Power loss estimation utilizing the flexibility of peak power loss regression equations based on 11 kV base case feeder

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ABSTRACT

Distribution network feeder characteristics can typically be divided into groups based on factors including length, load distribution along the feeder, peak demand, installed capacity, and load profile. By comparing the parameters to those of similar feeders with known losses, it is usually possible to predict the power losses and technical losses (TL) of the respective feeders pretty accurately. However, it is exceedingly difficult and time-consuming to estimate the losses with various variables and characteristics over such a large area. This paper proposed that through base case feeder modeling and simulation utilizing typical network and load data, feeders' peak power loss (PPL) functions can be established as a simple and effective power loss estimation method. Hence, the least time-consuming way of using a PPL regression equation based on a base case feeder is established in this paper to estimate the losses. The flexibility of PPL is proven through the case study. In the end, the results obtained between PPL and peak power demand (PPD) are demonstrated to be precisely proportional and the method is proven as a simple power loss estimation method due to the flexibility of the PPL regression equation.

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1. INTRODUCTION

Energy losses (EL), whether technical losses (TL) or non-technical losses (NTL) during the distribution of electricity have caused financial setbacks for electrical companies. These losses occur during times of high demand or stress on the grid and can also lead to voltage fluctuations, increased operating expenses, and potential damage to equipment. These losses have also resulted in a decrease in the reliability and stability of the electrical system [1]. Nonetheless, even the most advanced distribution systems face challenges related to what is known as power losses [2]. Hence, there is a need to accurately understand and mitigate losses within the electrical distribution system. By employing precise estimation methods, such as regression equations, to quantify losses, utilities can identify areas where energy is being wasted and take proactive measures to minimize these losses. This, in turn, contributes to the overall efficiency and reliability of the electricity supply chain, ensuring that homes, businesses, and industries receive the energy they require without interruptions. A number of theoretical calculation methods to estimate EL are found in the literature and are well established such as in reference [3]–[5]. On the other hand, numerical simulations of load flow over time intervals are commonly utilized by some researchers to analyze EL precisely in distribution feeders [2], [6], [7]. Also, heuristic approaches are found to compute losses, such as heuristic load characteristics [8], [9], stochastic simulation [10], [11], data mining clustering approach [12], and clustering algorithm [13].

Machine learning [14], artificial neural networks (ANN) [15], [16], and fuzzy recognition [17] are examples of artificial intelligence techniques.

However, traditionally, running load flow simulations for each feeder section to determine the peak power loss (PPL) for each peak power demand (PPD) seems impractical because it requires a large amount of data and resources. For instance, Barbosa *et al*. [7] stressed that the load flow-based approach requires a large amount of data, hence it is not always available in practice since it includes network parameters, switching configuration, as well as a complete set of actual load profiles or curves for each load in the system [10]. Therefore, it is crucial to comprehend and address PPL in distribution systems to maintain the stability and resilience of our electrical infrastructure. In order to do that, PPL can be estimated through base case modeling and simulation since it requires a significant amount of time, money, and resources to precisely model a big distribution network in order to establish the TL. The base case feeder serves as the fundamental building block upon which the entire system is constructed. Understanding the base case feeder is vital because it offers a foundational configuration that can be adjusted and improved to meet different operational requirements, enhance reliability, and accommodate the integration of renewable energy sources. In past research, Zhu *et al.* [18] utilized the base case feeder to assess the economic advantages of the new design, which led to enhanced efficiency and an increased capacity to host additional resources. Nevertheless, their research does not pertain to improving the estimation of power losses in the distribution system. Thus, there is a need to delve into the intricacies of the base case feeder, examining its essential characteristics, functions, and its pivotal role in the broader context of modern power distribution, which eventually leads to the production of regression equations.

Regression analysis is a statistical technique used to examine the relationship between a continuous value dependent variable, *y*, and one or more independent variables, *x* [19]. The premise of linear regression is that output values may be roughly predicted from input values using a rule-based regression. To put it another way, it relates to the case in which the data set in question and any additional unknown values are situated along a hyperplane that connects to a single point. A regression equation expresses the relationship between two sets of data. Since it shows the response that depends on the changed variable, a regression equation is adaptable. When dealing with PPL within an electrical distribution system, regression analysis becomes a valuable tool for identifying and measuring the variables that contribute to these losses. The connection between the PPL and the PPD is the focus of this paper in order to develop a simple estimation method. The PPD serves as the dependent variable, while the PPL serves as an independent variable. PPL functions are one of the straightforward and effective methods for estimating losses. A regression analysis was used by Manusov and Mogilenko [20] to evaluate the power losses in an electrical network. However, instead of using the base case feeder model to generate the regression equation, the study by Manusov and Mogilenko [20] focused on the fuzzy regression model which leaves the research still in its infancy. Another related study was found, where Sippola and Sepponen [21] used regression analysis to validate the accuracy of the power transformer losses. In practice, there are many ways to estimate the losses. However, at times when cost, resources, and availability of network data are major constraints, some utilities have to make use of whatever data is available, as long as the methodology can be easily deployed and yield reasonably accurate results.

In all, to establish a simple way to estimate EL, this paper focuses on developing the regression equations of PPL functions utilizing the base case feeder and showing the flexibility of these PPL functions allowing users to estimate the PPL of the feeder section for any PPD value. The feeder length, load distribution, cable characteristic, and feeder peak demand were taken into account in the formulation of generic PPL equations. The main contribution of this work can be summarized as follows: i) establishment of a base case feeder model based on the most used cable characteristics in Malaysia to cut the amount of time in estimating losses in a wide power system, ii) development of a simple way to estimate the losses using the PPL regression equation without having to collect vast amounts of data and calculate the losses at every load point, and iii) validation of the flexibility of PPL functions using real power distribution network data at two different base lengths.

2. METHOD

The main idea is that the PPL will be defined using the regression analysis through independent variables in the base case feeder. Firstly, in subsection 2.1, real data is collected and the base case feeder that represents 11 kV Malaysia's feeder is constructed through statistical analysis by Ibrahim *et al*. [22]. Subsequently, in subsection 2.2, the chosen model is constructed by fitting the data, specifically in the case of PPL, to understand the relationship between independent variables and power losses during PPD periods. Given the variable nature of PPL, it is crucial to continuously monitor and periodically update the model to account for changing conditions in the distribution system. To address this, a length correction factor (CF) is also introduced. This model's reliability is then verified by testing it against real-world data in a base case study, assessing its predictive accuracy.

2.1. Base case feeder modeling

The base case feeder section model is constructed as illustrated in Figure 1. The three (3) key parameters that define the base case feeder are; i) varied lengths, ii) load distribution, and iii) cable characteristics. The model of this base case feeder is set at 11 kV, 240 mm^2, three-core Cu XLPE cable type, load value of (10-100)%×3.0 MVA, the LF of 0.95, based on the statistical analysis by Ibrahim *et al.* [22]. The base case length which was originally set at 1 km, is varied from 1 km to 4 km to show the flexibility of PPL functions and the relationship of PPL functions with base case cable length.

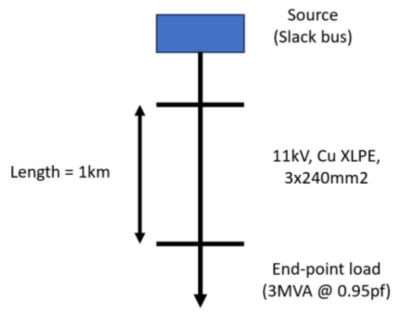


Figure 1. Model of the base case feeder section in a single-line

2.2. Peak power loss characteristics

A regression analysis is conducted using load flow data derived from the base case feeder configuration. The analysis involves static load flow simulations carried out at different loading levels: 10%, 30%, 50%, 70%, 90%, and 100%. At each of these loading points, the PPL is recorded, and this data is used to establish a third-order polynomial regression equation. A polynomial regression model is preferred over multiple regression or time-series regression in this context due to its suitability for the data and its ability to minimize errors. Then, the PPL for each segment of the feeder is directly related to its PPD expressed in megawatts (MW), which can vary over time. The calculation of PPD is based on the fundamental formulas presented in (1):

$$PPD = S\cos\theta \tag{1}$$

Then, this base case feeder section where a single feeder connected to a single end-point load as in Figure 1 is simulated in DigSILENT Powerfactory™ to find its PPL for the regression equation. The equation derived to estimate the PPL in different feeder sections assumes that each section has the same length and size as the base case feeder. In addition, using the same base case model, the result of PPL through simulation is added with a variation of cable length. These PPL results are then plotted in Excel in polynomial form to get the PPL functions at 1 km, 2 km, 3 km, and 4 km cable lengths.

However, to enhance the accuracy of PPL calculations based on PPD, adjustments are required. According to the findings in reference [22], the PPL equation is shown to have a linear correlation with the length of the cable. Consequently, length (C) for the base case feeder's PPL (PPL_b) are determined by multiplying the PPL equation by the ratio of the length of the specific feeder (l_i) to the base case feeder length (l_b), as shown in (2). The PPL coefficients for each section of the base case feeder are represented by the coefficients *a, b, c* and *d*. Subsequently, the 30-day EL for each feeder section, taking into account varying PPD and lengths, is computed in the following section.

$$PPL_b = \frac{l_i}{l_b} \times \{a\rho_i^3 + b\rho_i^2 - c\rho_i - d\} \tag{2}$$

2.3. Validation of proposed method using case study

After obtaining the crucial data, the PPD and PPL of each feeder, an EL can be estimated. In order to produce the estimates, a case study based on a base case feeder is used to demonstrate the proposed methodology. The case study is based on real data from Batu Caves, Kuala Lumpur. Overall, the case study aims to display the relationship between the flexibility of PPD and PPL with a base length feeder.

3. RESULTS AND DISCUSSION

In the case of feeders, a simple way of establishing its PPL functions is through modeling and simulation using typical network and load data. Thus, this section shows the results of the proposed methodology covering the case study of real networks.

3.1. Peak power loss functions

Based on the typical installation of the local power utility, the base case feeder is set at 11 kV, 240 mm^2, three-core, Cu XLPE cable type. These characteristics are based on a statistical study performed in reference [23], [24]. For simplification, loads are assumed to be balanced, with a power factor of 0.95 and a constant voltage along the feeder.

The peak loss functions are snapshots of power losses in relation to cable capacity, feeder length, and load distribution profile. The value of *S* is obtained based on the load percent. Since the base case model shows full load at 3 MVA, 100% load would be 3MVA, while 10% load would be 0.3 MVA, and so on. Then, the PPD is calculated using a basic formula based on apparent power, *S,* and power factor, *pf* in (1). After that, the value of PPL is obtained through the simulation of the base case model in DigSILENT at several base lengths (1 km, 2 km, 3 km, and 4 km). Table 1 indicates the value of the regression result, which shows that the higher the percent loading and apparent power, the higher the PPD and PPL. Also, it can be seen from Table 1 that the longer the cable length, the higher the PPL. Results in graphs expressed in terms of PPL functions for 11 kV MV feeders based on Table 1 are shown in Figure 2.

Table 1. Regression results with 1 km, 2 km, 3 km, and 4 km base case cable length

Load (%)	S (MVA)	PPD (MW)	PPL (MW)			
			1 km	2 km	3 km	4 km
10	0.3	0.2850	0.0001	0.0001	0.0002	0.0002
30	0.9	0.8550	0.0005	0.0012	0.0009	0.0020
50	1.5	1.4250	0.0014	0.0035	0.0022	0.0056
70	2.1	1.9950	0.0027	0.0069	0.0043	0.0110
90	2.7	2.5650	0.0046	0.0114	0.0070	0.0183
100	3	2.8500	0.0056	0.0142	0.0087	0.0227

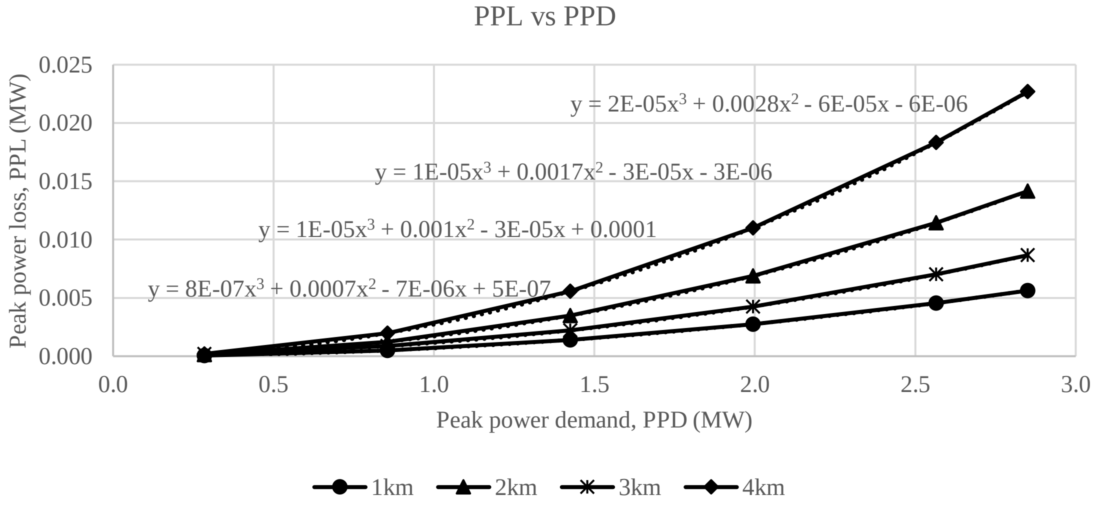


Figure 2. PPL functions of 11 kV feeders with distributed loads along the feeder

It can be seen from Figure 2 that the PPL of each feeder section is proportional to its PPD, measured in MW, which varies with time. The graph is displayed in a polynomial form. It is proven that the higher the power demand, the higher the power loss. Also, based on the steepness of the graph, the longer the cable length, the higher the power loss or PPL.

Table 2 depicts the same results of a regression equation that can be used to calculate the PPL based on PPD with different base lengths of 1 km and 4 km. From Table 2, the mathematical equation is converted into a regression equation. The *y* simply represents the PPL function, while the *x* simply represents the PPD.

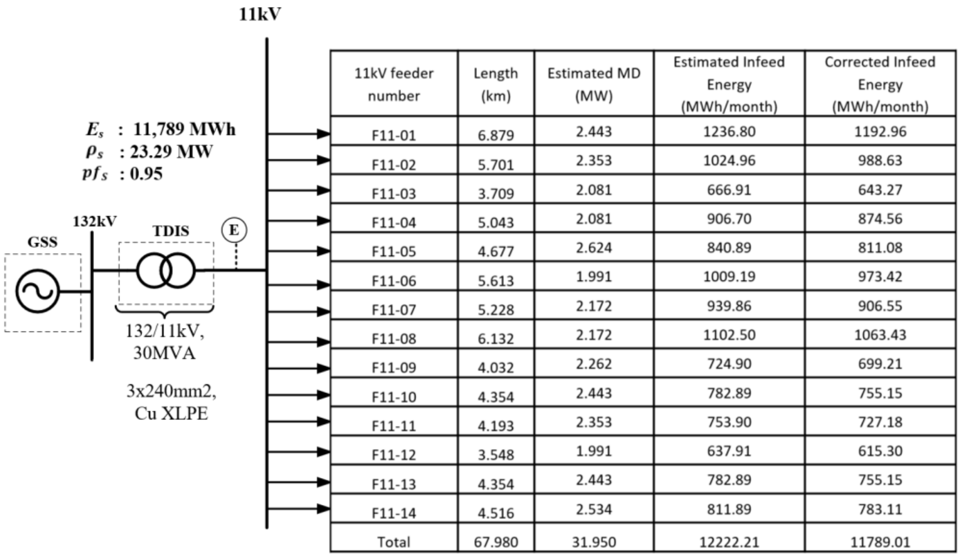
The results would be varied with a different base length. However, it still correlates and does not deny that the higher the power demand and cable length, the higher the losses. This statement has been proved by a previous study by Rozegnał *et al*. [25] where in cases that the lines are extended, the active power losses increase in direct proportion to the length of the line.

Table 2. Regression equation for the length of 1 km and 4 km

Length (km)	Mathematical equation	Regression equation
1	$y = 8e^{-7}x^3 + 7e^{-4}x^2 - 7e^{-6}x + 5e^{-7}$	$PPL(PPD) = 8e^{-7}PPD^3 + 7e^{-4}PPD^2 - 7e^{-6}PPD + 5e^{-7}$
2	$y = 1e^{-5}x^3 + 1e^{-3}x^2 - 3e^{-5}x + 1e^{-4}$	$PPL(PPD) = 1e^{-5}PPD^3 + 1e^{-3}PPD^2 - 3e^{-5}PPD + 1e^{-4}$
3	$y = 1e^{-5}x^3 + 17e^{-4}x^2 - 3e^{-5}x - 3e^{-6}$	$PPL(PPD) = 1e^{-5}PPD^3 + 17e^{-4}PPD^2 - 3e^{-5}PPD - 3e^{-6}$
4	$y = 2e^{-5}x^3 + 28e^{-4}x^2 - 6e^{-5}x - 6e^{-6}$	$PPL(PPD) = 2e^{-5}PPD^3 + 28e^{-4}PPD^2 - 6e^{-5}PPD - 6e^{-6}$

3.2. Case study

The case study aims to prove that regardless of any base case length chosen, the result is the same after taking length CF into consideration. In this case study, an average size distribution system of 11 kV illustrates the proposed approach to estimate TL and its results. To prove the length CF in (2) regardless of any regression equation with the same cable condition, two (2) base lengths were used which are 1 km and 4 km as highlighted in Table 2. Meanwhile, the real data of the distribution system for the case study is depicted in Figure 3. This case study is based on data from Batu Caves, Kuala Lumpur.



11kV feeder number	Length (km)	Estimated MD (MW)	Estimated Infeed Energy (MWh/month)	Corrected Infeed Energy (MWh/month)
F11-01	6.879	2.443	1236.80	1192.96
F11-02	5.701	2.353	1024.96	988.63
F11-03	3.709	2.081	666.91	643.27
F11-04	5.043	2.081	906.70	874.56
F11-05	4.677	2.624	840.89	811.08
F11-06	5.613	1.991	1009.19	973.42
F11-07	5.228	2.172	939.86	906.55
F11-08	6.132	2.172	1102.50	1063.43
F11-09	4.032	2.262	724.90	699.21
F11-10	4.354	2.443	782.89	755.15
F11-11	4.193	2.353	753.90	727.18
F11-12	3.548	1.991	637.91	615.30
F11-13	4.354	2.443	782.89	755.15
F11-14	4.516	2.534	811.89	783.11
Total	67.980	31.950	12222.21	11789.01

Figure 3. Case study's distribution system

Table 3 shows the distribution PPL for a 1 km and 4 km base length. The CF length is calculated by dividing the real length by the base length. Then, the PPL base is calculated by (2). From Table 3, it can be observed that the longer the cable length, the higher the PPL value. For example, the longer cable length, which is 6.88 km, shows the largest PPL value of 28.72 kW and 28.66 kW for both base lengths of 1 km and 4 km respectively. Similarly, the shorter cable length will result in lower PPL. From the same Table 3, the shortest cable length at 3.55 km, results in the lowest PPL value which is 9.82 kW and 9.746 kW for both base lengths of 1 km and 4 km respectively. The reason for this is that extended cables contain a greater amount of conductor material, which results in elevated cable resistance due to the additional length. This increased resistance gives rise to increased power losses in the form of heat as electrical current traverses the cable. Additionally, longer cables bring about added impedance due to heightened inductance and capacitance. This impedance has the potential to impact the power factor and result in losses associated with reactive power, in line with or corroborating the findings of a previous study by Esobinenwu and Oniyeburutan [26] and also Abdelhady *et al.* [27].

Besides, the highlighted value in Table 3 indicates the PPL comparison between base lengths of 1 km and 4 km. At the base length of 1 km, total PPL estimation shows 249.88 kW, while at the base length of 4 km, total PPL estimation displays 248.59 kW. The value PPL of 1km base length is slightly higher than 4 km base length. There is a difference of approximately 1.29 kW between the two values, with a 1 km base length being the larger of the two. The values exhibit a minor difference, but it is acceptable and in the permissible range and considered the same. It proves that different regression equations and the base length will produce the same result after length CF as long as it does not change the cable characteristics. Hence, the base case model needs to be changed if this method will be used in different countries or regions. Table 3 also proves that a simple way is established to estimate the losses using the flexibility of regression equation without having to calculate the losses at every load point.

Table 3. PPL estimation for 1 km and 4 km base length

11 kV feeder number	Length (km)	Base length=1 km				Base length=4 km			
		CF length	PPL (MW)	PPL (kW)	PPL base, PPL_b (kW)	CF length	PPL (MW)	PPL (kW)	PPL base, PPL_b (kW)
F11-01	6.879	6.879	0.004	4.175	28.717	1.720	0.017	16.667	28.663
F11-02	5.701	5.701	0.004	3.870	22.063	1.425	0.015	15.413	21.967
F11-03	3.709	3.709	0.003	3.026	11.224	0.927	0.012	12.016	11.143
F11-04	5.043	5.043	0.003	3.026	15.260	1.261	0.012	12.041	15.180
F11-05	4.677	4.677	0.005	4.818	22.535	1.169	0.019	19.155	22.397
F11-06	5.613	5.613	0.003	2.768	15.536	1.403	0.011	11.029	15.477
F11-07	5.228	5.228	0.003	3.296	17.229	1.3047	0.013	13.117	17.143
F11-08	6.132	6.132	0.003	3.296	20.210	1.533	0.013	13.145	20.152
F11-09	4.032	4.032	0.004	3.577	14.423	1.008	0.014	14.212	14.325
F11-10	4.354	4.354	0.004	4.175	18.178	1.089	0.017	16.591	18.061
F11-11	4.193	4.193	0.004	3.870	16.228	1.048	0.015	15.378	16.121
F11-12	3.548	3.548	0.003	2.768	9.820	0.887	0.011	10.988	9.746
F11-13	4.354	4.354	0.004	4.175	18.178	1.089	0.017	16.591	18.061
F11-14	4.516	4.516	0.004	4.491	20.278	1.129	0.018	17.850	20.151
Total	67.980	67.980	0.051	51.328	249.877	16.995	0.204	204.193	248.588

Overall, although the value of PPL in Table 1 shows different results at different base case cable lengths, the result of PPL after considering CF is almost the same. In other words, the proposed method of PPL regression equation can be varied depending on the base length used since there is a ratio of CF for the length, as in (2). Therefore, utilities can come out with any regression equation that is suitable for their choices of the base feeder. It is proven that this study makes it possible to compute the losses quickly and simply. To assess losses of large distribution networks, an analytical method based on equations created through energy distribution is used. This method can be used to assess a distribution network's performance based on the desired characteristics of different feeders. However, the limitation of this research is the established base case model only can be used in Malaysia's network due to the cable characteristics that only take into account Malaysia's network. Nevertheless, it can be overcome by changing the model of the base case to get the new regression equation depending on the cable characteristics in different areas or countries. The advantage of this method is it can calculate PPL for any value of PPD as long as the characteristics are the same as the base case feeder. If it is different, the base case can be modified according to a specific area, and then the new regression equation needs to be changed too, but it is still a simple procedure because there is no need to do the power flow for all areas.

4. CONCLUSION

In conclusion, this paper introduces an optimal method and effective approach for estimating the EL. The focus is on constructing regression equations for PPL functions using data from the base case feeder. The findings highlight that regression analysis can be a powerful tool in identifying the key factors influencing PPL and making informed decisions to improve the efficiency and reliability of electrical distribution systems. Furthermore, the method demonstrates that utilizing a base case feeder model can significantly reduce the time required for loss estimation across wide power systems. By showcasing the adaptability and flexibility of PPL functions, researchers and utilities can efficiently estimate the PPL of feeder sections for various PPD values, offering a versatile approach for EL estimation. In essence, the more accurate the estimation method, the better-equipped utilities are to optimize their systems and maintain a consistent and reliable flow of electricity to consumers. In the future, this method can also help to make forecasts and decisions about managing and mitigating PPL. For example, it can help in optimizing maintenance schedules, load management, or infrastructure improvements.

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