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Industrial Electricity Consumption and Expropriate Analysis Technique

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Abstract: Electricity power losses activity is a major problem for many electrical utilities worldwide. Not only does it affect a company's profitability and credibility, but it also increases the cost of electricity to industrial consumers. Therefore, the need to minimize the extent and impact this problem is crucial for both the utilities, including MGVCL Gujarat that is the focus here, and their industrial consumers.

Keywords: Industrial, ELM, Power Losses, Sigmoid, Radial basis function, Classifications, Prediction, T&D.

I. INTRODUCTION

In India, average power losses, have been officially indicated as 23 percent of the electricity generated. However, as per sample studies carried out by independent agencies including TERI, these losses have been estimated to be as high as 50 percent in some states. With the setting up of State Regulatory Commissions [1] in the country, accurate estimation of T&D Losses has gained importance as the level of losses directly affects the sales and power purchase requirements and hence has a bearing on the determination of electricity tariff of a utility by the commission [2].

II. FACTOR OF POWER LOSSES

Power losses occur in the process of supplying electricity to consumers because of commercial and technical losses. The commercial losses are due to pilferage, **defective meters**, and **errors in meter reading** and in estimating **unmetered supply** of energy. The technical losses are caused by power dissipated in the conductors and equipment used for transmission, transformation, sub-transmission and distribution of power. These technical losses are inherent in system and can be reduced to an optimum level. The losses can be further sub grouped depending upon the stage of power transformation & transmission system as Transmission Losses (400kV /220kV /132kV / 66kV), as Sub transmission losses [3] (33kV /11kV) and Distribution losses (11kV /0.4kv).

III. REASON FOR HIGH POWER LOSSES

In many parts of the world experiences demonstrate that it is possible to reduce the losses in a reasonably short period of time and that such investments have a high internal rate of return. A clear understanding on the magnitude of technical and commercial power losses is the first step in the direction of reducing power losses. It can be achieved by putting in place a system for accurate energy accounting. This system is essentially a tool for energy management and helps in breaking down the total energy consumption into all its components [4]. It aims at accounting for energy generated and its consumption by various categories of consumers as well as, for energy required for meeting technical requirement of system elements. It also helps the utility in bringing accountability and efficiency in its working.

3.1 Features selection

Feature selection has been considered from the three perspectives of 1) search problem, 2) evaluation criteria, and 3) model selection. It comprises a process of searching the attributes space for the required subsets, with this being achieved by eliminating irrelevant attributes.

3.2 Classifications

These classifications rely on given load profiles and on other relevant factors, such as weather, holiday banks, rates, and the nature of customers' businesses. This task forms a very important module within the proposed unmetered power losses framework of analysis because the classification behavior results obtained are useful for monitoring any suspicious behavior and because the developed behavior model can be used to predict behavior classes for new customers.

3.3 Prediction

Applying prediction techniques in electric power utilities involves the prediction of daily, weekly, monthly, and yearly of system loads, peak loads, and system energy. Such a prediction task is one of the most important among the planning and operational activities of these utilities that are designed to maximize the benefits accruing to them.

The customers are divided into the two major supply areas of MGVCL, Gujarat. The daily data are captured for the years from 2013 to 2014 as shown in table 1 and load profile is given in figure 1.

Table 1: Number of customers provided by MGVCL, Gujarat based on the two-city selected

City	Area	No. of Customer	Mean	Std. Deviation

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BARODA O&M CIRCLE	Industrial	31	104.09	8.890
	GIDC	07	106.45	8.666
ANAND O&M CIRCLE	Industrial	26	104.33	4.611
	GIDC	25	105.75	7.593

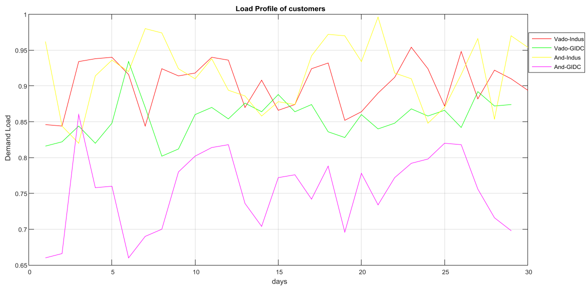

Figure 1 Customers' load profiles

IV. ANALYSIS TECHNIQUES

Several data mining classification techniques have been reviewed, including Decision Tree, Naïve Bayes, Back Propagation, Extreme Learning Machine, Online Sequential Extreme Learning Machine, and Support Vector Machine. Among these existing classification techniques, Extreme Learning Machine [5] and Online Sequential-Extreme Learning Machine [6] have been selected as appropriate for predicting customer behavior classes in the present research. The Extreme Learning Machine learning algorithm and its variant, Online Sequential-Extreme Learning Machine, were chosen because of the claim that these two classifiers have superior generalization performance and extremely fast learning speeds when compared to other traditional neural network algorithms, including Back Propagation.

Table 2: Results for time processing duration in seconds with ELM

No. of hidden neurons	ELM	
	Training (secs)	Testing (secs)
20	0.135	0.131
40	0.265	0.182
60	0.342	0.210
80	0.587	0.226
100	0.732	0.253
120	0.987	0.268
140	1.232	0.292
160	1.356	0.323
180	1.490	0.345
200	1.643	0.376

Table 2 shows the time processing durations in seconds. Training datasets took longer times than did testing datasets to complete the classification task due to the larger datasets compared to other types of days. The other datasets, have similar time processing speeds and improved significantly in testing data.

Table 3: Results for classification accuracy as percentages with ELM

No. of hidden neurons	Winter	
	Training (%)	Testing (%)
20	88.87	88.37
40	89.65	89.08
60	91.76	90.79
80	92.00	91.04
100	92.50	91.33
120	92.65	91.40
140	93.28	91.52
160	94.09	92.66
180	94.31	92.77
200	94.97	92.82

Table 3 shows the for-classification accuracies as percentages. As the number of hidden neurons increases, the classification success rate increases accordingly. The classification accuracy results for testing datasets are slightly lower than for training datasets for all types of days, although the patterns remain the same consistently.

Table 4: Mean and standard deviation of seasonal consumption for industrial consumers

Area	Mean	Std. Deviation	Upper Limit Threshold	Lower Limit Threshold
Industrial	103.19	6.830	123.68	82.7
GIDC	105.85	7.606	128.668	83.032

Table 4 shows the mean and standard deviation of electricity consumption for industrial consumers. From these values, upper and lower limit thresholds were established.

Table 5: Root Mean Squared Error Results with the Prediction Algorithm

Area	ELM Sigmoid		ELM Radial basis function	
	Training	Testing	Training	Testing
Industrial	0.0323	0.0434	0.0122	0.0258
GIDC	0.0424	0.0556	0.0174	0.0393

It is apparent from Table 5 that different prediction algorithms generate different error rates. For Industrial and GIDC Extreme Learning Machine with the sigmoid function gives the lowest error rates.

V. CONCLUSION

The base of the data, for conducting the test, was accommodating two years inter-data intervals. Extreme Learning Machine, has been used to carry out the study. Relative performances of the two said methods has been compared and analyzed. Extreme Learning Machine algorithm has been proven to be faster. It has been found that algorithm of Extreme Learning Machine with the sigmoid function produces the lowest error rates in forecasting load results, while Extreme Learning Machine with radial basis function nodes produced the highest error rates in forecasting load results.

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