Agriculture Customers Power Consumption Analysis to Reduced Power Losses in Winter

Bharat Dangar, S. K. Joshi

Abstract: Indian agriculture crop production mostly yields in winter season. To increase the food output, almost all the State Governments show benevolence to farmers and arrange supply of electric power for irrigation to the farmers at a nominal rate, and in some States, without charges at all. In view of this, most Electricity Boards supply power to agriculture sector and claim subsidy from the State Govt. based on energy consumption. Since the energy supplied to the agriculture sector is a generous gesture by the State Govt., all the electricity boards have eliminated energy meters for agriculture sector services. The absence of energy meters provides ample opportunities to SEBs to estimate average consumption in agriculture sector at a much higher value than the actual. In the absence of energy meters, most of the SEBs resort to fudging consumption figures to include not only the under estimated T&D Losses but also energy theft from their system. The extent of fudging is more in the States where agricultural activity is high. The benefit derived by these boards is not only the extent of subsidy from the respective States but also self-praise by showing much less transmission and distribution losses. Further the boards are ignoring the inefficiency in operating the distribution system by blaming the agricultural supply for all ills and raising the tariff of other consumers.

Keywords: Agriculture, Winter, Electricity boards, SEBs, T&D Losses, Farmers, Power Loss, Horse Power, Distribution system, Energy Meters, Load Forecasting

I. INTRODUCTION

Unmetered supply to agricultural pumps and single point connections to small domestic consumers of weaker sections of the society is one of the major reasons for commercial losses. In most states, the agricultural tariff [1] is based on the unit horsepower (H.P.) of the motors. Such power loads get sanctioned at the low load declarations. Once the connections are released, the consumers get into the habit of increasing their connected loads, without obtaining necessary sanction, for increased loading, from the utility. Further estimation of the energy consumed in unmetered supply has a great bearing on the estimation of power losses because inherent errors in estimation. Most of the utilities intentionally overestimate the unmetered agricultural consumption to get higher subsidy from the State Government and project reduction in losses. In other words, higher the estimates of the unmetered consumption, lesser the transmission and distribution loss figure and vice versa [2]. Moreover, the correct estimation of unmetered consumption through the agricultural sector greatly de- pends upon the cropping pattern, ground water level, seasonal in winter variation, hours of operation etc.

Revised Manuscript Received October 05, 2019

Bharat Dangar, Electrical Engineering Department, Faculty of Technology and Engineering, The M S University of Baroda

S. K. Joshi, Electrical Engineering Department, Faculty of Technology and Engineering, The M S University of Baroda

II. SIGNIFICANT BENEFITS

Table 1: Benefits gained from the unmetered power losses reduction by means of the proposed alternatives

Power Utilities	Consumers
Reduction of the operational costs of on-site physical checking as the inspection team is able directly to target suspicious unmetered power losses activities such as meter tampering and bypassing.	Reduction in the cost of electricity as the extent of unmetered power losses activity is decreased and the transfer of its cost impact to consumers is reduced.
Minimization of unmetered power losses problems such as faulty metering and illegal connections due to the more rapid method of detecting and predicting consumers' behavior.	Improved consumer satisfaction as the system provides them with more reliable and efficient services.
Increased system efficiency and reliability as the generation of electricity is based on actual economic demand.	Strengthening consumer relationships as timely and reliable results can be produced to assist decision-making process.

III. LOAD DATA ANALYSIS

In this case the Load data is categorized into two models which are area model and category model which is based on Different regions & on equivalent power consumption categories. The limitation of the geographic region based on area model is that all the power consumers have same load patterns because they are supplied from the same power substations. While the Category model has its own limitations, which is related to dissimilarities in the rest curve and power consumption pattern that's why based on the rest curve & particular power consumption data found new model device put forward for load data based settlement services. To get the benefits from both the above given models the third model was designed which was more advanced and efficient. Then too the modelling power consumers load profile the category model would be applied reason being it was strongly believed that the mode would have the greater cognizance into the power consumers demand model.In some of the countries the innovative technology has come up with lot of modern go towards to power consumption data analysis.

The two groups were profound in determining power consumption data by different approaches in which the first set of models was obtained from the complete power consumption survey & was developed load profiles Different pattern recognition techniques have been used as tool to determine the data of power consumption to acquire power consumption profile based on types of power consumptions techniques noted in the second group.The first group has its own limitation with the measurements time consumption & the other group has the constraint that the actual method to make the consumer attributes is costly & lengthy. In the previous case because of the calculation was requiring more time & the alternative analysis & it's features of the consumer groups was analyzed, the time required for determination is quite high.

IV. LOAD FORECASTING

load forecasting can be categorized into Short-Term Load Forecasting, Medium-Term Load Forecasting, and Long-Term Load Forecasting. Short-Term Load Forecasting (STLF) [3] is used to forecast loads over short periods of time, such as in daily forecasts. It is also defined as predictions of system loads with forecasted intervals ranging daily to one week. Three principle objectives of STLF are cited as 1) formulating the basic generation scheduling function, 2) assessing the security of the power system at any point, and 3) providing timely dispatcher information. In addition, STLF has been used for on-line scheduling and providing security functions in an energy management system (EMS).Generally, two approaches can be used in formulating STLF, MTLF, and LTLF, namely a deterministic approach and a probabilistic approach. A deterministic approach using a pattern recognition algorithm was applied to forecasting [4] hourly loads with lead times of 24 hours. Even though this method considers sensitive loads, special occasions, and economic changes, along with demographic and geographical factors, it has the drawback that it is only intended for use in small-area power systems. The effects of probabilistic inputs have been considered in a study of the effects of load forecasting accuracy. Electricity load formulation is known as a non-stationary process that is influenced by many factors, including weather factors, time factors, seasonal factors, calendar or holiday events, economic factors, and a range of other random effects. It is because of these factors that load forecasting has always been a challenging task and one concerning which research is ongoing.

V. DATA NORMALIZATION

The electricity customer consumption data gathered from the electronic metering were normalized because this data has been needed to represent with a common scale for comparison purposes. In the present study, the data has been normalized in the specific scale of [0, 1] by using as the normalizing ratio the peak value of the pattern over the time interval of the definition.

$$NL=\frac{X-\mathrm{Min}(X)}{\mathrm{Max}(X)-\mathrm{Min}(X)}$$

All the individual normalized customer load demands used for comparisons here are detailed in figure-1. In these Appendices, the table 1 show the load profiles for 48 customers that have been separated based on types of days comprising weekdays from Monday to Friday, Saturdays, Sundays, and public holidays in winter. The total winter profiles from 2013 to 2014 and the total yearly load profiles for the same period have also been generated for each individual customer. The data used for this study consists of 70 attributes gathered from different data sources. The customer data that allows for time factors, weather data, and events data were provided by the two types of metering, main reading and check reading as shown in table 2.

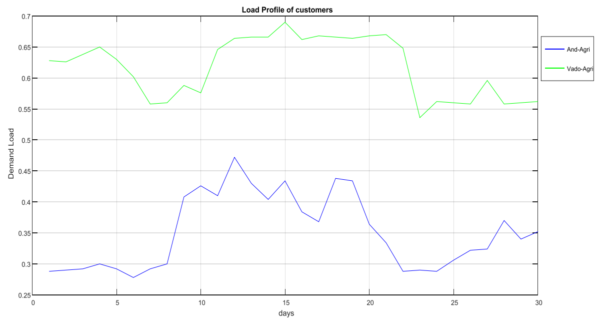

Figure 1 Customers' load profiles of winter

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

City	Area	No. of Customer	Mean	Std. Deviation
BARODA O&M CIRCLE	Agriculture	31	103.11	4.900
ANAND O&M CIRCLE	Agriculture	17	102.91	5.075

Table 2 Decision based on main and check meter

Main Meter Reading	Check Meter Reading	Decision or Final Reading
0	0	0
0	1	Check Reading
1	0	Main Reading
1	1	Main Reading

If the power consumption detects outside of the range generated by the techniques, then the load power consumption is fall in abnormal behaviour on that day. Its required on-site field visit and it is generating an alert to maintain department for observation.

VI. ALGORITHM FOR CUSTOMERS BEHAVIOR

The two algorithms Extreme Learning Machine and OS-Extreme Learning Machine have been selected for use in the classification and prediction procedures that are applied to electricity utility of winter agriculture customers behaviour in the present paper.

Table 3: Results for time processing duration in seconds with ELM and OS-ELM in winter season

No. of hidden neurons	Winter ELM		Winter OS-ELM	
	Training (secs)	Testing (secs)	Training (secs)	Testing (secs)
20	0.023	0.023	0.095	0.095
40	0.143	0.112	0.145	0.132
60	0.198	0.209	0.158	0.141
80	0.388	0.237	0.237	0.178
100	0.390	0.239	0.373	0.261
120	0.679	0.289	0.463	0.367
140	0.937	0.308	0.589	0.422
160	1.072	0.312	0.655	0.494
180	1.328	0.321	0.687	0.573
200	1.398	0.336	0.865	0.733

Table 4: Results for classification accuracy as percentages with ELM and OS-ELM in winter season

No. of hidden neurons	Winter ELM		Winter OS-ELM	
	Training (%)	Testing (%)	Training (%)	Testing (%)
20	88.87	88.37	92.22	92.33
40	89.65	89.08	92.64	92.34
60	91.76	90.79	93.78	92.87
80	92.00	91.04	94.01	92.99
100	92.50	91.33	94.40	93.08
120	92.65	91.40	94.69	93.27
140	93.28	91.52	95.09	93.44
160	94.09	92.66	95.34	93.56
180	94.31	92.77	95.37	93.70
200	94.97	92.82	95.98	94.05

For this testing with the customers' data separated by types of days (winter datasets) using the ELM Sigmoid algorithm with different numbers of hidden neurons from 20 to 200 was conducted. The Extreme Learning Machine sigmoid results are separated into two tables. Table 3 presents the time processing durations in seconds. Table 4 presents classification success rates as percentages. The best classifier for each type of days is chosen based on the highest classification accuracy ascertained from the simulations.Table 3 shows the results for time processing durations in seconds applying the Extreme Learning Machine with the sigmoid function. Datasets with smaller hidden numbers of neurons produced faster time processing speeds compared to datasets with larger hidden numbers of neurons. The larger the numbers of hidden neurons, the longer the time processing duration in seconds. Overall, the number of hidden neurons equal to 20 is the most suitable, with the fastest results being for winter = 0.023 seconds. However, the number of hidden neurons equal to 20 is found to be faster on winter = 0.023 seconds. Table 3 shows the results for time processing durations in seconds applying the OS-Extreme Learning Machine with the sigmoid function. Datasets with smaller hidden numbers of neurons produced faster time processing speeds compared to datasets with larger hidden numbers of neurons. The larger the number of hidden neurons, the longer the time processing duration in seconds. Overall, minimum 20 hidden neurons are the most suitable and gave the fastest results for all types of days, with winter = 0.095 seconds. Table 4 shows the results for classification accuracies as percentages applying the Extreme Learning Machine with the sigmoid function. It is apparent that datasets with larger hidden numbers of neurons produced higher classification accuracies except for Sunday datasets. Overall, the number of hidden neurons are different between different types of days. The best number of hidden neurons for winter is found to be 160 with 92.66% accuracy. Table 4 shows the results for classification accuracies as percentages applying the OS- Extreme Learning Machine with the sigmoid function. The winter have higher classification accuracies with the number of hidden neurons equal to 200. The best number of hidden neurons for summer is found to be for winter it is 200 with 95.98% accuracy.

Table 5: Root Mean Squared Error Results for winter customers

Area	ELM Sigmoid		ELM Radial basis function	
	Training	Testing	Training	Testing
Winter Agriculture Consumers	0.0480	0.0492	0.0428	0.0828
	OSELM Sigmoid		OSELM Radial basis function	
	0.0587	0.1111	0.0402	0.0420

In Table 5, it is apparent that for winter customer with abnormal behavior, Extreme Learning Machine with the sigmoid function produced lowest error rates for winter (Agriculture) It is apparent, too, that the highest error rates are produced mainly by Extreme Learning Machine with radial basis function nodes on winter (Agriculture). The Online Sequential-Extreme Learning Machine with radial basis function nodes tends to produce both highest error rates on winter (Agriculture).

VII. CONCLUSION

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, based on winter agriculture customers. Online Sequential-Extreme Learning Machine with the sigmoid function produces lowest error rates in forecasting load results. Online Sequential-Extreme Learning Machine with radial basis function nodes produces the highest error rates in forecasting load results, based on winter agriculture customers.

REFERENCES

1. Guidelines for Energy Audit in Power Systems, CEA, New Delhi May 1992 "All India Electricity Statistics", Central Electricity Authority, Ministry of Power, Government of India, New Delhi, March 2005.
2. Shelke, M. Thakare, P.D. Short Term Load Forecasting by Using Data Mining Techniques. Int. J.
3. Sci. Res. 2014, 3, 1363–1367.
4. S. Rahman, R. Bhatnagar, "An Expert System Based Algorithm for Short Term Load Forecast", IEEE Transactions on Power Systems, Volume 3, Number 2, 1988, pp. 392-399.
5. G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: a new learning scheme of feedforward neural networks," presented at the the Proceedings of International Joint Conference on Neural networks (IJCNN2004), Budapest, Hungary, July 2004.