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Short Term Electricity Demand Forecasting for an Isolated Area using Two Different Approaches

Asif Islam[*,a], Samiur Rahman Hasib[b], Md. Shariful Islam[c]

[a]*Planning & Development Division (Design)*
Power Grid Company of Bangladesh (PGCB) Ltd., Dhaka-1000, Bangladesh
[b]*Electrical & Electronic Engineering*
Bangladesh University (BU), Dhaka-1207, Bangladesh
[c]*Electrical & Electronic Engineering*
Bangladesh University of Engineering & Technology (BUET), Dhaka-1000, Bangladesh

Abstract

Electricity demand forecasting for an off-grid area where no previous load data is available is an important prerequisite for power system expansion planning. Bangladesh is a relatively small, densely-populated country in South Asia with a large percentage of the population living below the poverty line. About 48.5% of the population has access to grid electricity. An uninterruptable power supply is one of the most important parameters for future development, with the logical conclusion being in the long run to expand present grid coverage. This paper presents an analysis to forecast the electricity demand of an isolated island in Bangladesh where past history of electrical load demand is not available. The analysis is based on the identification of the key, driving factors for electrical load growth of an area. The forecasting was done through inverse matrix calculation and linear regression analysis. It was found that the demand data, calculated from these two different approaches, are close enough to support the reliability of the proposed method. This method can be applicable for short term load forecasting of any isolated area throughout the world.

Keywords: Load Forecasting, Regression Analysis, Inverse Matrix, Isolated Area

1. Introduction

The primary requirement for operation and planning of a power utility system is electricity demand forecasting. Load forecasting plays a key role in making important decisions on power supply, load switching, voltage control, network reconfiguration, and infrastructure development [1]. In generation expansion planning as well as in distribution planning, load forecasting is an essential step. The importance of accurate forecast in planning is that it ensures the uninterrupted supply of electricity as well as provides the means to avoid over and under utilization of generating capacity and leads to the best possible use of capacity. Obviously, errors in forecasting can lead to bad planning [2, 3] which will be costly. Too high a forecast leads to more plants than are required which will be an unnecessary capital expenditure. Too low a forecast prevents optimum economic growth and results in the installation of many costly and expensive-to-run generators. These costs will be borne in the final analysis by the consumers [4].

*Corresponding author

Email addresses: asif038@gmail.com (Asif Islam*), samibueee@gmail.com (Samiur Rahman Hasib), sabuz03@gmail.com (Md. Shariful Islam)

Electric load forecasting is the process used to forecast future electric load, given historical load data as well as current and forecasted weather information. In the past few decades, several models [1–5] have been developed to forecast electric load more accurately. Techniques include price elasticity, weather and demand response/load analysis, and renewable generation [6] predictive modelling. Forecasts must use regional customer load data, with time series customer load profiles. Accurate forecasts require adjustments for seasonality. Distributed load forecasting must be reconciled with distribution network configuration [7] as a part of the distribution circuit load measurements. Typically, load forecasting can be long-term, medium-term, short-term or very short-term. Long-term load forecasting is used to assist electric utility company management to make predictions for future expansion, equipment purchases, or staff hiring. Medium-term forecasting focuses on the purpose of scheduling fuel supplies and unit maintenance whereas short-term forecasting is done to supply necessary information for the system management about day-to-day operations and unit commitment. For short-term load forecasting, several factors should be considered, such as time factors, weather data, and possible customers' classes. Medium and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, appliance sales data, and other factors.

In many countries, especially in developing ones, a large part of the population live in remote and isolated areas. In terms of electrical energy use, isolated areas often cannot be connected to the main electrical grid system [8–12] due to commercial or technical reasons. The commercial and technical incapability of connecting isolated areas to the main grid may derive from the distance between the grid and the isolated area or challenging geographical conditions. The load forecasting of an isolated area is neatly described in [1, 2]. But the main limitation of these works is that the load histories are assumed as known, which is not realistic [13–19]. Recently, optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming is proposed in [13], where various aspects of generation scheduling are taken into consideration with a view to meeting the demand of the community.

This paper aims to forecast the electricity demand of an isolated area in Bangladesh where not only is there no indication of past history of load but also no chance of national grid expansion. The study area is known as Kutubdia which is known as one of the most strategically important islands of Bangladesh, as the country will strengthen its naval defense of the Bay of Bengal centering on this island. The load forecasting was done through two different methods: Linear Regression Analysis and Inverse Matrix Calculation. The load predictions under both methods were in relative proximity to each other.

2. Regression Analysis

In statistics, regression analysis is a statistical technique [5] for estimating relationships among variables. It includes many techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. In this kind of analysis the off grid area is indicated as dependent variables [17] while the on grid area is taken as independent variables. So in this analysis Kutubdia (an off-grid island) is indicated as dependent variables and Maheshkhali (a semi isolated grid connected, slightly larger neighboring island) indicated as independent variables.

In linear regression, the model specification is that the dependent variable y_i is a linear combination of the parameters. For example, in simple linear regression for modelling n data points, there is one independent variable x_i and two parameters, α and β

Straight line:

$$y_i = \alpha + \beta x_i + \dot{\varepsilon}_i \tag{1}$$

Where $i = 1, 2 \ldots n$. This is still linear regression, i.e. although the expression on the right hand side is quadratic in the independent variable xi it is linear in the parameters α and β.

In both cases $\dot{\varepsilon}_i$ is an error term and the subscript i indexes a particular observation. Given a random sample from the population, we estimate the population parameters and obtain the sample linear regression model:

$$\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i \tag{2}$$

The residuals $e_i = y_i - \hat{y}_i$ is the difference between the value of the dependent variable predicted by the model, $\hat{y}_i$ and the true value of the dependent variable, y_i.

Minimization of this function results in a set of normal equations, a set of simultaneous linear equations in the parameters, which are solved to yield the parameter estimators $\hat{\alpha}$ and $\hat{\beta}$.

$$\hat{\beta} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \tag{3}$$

$$\hat{\alpha} = \bar{y} - \hat{\beta}\bar{x} \tag{4}$$

Where $\bar{x}$ is the mean (average) of the x values and $\bar{y}$ is the mean of the y values.

So from this equation (3) and (4), we will find the value of $\hat{\alpha}$ and $\hat{\beta}$ [5] and then from (2), we will find the value of y_i.

3. Inverse Matrix Technique

Total load of an isolated area can be divided into four sub loads: domestic load, commercial load, irrigation load and industrial load. This load also depends on factors such as population, per capital income, adult literacy rate, agricultural land, distance from the mainland and inland communication length.

3.1. Domestic Loads

The domestic load may be a function of population and standard of living of people. The variation of standard of living is caused by per capita income and adult literacy rate. All these factors are time varying quantities. The domestic load, L_D may then be expressed as:

$$L_D(t) = f_1(P(t), L_R(t), P_I(t)) \tag{5}$$

Where $P(t)$ = Population at time t, $L_R(t)$ = Adult literacy rate at time t, $P_I(t)$ = Per capita income at time t.

3.2. Industrial Loads

Industrial load may depend on the per capita income, inland communication in per unit area of total area, distance from the local town, literacy rate and agricultural land in per unit area of total area. This industrial load L_I can be calculated as:

$$L_I(t) = f_2(P_I(t), R_L(t), D_T(t), A_L(t)) \tag{6}$$

Where $R_L(t)$ = Inland communication length in per unit area at time t, $D_T(t)$ = Distance from local town, $A_L(t)$ = Agricultural land in percent of total area at time t. In some isolated areas, instead of inland communication, transport across the sea may be the major type of communication. In that case the communication must include the sea route length too.

3.3. Commercial Loads

The commercial load mainly depends on per capita income, inland communication in per unit area and distance from local town. The commercial load L_C may then be expressed as:

$$L_C(t) = f_3(P_I(t), R_L(t), D_T(t)) \tag{7}$$

3.4. Irrigation Loads

The load for irrigation mainly depends on agricultural land in per unit area of total area and per capita income. This irrigation load L_{IR} can be calculated as:

$$L_{IR}(t) = f_4(A_L(t), P_I(t)) \tag{8}$$

3.5. Total Load

The total electrical load demand $L(t)$ in an isolated area is the sum of the above four loads. That is:

$$L(t) = L_D(t) + L_I(t) + L_C(t) + L_{IR}(t) \tag{9}$$

Therefore, the load of an isolated area can be expressed as:

$$L(t) = f(P(t), L_R(t), P_I(t), R_L(t), A_L(t), D_T(t)) \tag{10}$$

Equation (10) expresses that the load is a function of six time dependent variables. However, these variables will not all contribute equally to the generation of load. Let X_1, X_2, X_3, X_4, X_5, and X_6 represent the weighting factors by which each time varying factor $P(t)$, $L_R(t)$, $P_I(t)$, $R_L(t)$, $A_L(t)$, and $D_T(t)$ respectively contribute towards the load growth. The weighting factors $[X]$ are also random in nature. They may vary with different areas. Now the load can be expressed as,

$$[L(t)] = [X] \times \begin{bmatrix} P(t) \\ L_R(t) \\ P_I(t) \\ R_L(t) \\ A_L(t) \\ D_T(t) \end{bmatrix} \tag{11}$$

From Equation (11), the weight factors $[X]$ can be calculated as:

$$[X] = [L_T] \times P_{inv} \begin{bmatrix} P(t) \\ L_R(t) \\ P_I(t) \\ R_L(t) \\ A_L(t) \\ D_T(t) \end{bmatrix} \tag{12}$$

To calculate the value of these weighted factors, the past history of the considered area needs to be known. Another option is to consider an area whose behaviours are similar to that of the isolated area. This will be clarified through the practical implementation of the proposed method.

4. Study Area and Collected Data

To forecast the electricity demand of the isolated island Kutubdia (Figure 1), data was gathered from Kutubdia and from another, neighbouring, semi-isolated area (connected with the mainland just on one side) called Maheshkhali (Figure 2), which is connected with the mainland through a narrow road bridge connection. The weather and cultural characteristics of Maheshkhali are pretty similar to Kutubdia. Both Kutubdia and Maheshkhali are subdistricts (upazila) in Cox's Bazar district in Chittagong administrative division, Bangladesh. Kutubdia is located at 21.8167°N 91.8583°E and Maheshkhali is

Figure 1: Kutubdia Island

Figure 2: Map of Maheshkhali

located at 21.5500°N 91.9500°E.

Table 1: Collected Data for Maheshkhali & Kutubdia

	Data	Maheshkhali (Grid Connected)	Kutubdia (Isolated Area)
1	POP, 1000	321.21	125.27
2	L_R, %	30.08	34
3	P_I, USD	64.98	66.04
4	R_L, km	284.75	245.03
5	A_L, Hector	5275.36	8903.28
6	D_T, km	89.1	90

Table 2: Average load of Maheshkhali, 2008–2011

	Average Demand/Load, kW			
	2011	2010	2009	2008
January	1647	1528	1302	1170
February	1610	1500	1353	1270
March	1582	1470	1366	1372
April	1653	1608	1370	1476
May	1562	1604	1454	1466
June	1733	1460	1554	1382
July	1678	1595	1576	1407
August	1660	1500	1420	1431
September	1400	1648	1458	1513
October	1688	1708	1462	1483
November	1558	1536	1426	1406
December	1570	1520	1309	1384

Data was gathered in 4 stages. First, time invariant data such as population, per capital income, adult literacy rate, agricultural land, distance from the mainland and inland communication length data of Maheshkhali and Kutubdia was gathered from the offices of the UNO administrator (UpazilaNirbahi (Executive) Officer). Then the maximum and average load data of Maheshkhali was collected from the REB (Rural Electrification Board) office of Maheshkhali. To gain a clear concept of per capita income and enhance the reliability of previously collected data, technical as well as data support was collected from the Bangladesh Bureau of Statistics. The data collected from the UNO and REB offices for those areas are summarized in Tables 1, 2 and 3.

Table 3: Maximum load of Maheshkhali, 2008–2011

	Maximum Demand/Load, kW			
	2011	2010	2009	2008
January	3660	3396	2894	2600
February	3576	3334	3007	2824
March	3514	3267	3037	3049
April	3674	3574	3045	3280
May	3469	3566	3232	3258
June	3853	3243	3253	3072
July	3731	3545	3503	3128
August	3689	3335	3157	3182
September	3109	3663	3242	3364
October	3751	3796	3250	3296
November	3460	3415	3169	3125
December	3490	3380	2909	3076

Here, POP = Population (1000), L_R = Adult Literacy Rate (%), P_I = Per Capita Income (BDT), A_L = Agricultural Land (Hector), R_L = Road Length or Inland communication length (km), D_T = Distance from Local Town (km).

5. Results and Discussion

First, the demand forecasting of Kutubdia was done using linear regression analysis. This was then repeated using inverse matrix calculation. The results from both approaches are summarized below.

5.1. Linear Regression Analysis Result

The parameters of Maheshkhali and Kutubdia are defined by P_M and P_K whereas the load of these areas are defined by L_M and L_K. Using the data of Table 1, $\sum P_M = 702.293$, $\sum P_K = 501.578$, $\sum P_M^2 = 147830.272$ and $\sum P_M P_K = 81093.301$.

Then from equation (3) & (4), $\beta = 0.34$ and $\alpha = 43.8$. So, the equation to calculate the load of Kutubdia considering Maheshkhali as standard takes the form:

$$L_K = 43.8 + 0.34\, L_M$$

Table 4: Forecasted electricity consumption of Kutubdia Island (Regression Analysis)

Month	Average Load, kW	Maximum Load, kW
January	603.780	1288.2
February	591.200	1259.6
March	581.680	1238.6
April	605.820	1293.0
May	574.880	1293.0
June	633.020	1353.8
July	614.320	1312.3
August	608.200	1298.1
September	519.800	1100.9
October	617.720	1319.1
November	573.520	1220.2
December	577.600	1230.4

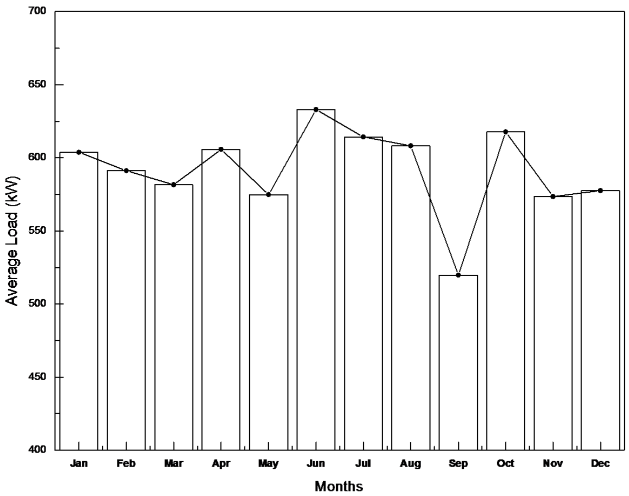

Figure 3: Estimated average load of Kutubdia using Regression Analysis

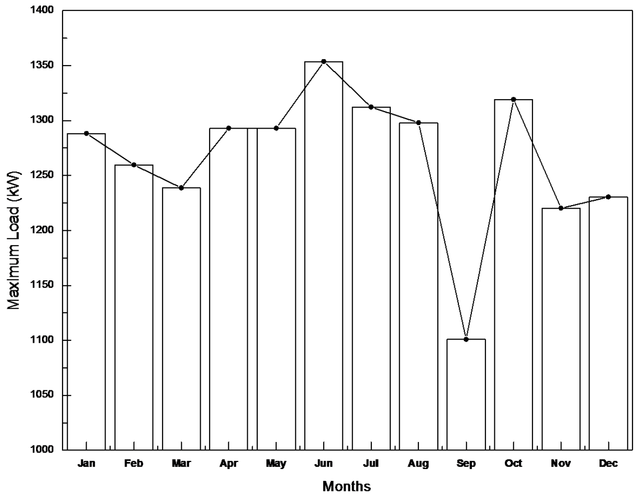

Figure 4: Estimated maximum load of Kutubdia using Regression Analysis

Table 5: Weighting factors X of load growth for average demand

Month	X_1	X_2	X_3	X_4	X_5	X_6
January	0.0051	0	0.0001	0	0.0001	0
February	0.0052	0	0.0001	0	0.0001	0
March	0.0049	0	0.0001	0	0.0001	0
April	0.0051	0	0.0001	0	0.0001	0
May	0.0049	0	0.0001	0	0.0001	0
June	0.0054	0	0.0001	0	0.0001	0
July	0.0052	0	0.0001	0	0.0001	0
August	0.0052	0	0.0001	0	0.0001	0
September	0.0044	0	0.0001	0	0.0001	0
October	0.0053	0	0.0001	0	0.0001	0
November	0.0048	0	0.0001	0	0.0001	0
December	0.0049	0	0.0001	0	0.0001	0

Based on the 2011 load of Maheshkhali, the forecasted average and maximum demand of Kutubdia is summarized in Table 4 and plotted in Figures 3 & 4.

5.2. Inverse Matrix Calculation Result

The calculation was done using Matlab software. The inverse of non square matrices is not possible. To solve this problem, a new term P_{in} was used. In mathematics, and in particular linear algebra, a pseudo-inverse A^+ of a matrix A is a generalization of the inverse matrix. The most widely known type of matrix pseudo-inverse is the Moore-Penrose pseudo-inverse, which was independently described by E. H. Moore in 1920, Arne Bjerhammar in 1951 and Roger Penrose in 1955. When referring to a matrix, the term pseudo-inverse, without further specification, is often used to indicate the Moore-Penrose pseudo-inverse. The term generalized inverse is sometimes used as a synonym for pseudo-inverse. A common use of the Moore-Penrose pseudo-inverse (hereafter, just pseudo-inverse) is to compute a 'best fit' (least

Table 6: Weighting factors X of load growth for maximum demand

Month	X_1	X_2	X_3	X_4	X_5	X_6
January	0.0114	0	0.0002	0	0.0002	0
February	0.0111	0	0.0002	0	0.0002	0
March	0.0109	0	0.0002	0	0.0002	0
April	0.0114	0	0.0002	0	0.0002	0
May	0.0108	0	0.0002	0	0.0002	0
June	0.0120	0	0.0002	0	0.0002	0
July	0.0116	0	0.0002	0	0.0002	0
August	0.0115	0	0.0002	0	0.0002	0
September	0.0097	0	0.0002	0	0.0002	0
October	0.0117	0	0.0002	0	0.0002	0
November	0.0108	0	0.0002	0	0.0002	0
December	0.0109	0	0.0002	0	0.0002	0

squares) solution to a system of linear equations that lacks a unique solution. Another use is to find the minimum (Euclidean) norm solution to a system of linear equations with multiple solutions. The pseudo-inverse facilitates the statement and proof of results in linear algebra. So putting P_{inv} we get the values of X corresponding to average and maximum load which are shown in Tables 5 & 6.

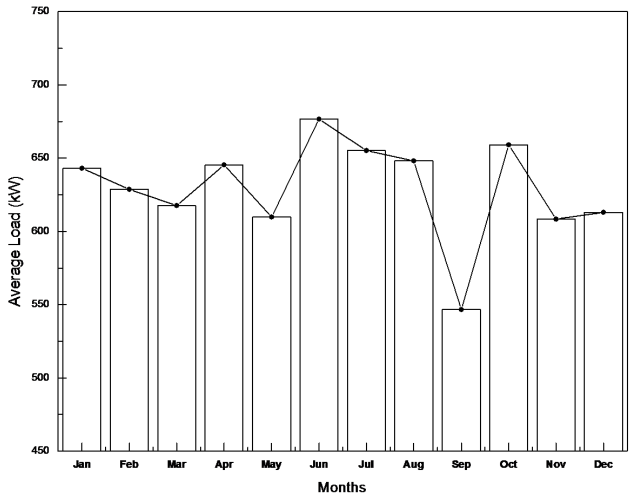

Figure 5: Estimated average load of Kutubdia using the Inverse Matrix Technique

Then by using the values of weighting factors, the average and maximum demand of Kutubdia are calculated and tabulated in Table 7. Figures 5 and 6 show the forecasted average and maximum electricity demand of Kutubdia using inverse matrix calculation.

Table 7: Forecasted electricity consumption of Kutubdia Island (Inverse Matrix Technique)

Month	Average Load, kW	Maximum Load, kW
January	643.1	1429.2
February	628.7	1396.4
March	617.7	1372.2
April	645.5	1434.7
May	609.9	1354.7
June	676.7	1504.6
July	655.2	1457.1
August	648.2	1440.6
September	546.7	1214.6
October	659.1	1464.8
November	608.4	1351.1
December	613.0	1362.9

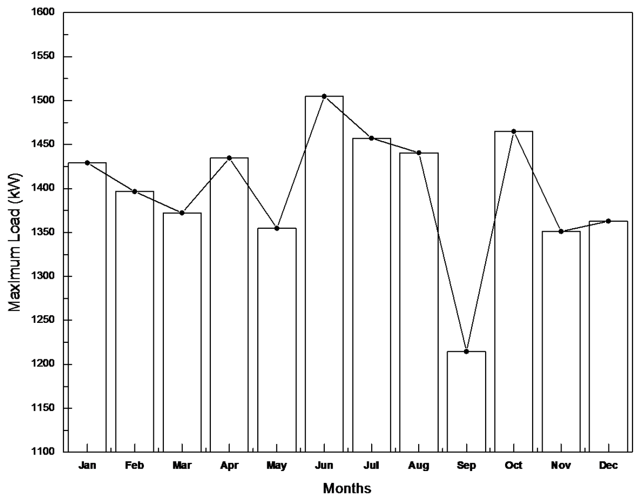

Figure 6: Estimated maximum load of Kutubdia using the Inverse Matrix Technique

6. Conclusions

In this paper, the load forecasting of an isolated area was performed using two different methods. A comparison shows that the two methods delivered

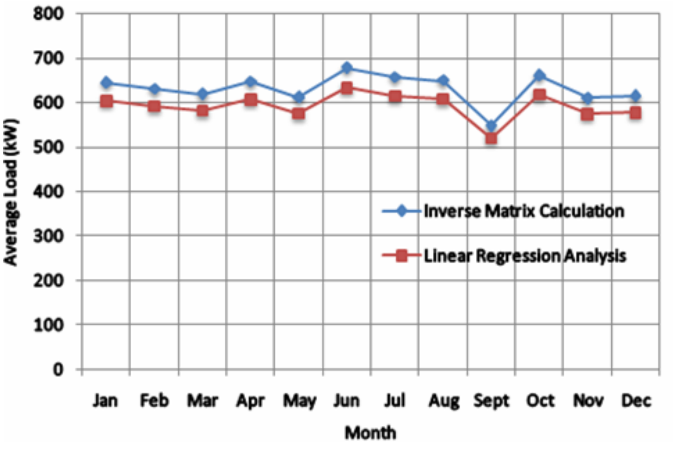

Figure 7: Comparison of estimated average load of Kutubdia using two methods

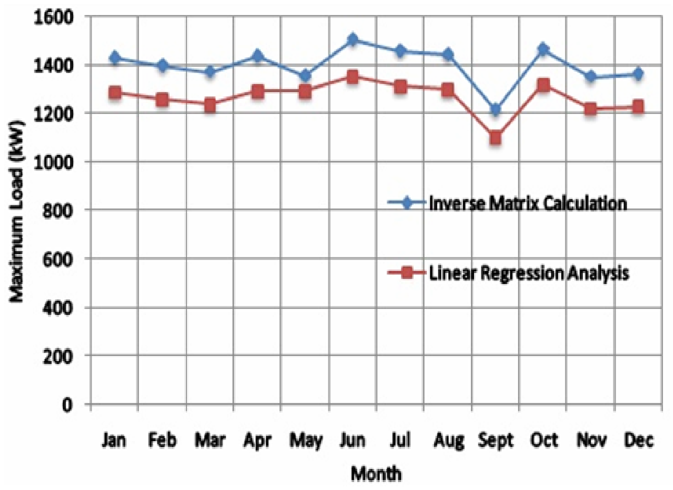

Figure 8: Comparison of estimated maximum load of Kutubdia using two methods

similar figures for estimated electricity demand (Figures 7 & 8). The forecast performed was short term forecasting. If more factors such as time, temperature [20, 21], area, peak and off peak time, lifestyle of the people etc. could be included then the result would be more precise and accurate. But the forecasted demand of this paper is reasonably accurate, as the calculation is based on On-Load readings. In summary, this data can help electricity utility companies to make important decisions on purchasing and generating electric power, load switching and infrastructure development. Above all, the mathematical model of this paper is applicable for any isolated island or off-grid area.

Acknowledgments

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