time, measured time, throughput and type of network activities. Table 2 shows the list of *r* coefficients classified by three distances of copper cable, cable condition and data flow. It also includes the continuous manipulated variables (*X*) which were recorded from IxChariot and the continuous dependent variable (*Y*) which was the output power from the DSL modem. The values of *the r correlation* coefficient were basically calculated from formula Eq. (2).

$$r=\frac{n\sum XY-\sum X\sum Y}{\sqrt{\left[\ln\sum X^2-\left(\sum X\right)^2\right]\left[n\sum Y^2-\left(\sum Y\right)^2\right]}} \tag{2}$$

The results indicated a weak correlation between power and elapsed time as a coefficient below 0.3. This weak correlation may be due to the limited range of the data to potentially reduce the strength of the correlation. Conversely, the mediate to strong relationship were seen between power and measured time for both upstream and downstream except for cable with bridge tap condition under 1000m where weak correlation was identified. This suggested that the high network activities had weak correlation to the power changes. Meanwhile, the correlation between output power and throughput appeared to have the high *r* coefficients for both conditions within upstream and downstream directions. However, an exception was noted for the copper cable of 1000m with bridge tap condition that had lower *r* coefficients which marked a medium strength of correlation.

Table 2
The correlation between power and variables of IxChariot

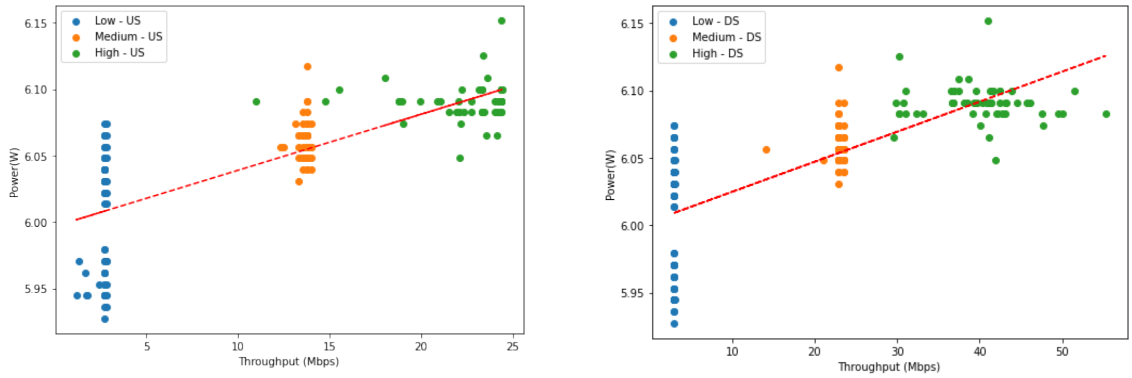
Distance (m)	*Y*	*X*	Ideal		Bridge Tap	
			US	DS	US	DS
100	Power (W)	Elapsed Time (s)	0.258028	0.248074	0.005594	-0.010620
	Power (W)	Measured Time (s)	0.591959	0.597157	0.964407	0.972421
	Power (W)	Throughput (Mbps)	0.765250	0.752102	0.849320	0.851219
500	Power (W)	Elapsed Time (s)	0.024928	0.031754	-0.013881	-0.012061
	Power (W)	Measured Time (s)	0.807409	0.851655	0.546511	0.577528
	Power (W)	Throughput (Mbps)	0.854095	0.873281	0.867516	0.854596
1000	Power (W)	Elapsed Time (s)	-0.2459558	-0.069608	-0.106841	-0.075904
	Power (W)	Measured Time (s)	0.818305	0.816292	0.118605	0.113327
	Power (W)	Throughput (Mbps)	0.887539	0.911077	0.435407	0.308536

With the listed *r* coefficients for correlations between power and throughput, the graphs are created as shown in Figure 6 and Figure 7. These visualizations give more comprehensive insights, classified into distances, cable conditions and directions of network flow. The scatter plots show three obvious groups of points, clusters (represented in colours) which were obtained by three types of network activities (low, medium and high). However, there were several points called outliers that are located far from the general pattern of the other points which are outside of the clusters. The regression line in the plots is created by formula Eq. (3) where *Y* represents power consumption and *X* is throughput while m is the slope of the regression line and b represents y-intercept.

$$Y = mX + b \tag{3}$$

For the power and throughput based on upstream (US) and downstream (DS) in the ideal condition, the scatter plot displays a strong and positive relationship. This positive linearity explained that power consumption also tended to increase as the throughput increased. Based on the observation for the patterns of data points distribution, the dispersion of highest throughput tends to spread out more compared to medium and low. This could be possibly come from the presence of outliers that noticeably differ from the rest of the data and can distort the measures of central tendency. Meanwhile, Figure 7, which is the plot of power against throughput in bridge tap condition, also shows the positive linear relationships that explain why as the throughput raised, there were increments in power. However, a weak correlation is observed in Figure 7(c) and can be evaluated through the shallow slope of regression line. It was also the point where the gain of power was much slower as the throughput increased that as well contributing to the weak correlation between both variables. Same as in the ideal condition, the trends of data points for high throughput spread out with some outliers rather than low and medium throughput that form a recognizable shape of data points.

One of the main insights gained from the relationship of power usage and Internet's throughput is that it has a positive regression line, indicating that the power consumption of the DSL modems may increase with higher usage of Internet activities regardless the condition of copper cable either with ideal or bridge tap cable condition. Nevertheless, every distance and copper cable condition have different strength of correlation. Then, the optimal predictions can be made using these regression lines to estimate the target variable (power consumption) based on the level of Internet activities as an input.



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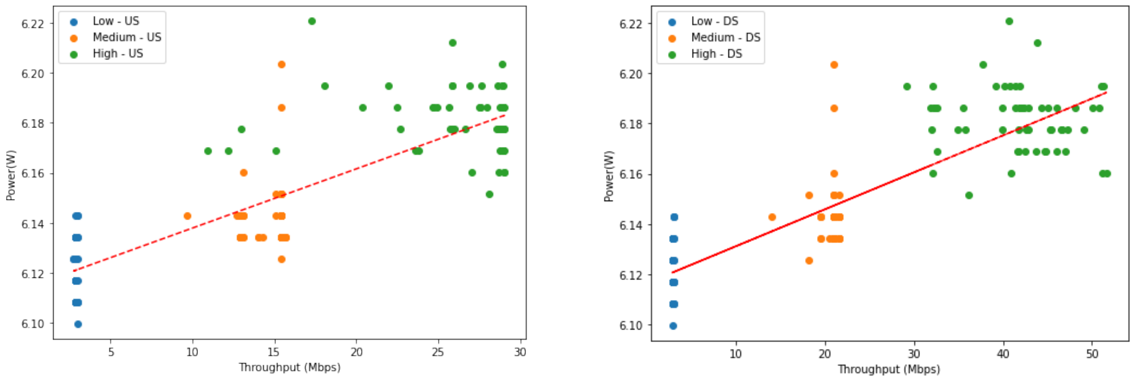

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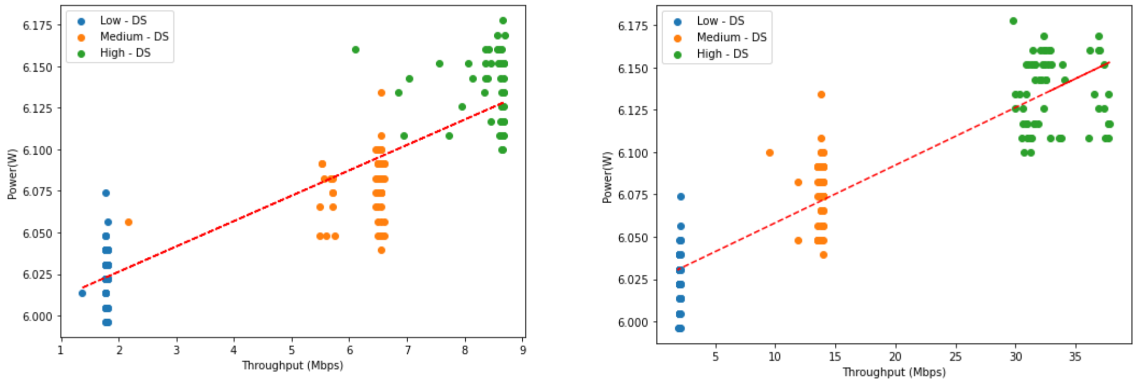

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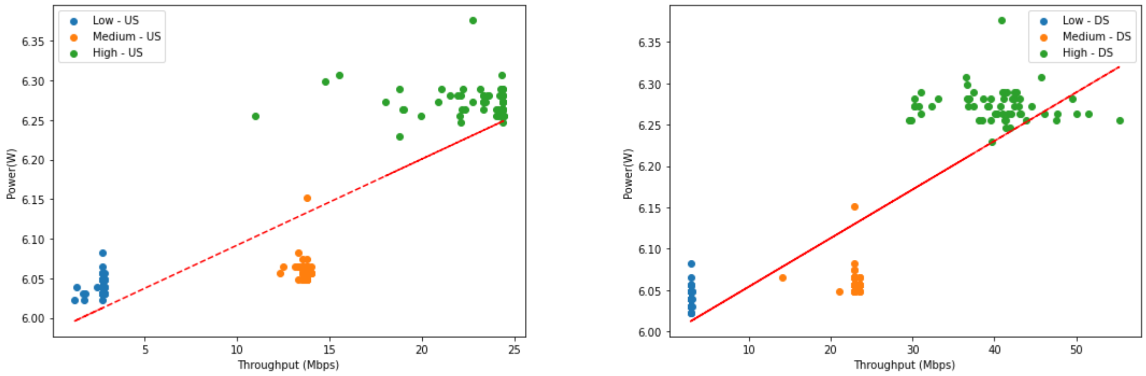
Fig. 6. Plot of power against throughput for upstream and downstream in ideal conditions for (a) 100m (b) 500m (c) 1000m length of copper cable



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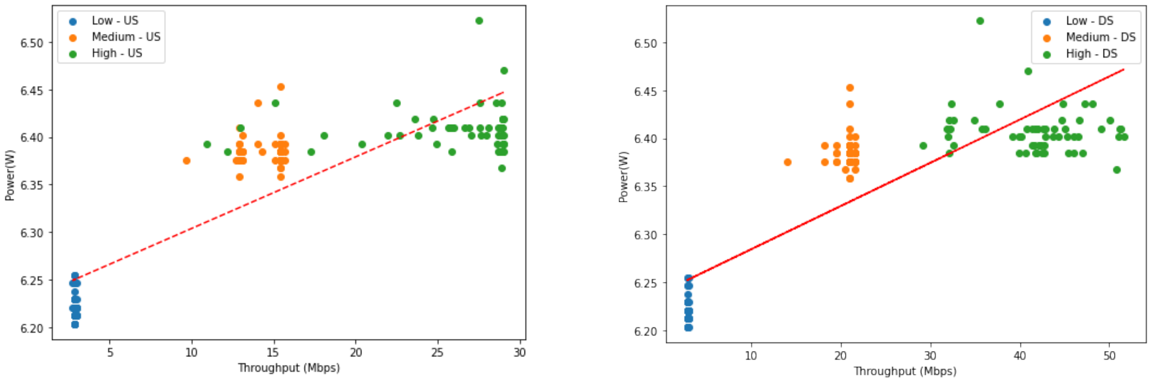

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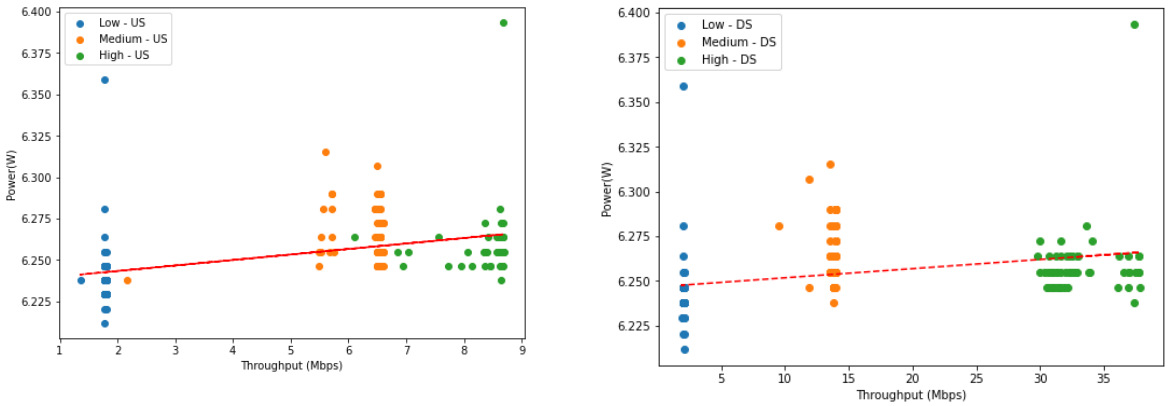


(c)

Fig. 7. Plot of power against throughput for upstream and downstream in bridge tap conditions for (a) 100m (b) 500m (c) 1000m length of copper cable

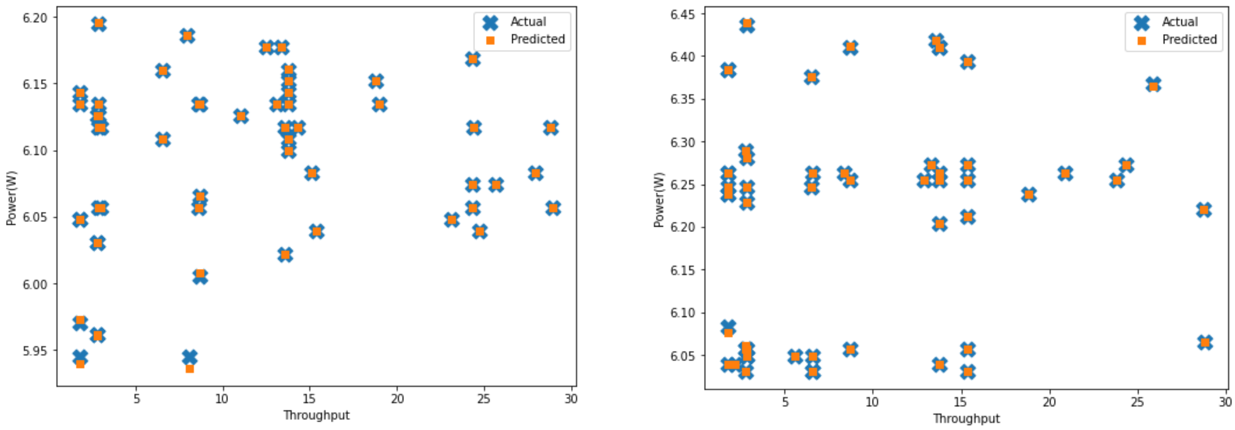
The linear regression line equations for different copper cable conditions and length are shown in Table 3. The slope represents the rate of change that provides the sensitivity of power consumption where steeper slopes mean higher sensitivity. While the intercept shows the baseline power consumption, providing a benchmark for the DSL modem's power consumption in the absence of data transmission. Based on the ideal condition, it suggests that power consumption is more sensitive to changes as the cable length is longer. Contrary to bridge tap cases where a lesser sensitive response happens as the cable length increase. This may be due to the signal distortion comes from the presence of bridge tap faults, causing uneven signal compared to ideal condition with more consistent signal quality across different cable lengths, allowing a higher sensitivity to copper cable length.

Table 3
The equations of linear regression line

Copper cable condition	Length	Linear regression line US	DS
Ideal	100	$Y = 0.00423 * X + 5.99657$	$Y = 0.00223 * X + 6.00251$
	500	$Y = 0.00236 * X + 6.11433$	$Y = 0.00147 * X + 6.11653$
	1000	$Y = 0.01525 * X + 5.99583$	$Y = 0.00341 * X + 6.02414$
Bridge Tap	100	$Y = 0.01091 * X + 5.98264$	$Y = 0.00587 * X + 5.99548$
	500	$Y = 0.00753 * X + 6.22846$	$Y = 0.00451 * X + 6.23921$
	1000	$Y = 0.00332 * X + 6.23677$	$Y = 0.00051 * X + 6.24666$

3.3 Machine Learning Model for Power Consumption Forecasting

The systematic process started by dividing into several key steps. With Train-Valid-Test method, initially, out of a total of (540 data points) for each set corresponding to ideal and bridge tap conditions, 80% of them (432 data points) had been allocated to the training set. Another remaining 108 numbers of data were halved for validating test (10%) and testing set (10%) which was 54 data each. In addition, the model was fitted with known variables such as elapsed time, measured time, throughput and network activities and distances of copper cable. The training data were then employed to fit the Random Forest Regressor algorithm allowing the model to be trained and learn the patterns of the data. Following the training phase, the testing data set was later utilized to make a predictive capabilities of the ML model. On the other hand, the validating data were used to justify the model's performance. The general data of actual against predicted power consumption was visualized by scatterplot as shown in Figure 8 without classifying the distance or network activities. Notably, it could be observed that the points of predicted data were located at a similar location and closely aligned with the actual data.



(a) (b)

Fig. 8. Plots of actual and predicted power against throughput in (a) ideal (b) bridge tap condition

To evaluate the final machine learning model's performances, the evaluation metrics like the Minimum Absolute Error (MAE), Mean Square Root Error (MSE) and Root Mean Square Error (RMSE) were employed to measure the disparity between actual and model-predicted values. The larger the value of the indicator means the bigger disparity between actual and predicted values and the lower the model's performance. MAE is the total of absolute mean differences between actual data and predicted output power with formula as in Eq. (4).

$$\mathrm{MAE} = \frac{1}{\text{Total data points}} \sum \left| \text{Actual} - \text{Predicted} \right| \tag{4}$$

Meanwhile, the average magnitude of error between actual and predicted power was measured by MSE with formula as in Eq. (5) and RMSE with formula as in Eq. (6).

$$\mathrm{MSE} = \frac{1}{\text{Total data points}} \sum (\text{Actual} - \text{Predicted})^2 \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{6}$$

These performance measures were calculated using the training and test models on the power data using a random forest regression model. Table 4 displays the MAE, MSE and RMSE for both copper condition as the quantitative indicators to evaluate of the Random Forest Regression model's performance. The smaller values of these metrics reflect minimal discrepancies between actual and predicted power consumption. With lower metrics when the copper cable is in the ideal condition compared to bridge tap scenario and it shows that it had slightly better prediction. This means that the ML model performs slightly more accurately in ideal condition. However, the small values under both conditions highlight how reliable and accurate the forecasting model is at predicting power consumption.

Table 4
Evaluation metrics of ML model

Condition	MAE	MSE	RMSE
Ideal	0.00037	1.97589×10^{-6}	0.00141
Bridge Tap	0.00032	1.24778×10^{-6}	0.00112

This research utilized the findings from prior research on predicting energy consumption, specifically referencing the benchmark study conducted by Shapi, Ramli and Awalin [15]. Contrasting the conventional method outlined by Shapi, Ramli and Awalin [15], the Random Forest Regression model employed in this study successfully captured the relationship between power consumption and network activities which resulted in more precise predictions, as evidenced by lower values of evaluation metrics.

4. Conclusions

In conclusion, this research presents the analysis on relationship between DSL modem power consumption and network activities in varying network activities which are low, medium and high activities across copper cable lengths includes 100m, 500m and 1000m. Increased Internet user's activity is correlated with higher power consumption, highlighting the effect of network load on energy use. Furthermore, an existence of a bridge tap fault also led to higher power consumption compared to ideal copper cable. Other than that, the machine learning model also has been successfully developed with the help of Jupyter software and Python programming. The model also makes use of the Train-Valid-Test Split and Random Forest Regressor technique to forecast the values of power consumption with the changes in network activities, lengths and conditions of the cable. The proposed model demonstrates its performance with high accuracy for both ideal and faulty condition. The small values of performance metrics indicate a high level of reliability in predicting power consumption. This research has specifically focused on various scenarios on DSL modem that could contribute to industries and its use in practical applications. This adaptability makes the model may be useful in real-world situations where network configurations could differ. Although the precision of the model is commendable, it is important to acknowledge its potential limitations since more validation may be necessary before extrapolating its results to another network configurations and scenarios. This is where further investigations are needed by exploring innovative techniques and broader range of diverse dataset for more robust machine learning model. Through continued research and collaborative efforts, the telecom sector can strive for greater sustainability and broader energy conservation objectives.

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