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Short-term load prediction model for electrical power distribution network

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Abstract
Electrical Load prediction model for power distribution network becomes necessary as a result of fast increase in the demand for electricity for residential and industrial usage. This work developed a short-term model for an 11-KV feeder that supplied a particular area. The model was based on the multiple linear regression principle that used the past data of the feeder line. The model was used to predict the consumers' load demand for a period of 1 week. The result of the regression analysis gave a Mean Absolute Percentage Error (MAPE) of forecast of 0.9% for the 11-KV feeder. Conclusively, the accuracy of the developed load forecast model was 99.1%.

Keywords: Forecast, load-demand, data, regression, short-term

1. Introduction
Electric load forecasting is important in generation, transmission, and distribution for the goal of providing affordable and efficient electricity to satisfy a variety of load needs over a certain period of time (Isaac *et al*., 2014; Singh *et al*., 2012; The-Hien *et al*., 2017) [8, 15, 19]. Customers' energy needs are estimated in advance by the power company, which then provides the required energy (Ghods & Kalantar, 2011) [6]. Load forecasting is the term for the process of estimating load in advance (Tahreem *et al*., 2018) [18]. However, because of its stochastic and unpredictable nature, correctly forecasting future load demand has proven to be a difficult task for electrical utilities (Khuntia *et al*., 2016). The historical operational data of an 11-KV feeder that served an area with a fast increasing load pattern was examined. For the aim of predicting electrical energy consumption, a short-term linear regression model was built for the 11-KV feeder.

2. Literature review
2.1 Factors Affecting Load Forecast
Weather, holidays, festivals, or events, tariff structures, historical data, time of year, day of week, and time of day are all factors to consider. Temperature, moisture, rain, and wind are among weather factors that influence forecast accuracy. (Dhaval and Deshpande, 2020).

2.1.1 Time Factor
The daily load pattern is based on daily activities such as working hours, leisure hours, and sleeping hours, and there is a particular pattern of load changes with time. Due to less activities and work, weekend and holiday loads in industries and offices are lower than weekday loads. (Xue *et al.,* 2012).

2.1.2 Economic Factor
Economic variables such as industrial expansion, population growth, Gross Domestic Product (GDP), and energy cost all influence load patterns. (Khatoon *et al.,* 2014).

2.1.3 Weather Condition
Temperature and humidity have a significant impact on power consumption because when the temperature increases, people will switch on air conditioners, and if the temperature drops, people will turn on air heaters, resulting in an increase in energy demand. (Dhaval and Deshpande, 2020).

2.1.4 Customer Factor
The quantity, kind, and size of the customer's electrical equipment are the primary consumer variables that influence energy usage. Electrical equipment and installations differ from one client to the next. Residential consumers have a distinct load curve than business and industrial customers. (Phuangpornpita & Prommee, 2016) [11].

2.2 Load forecasting methods
Short-term, medium-term, and long-term forecasting techniques are used (Lal *et al*., 2016) [10]. Forecasts for the short term range from one hour to a week. This may be applied to a utility's day-to-day operations in terms of unit commitment, economic dispatch, and load management. Forecasts for the medium term may vary from a few weeks to a few months, and even a few years (Phuangpornpitak and Prommee, 2016) [11]. It is primarily affected by variables such as the installation of new loads, seasonal fluctuations, demand patterns of big facilities, and significant consumer maintenance needs (Abu-Shikhah *et al*., 2011) [1].
A long-term prediction must be valid for a period of 5 to 25 years. It is utilised to make decisions on the generating and transmission expansion plans for the system (Phuangpornpitak & Prommee, 2016) [11].
Swaroop *et al*. (2012) [17] utilised a neural network method to predict the quantity of energy consumption in certain Oman regions. The absolute mean error (AME) was 2.64 percent, indicating a good level of accuracy. Based on data from the power distribution business, Bamigboye *et al*. (2016) [5] used the particle swarm optimization method to forecast electrical energy. The model predicted energy use half an hour ahead of time. For electrical energy prediction, Isaac *et al*. (2016) used Time Series and Artificial Neural Network techniques. With a Mean Absolute Deviation (MAD) of 0.225, a Mean Squared Error (MSE) of 0.095, and a Mean Absolute Percent Error (MAPE) of 8.25, the findings are compared in terms of error measurements. Ade-Ikuesan *et al*. (2018) [2] utilised a probabilistic load forecasting method to estimate the load demand trend in Ogun State for the year 2018. According to the study's findings, the likelihood of energy consumption falling between 98,469.40 MWHR and 46,494.68 MWHR in 2018 is 91.84 percent.

2.3 Techniques of Short-Term Load Demand Forecasting
The time series technique, comparable day method, neural network method, regression analysis, and time series analysis are some of the most frequently utilised short-term load forecasting methods. There are also many new methods in the horizon, such as gradient boosting machines and random forests (Hannah *et al*. 2019) [7].
In order to create forecasts, the similar-day-look-up method examines historical data on days from one, two, or three years ago that have similar features such as weather, day of the week, or date (Qingqing *et al*., 2010) [13].
Time series forecasting is founded on the concept that by modelling patterns in a time series plot and projecting those patterns into the future, accurate predictions may be made. Time series analysis fits a model according to seasonality and trend using historical data as input. In certain cases, time series models may be correct, but they are very complicated and need a significant quantity of previous data (Vikas & Seema, 2017).

2.3.1 Expert Systems
An expert system is a computer software that may integrate several forms of human intellect and function as a decision-making system. The load prediction model is constructed utilising an expert's knowledge of the load forecast domain (Kandil *et al*., 2002).

2.4 Linear Regression
The relationship between a continuous (real-valued) dependent variable y and one or more independent variables is modelled in regression analysis in order to find a function that closely describes the dependent variable for the purpose of possible dependent variable prediction using a range of independent variable values. For example, in the multiple linear regression technique of electrical load forecasting, the load is determined in terms of factors that affect the electrical load (Amral *et al*., 2007) [3]. The load model for this technique is written as follows: (Reddy *et al*., 2017) [14].

$$Y = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + ... + \beta_n X_{nt} + U_t \tag{3}$$

Where, $t = 1, 2, \ldots, n$

Y is dependent variable, X $_{\text{is}}$ Independent variable, U_t is the error term and β's are constant parameters that are estimated using the available data X and Y.
The dependent variable in energy forecasting is typically electricity demand since it is reliant on production, which is dependent on the independent factors (Jing-Min & Li-Ping, 2008) [9].
This model may be used for prediction once the parameters have been determined. Assuming that all independent variables have been properly identified, the standard error will be low (Reddy *et al*., 2017) [14].

2.4.1 Multiple Linear Regression Techniques and Short-Term Load Forecast
Multiple linear regression methods have been used in a number of studies. Amral *et al*. (2007) [3] used a Multiple Linear Regression (MLR) method implemented with Microsoft Excel software to model the 24-hour short term load demand of the South Sulewesi Power System for both dry and rainy seasons, using historical data consisting of hourly load demand and temperatures of the electrical system. MAPE 3.52 and MAPE 4.34 were the short-term forecasts for the dry and rainy seasons, respectively.
Singh *et al*. (2014) [16] utilised the multiple linear regression method to construct a short-term load prediction model in two instances. In addition to the prediction model used in the first instance, the model for the second case contained some polynomial terms. Independent factors included dry bulb, dew bulb temperature, energy public relations, and so on. For the first and second instances, the mean average percentage errors (MAPE) were 13.59 percent and 9.7 percent, respectively. The model, however, requires a highly precise temperature forecast, since even a little change in temperature may result in a large change in load prediction.

3. Material and Methods
In this research multiple linear regression (MLR) model was developed from the historical data in Table 1 of the energy consumption of an 11-KV distribution substation. Then a forecast was made for a period of one week for the substation.

Table 1: Load on 11KV Feeder Pillar

Day	Current	Voltage (KV)	Power Factor	Power Absorbed/day(KW)
1	80	11	0.93	818.40
2	84	11	0.95	877.80
3	80	11	0.93	818.40
4	80	11	0.94	827.20
5	75	11	0.91	750.75
6	84	11	0.93	859.32
7	71	11	0.93	726.33
8	74	11	0.94	765.16
9	75	11	0.93	765.25
10	74	11	0.93	757.02
11	74	11	0.92	748.88
12	77	11	0.93	787.71
13	71	11	0.92	718.52
14	74	11	0.93	757.02
15	71	11	0.92	718.52
16	74	11	0.92	748.88
17	74	11	0.92	748.88
18	75	11	0.93	767.25
19	72	11	0.93	736.56
20	72	11	0.93	736.56
21	71	11	0.92	718.52
22	79	11	0.92	799.48
23	70	11	0.93	716.10
24	74	11	0.91	740.74
25	73	11	0.93	746.79
26	76	11	0.92	769.12
27	76	11	0.92	769.12
28	85	11	0.93	869.55
29	80	11	0.94	827.20
30	79	11	0.91	790.79

Figure 1 shows the diagram of the plot of the daily load consumption for a period of 30 days for the 11-KV feeder.

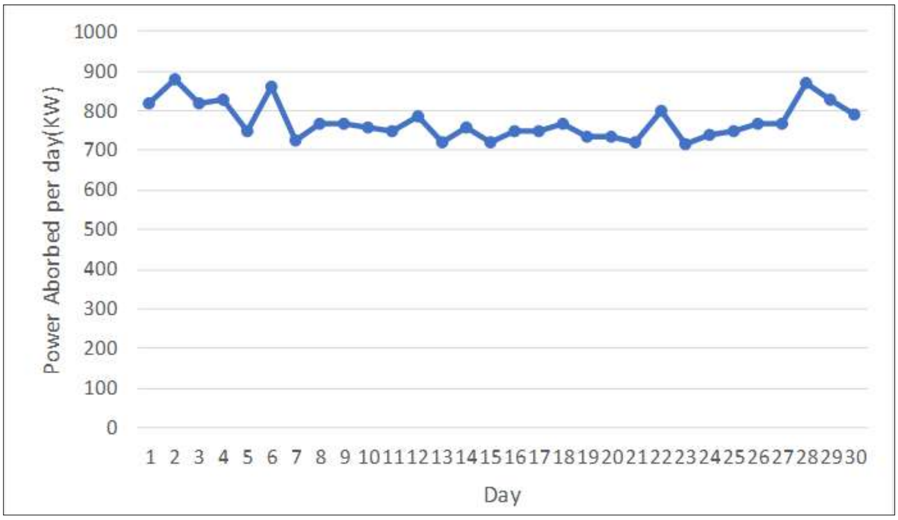

Fig 1: Daily Load Demand for a period of 1 month

The steps applied were as follows

1. The correlation coefficient and the coefficient of correlation between the dependent variable (i.e. load consumption per day, P) and the independent variables (i.e. current, I and power factor, *p.f*) were determined. This is to test whether a strong correlation exists between the load per day on the one hand and, current and power factor on the other hand, given the condition of a constant operating voltage of 11 KV.
2. The significance value, α_{actual} of the analysis of variance was determined.
3. Then, the objectives for a hypothesis testing was set as follows:
   a. The null hypothesis H_0: the model is insignificant and not good for estimation
   b. The alternative hypothesis: H_1: the model is significant and good for estimation
   c. Decision rule: reject H_0, if significance value, $\alpha_{actual} < 0.05$, if otherwise, accept H_0
4. The functional model of the 11-KV feeder of the sub-station was determined and was used to make a forecast

for a short-term period of 7 days.
5. The output of step (iv) was compared with the actual load of the same period of 7 days and the percentage of the error of forecast was determined.
6. The curves of the compared actual and forecasted load were plotted.

4.1 Results and Discussion

The correlation coefficient R and the coefficient of determination R^2 obtained were respectively 0.999927 and 0.999838. It indicated a strong correlation between load demand and, current and power factor given the condition of a constant operating voltage.

4.1.1 Estimating the Model for the 11-KV Feeder

Table 2: Analysis of Variance (ANOVA)

	df	SS	MS	F	Significance F
Regression	3	60615.84	20205.28	59670.77	$5.35\text{x}10^{-50}$
Residual	26	8.80393	0.338613		
Total	29	60624.65			

The significance value, α_{actual} of $5.35\text{x}10^{-50}$ obtained was far less than 0.05. Hence, the alternative hypothesis is accepted. As a result, the model was estimated to be good for forecasting the load demand for a short-term period.

4.2 Functional Model of the 11-KV Feeder

The functional model for the 11-KV feeder as a result of the multiple regression analysis applied to the data in Table 1 was estimated as shown in equation (4).

$$Y_{est} = -788.327 + 10.23513 * I + 847.3719 * p.f \quad (4)$$

4.3 Forecasting For Short-Term Basis

Table 3 gives the values obtained when equation (4) was used to make a forecast for a period of one week.

Table 3: Load Forecast for 1 Week for the 11-KV Feeder.

Day	Current	Power factor	Forecasted Load, Y_{est}(KW)
1	80	0.93	825.7393
2	84	0.95	883.9872
3	80	0.93	825.7393
4	80	0.94	834.2130
5	75	0.91	757.1662
6	84	0.93	867.0398
7	71	0.93	732.8131

4.4 The Forecasted Load and the Actual Load

Table 4 shows a comparative analysis of the estimated load with the actual load.

Table 4: Comparison of actual load with forecast load for 1 week

Days	Actual	Forecasted	Error of	%Error
1	818.4	825.7393	7.3393	0.896786
2	877.8	883.9872	6.1872	0.704853
3	818.4	825.7393	7.3393	0.896786
4	827.2	834.2130	7.0130	0.847800
5	750.75	757.1662	6.4162	0.854639
6	859.32	867.0398	7.7198	0.898361
7	726.33	732.8131	6.4831	0.892583

Figure 2 shows the diagram comparing the forecasted load demand with the actual load demand for a short-term.

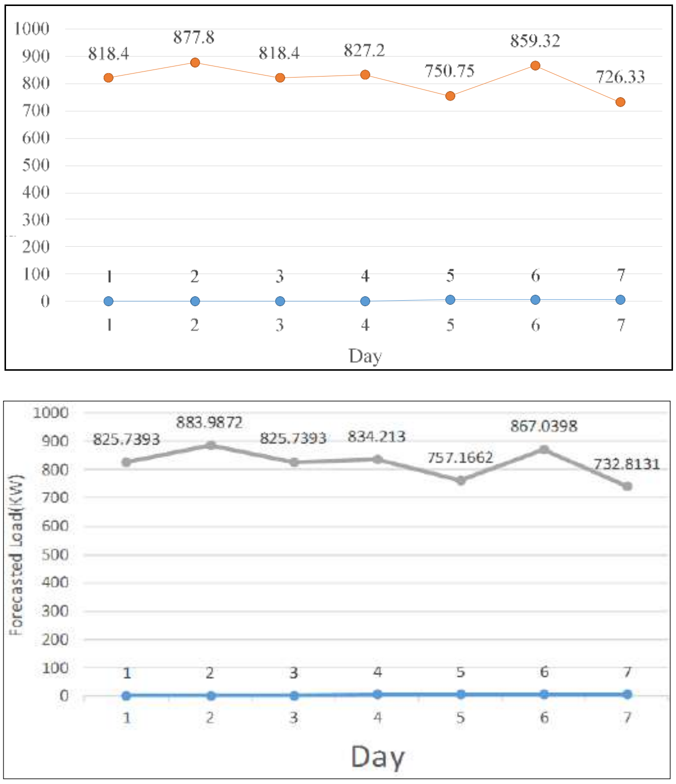

Fig 2: Comparison of the Actual and Forecasted Loads

The Mean Absolute Percentage Error (MAPE) of forecast is approximately 0.86%. That is, the accuracy of the model in forecasting the load demand on short-term basis is approximately 99.14%.

5. Conclusion

Multiple linear regression analysis carried out on the data obtained from IBEDC for an 11-KV feeder in Aiyekoto Area of Olorunda Local Government, Osun State was employed. A short-term consumer load forecast was estimated using the model developed as a result of a statistical analysis model in order to enable the electric energy supplier to be able to plan and provide for probable increase in the demand. The accuracy of forecast when the model is used by IBEDC is 99.1%.

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