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Interpretation of Urban Power Consumers Behaviors to Predict Power Loss in summer

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Abstract: ***High Temperature In The Summer Of India. Interpretation Of Electricity Consumption Is Crucial In Summer For Urban Consumers. We Are Focus Here For Only Indian Summer Urban Customers Energy Consumption To Analysis And Predict Behavior Of Electricity Theft. Data Mining Techniques Are Employing To Analyses Indian Summer Urban Customers. Online Sequential Machine And Support Vector Machine Is Used For This Behaviors Classification And Prediction.Mainly we focus Support vector machine to classified consumers and online sequential machine is used to detect and predict consumers behaviors.***

Keywords: ***Power Losses, Revenue, Urban, Summer, ELM, OS-ELM, Artificial Intelligent, Neural Network***

I. INTRODUCTION

In the absence of a realistic estimate of power losses, it is not possible for the regulatory commissions to correctly estimate the revenue requirements and avoid the situation where the consumers pay for the inefficiencies of the utilities. To determine an appropriate tariff, the first step is to justified cost incurred by the entity. This would provide an indication of the revenue requirement, which in turn is the basis of any tariff design. The regulator must be very careful about how losses are worked out. The aim of the regulator must be to encourage the utility to make every effort to reduce losses while at the same time ensuring that those conditions applied which threaten the viability of the utility are not applied. The lack of realistic estimates of power losses acts as a disincentive for private sector participation in power distribution as the party can't have an idea of the realistic revenue potential of the area being privatized.

II. REASON FOR HIGH URBAN POWER LOSSES

The following are the major reasons for high technical losses in urban area of our country [1]

- Inadequate investment on transmission and distribution, particularly in sub-transmission and distribution. While the desired investment ratio between generation and transmission and distribution should be 1:1, during the period 1956 -97 it decreased to 1:0.45. Low investment has resulted in overloading of the distribution system without commensurate strengthening and augmentation.
- Haphazard growths of sub-transmission and distribution system with the short-term objective of extension of power supply to new areas.
- Large scale rural electrification through long 11kV and LT lines.
- Too many stage of transformations.
- Improper load management.
- Inadequate reactive compensation
- Poor quality of equipment used in agricultural pumping in rural areas, cooler air-conditioners and industrial loads in urban areas.

III. LOAD DATA ANALYSIS AND PREDICTION TECHNIQUES

To investigate whether abnormalities and irregularities of urban summer consumer's behavior that signal illegal power tapping activity can be predicted through this research paper by investigating and monitoring significant deviations in consumers' load consumption. GUVCL Gujarat data required for this study consists of the accumulated records of 73 commercial urban customers from summer 2014 as shown in table 1 and load profile of customers shown in figure 1. for the purposes of this study, it was determined to cultivate a sample of illustrative load profiles for commercial customers under the load conditions category of "type of seasons". The pertinent empirical details are set out in the several ensuing tables and figures. We are divided all customer according to season of the year. There three types of customer's monsoon, winter and summer but in urban areas of city high power consumption in winter. We decided to analyst winter customers.

Table 1 Datasets for urban summer consumers of two city

City	Area	No. of Customer	Mean	Std. Deviation
BARODA O&M CIRCLE	Urban	35	109.01	7.780
	GIDC	08	108.87	6.234
ANAND O&M CIRCLE	Urban	27	105.45	5.565
	GIDC	03	102.61	6.521

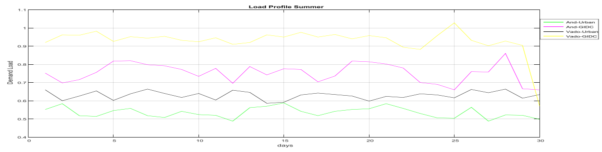

Figure 1 Load Profile of summer consumers

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IV. FEATURES SELECTION

The selection of search directions influences the performance of feature selection and the selection of search strategies influences the search directions. The combination of search directions and the accompanying determination of search strategies can improve the feature selection technique performance to an extent that depends on the demands of the problem. Three categories of search strategies are included here: 1) Complete/Exhaustive Search, 2) Heuristic Search, and 3) Nondeterministic Search. The second perspective to be reviewed concerns evaluation criteria. The goodness of a subset is always determined by certain criteria and these are categorized in two groups, criteria in form of independent and dependent, respectively. A special method is used to evaluate the strength of a feature or subset of features [2] through exploiting the intrinsic behavior of the training set. Some popular independent methods are cited with the four types of measures involved in evaluation criteria considered here being 1) Distance Measures, 2) Information Measures, 3) Dependence Measures, and 4) Consistency Measures

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. Three approaches have been reviewed above, including the statistical approach, the time series approach, and the neural network approach.Table 2 shows the results for time processing durations in seconds applying SVM [5,6,7] with the sigmoid function. Datasets with different cost parameters with different time processing speeds. The cost parameters suitable for each type of days are different, including summer with 40 and 1.213 seconds.

Table 3 shows the results for classification accuracies as percentages applying SVM with the sigmoid function. It can be seen that different types of days have different numbers of cost parameters for the highest classification accuracy. The best cost parameter for summer is found to be 50 with 91.64% accuracy.

Table 3: Results for time processing durations in seconds using summer datasets

C Cost Parameters	SVM Sigmoid	
	Training (secs)	Testing (secs)
5	2.780	2.694
10	2.561	2.637
15	2.335	2.452
20	2.870	2.730
25	2.347	2.237
30	2.114	2.087
35	1.006	1.006
40	1.239	1.213
45	1.652	1.493
50	1.679	1.582

Table 4: Results for classification success rate as percentages using summer datasets

C Cost Parameters	SVM Sigmoid	
	Training (%)	Testing (%)
5	91.76	89.65
10	92.24	90.05
15	92.37	90.13
20	92.60	90.26
25	92.81	90.98
30	92.92	91.08
35	93.01	91.20
40	93.25	91.33
45	93.27	91.52
50	93.49	91.64

Table 5 shows the time processing durations in seconds. Summer datasets training datasets took longer times than testing datasets to complete the classification task due to the larger datasets compared to other types of days. The other datasets, including summer have similar time processing speeds and improved significantly in testing data.

Table 5: Results for time processing durations in seconds with Summer datasets

No. of hidden neurons	OS-ELM Sigmoid	
	Training (secs)	Testing (secs)
20	0.045	0.044
40	0.156	0.097
60	0.271	0.198
80	0.297	0.203
100	0.311	0.257
120	0.514	0.312
140	0.672	0.432
160	0.892	0.478
180	1.070	0.622
200	1.179	0.800

Table 6 shows the classification accuracies as percentages. As the classification success rate fluctuates as the number of hidden neurons increases. The classification accuracy results for testing datasets are slightly lower than for training datasets for all types of days.

Table 6: Results for classification accuracy as percentages with summer datasets

No. of hidden neurons	OS-ELM Sigmoid	
	Training (%)	Testing (%)
20	94.74	94.73
40	94.22	94.06
60	94.34	94.14
80	95.69	94.27
100	95.88	94.96
120	95.93	95.05
140	96.08	95.05
160	96.24	95.36
180	97.26	95.58
200	97.40	95.66

In Table 7, Online Sequential-Extreme Learning Machine with the sigmoid function produced the lowest error rates on summer (GIDC and Urban). while Online Sequential-Extreme Learning Machine with radial basis function nodes produced the highest error rates on summer (GIDC and Urban).

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Table 7: Root Mean Squared Error Results with Online Sequential-Extreme Learning Machine Prediction Algorithms based on summer datasets

Area	OSELM Sigmoid		OSELM Radial basis function	
	Training	Testing	Training	Testing
GIDC	0.0183	0.0393	0.0595	0.1178
Urban	0.0337	0.0385	0.0736	0.0752

V. CONCLUSION

The Prediction required time duration, Interpretation of electricity consumption for urban summer consumers, it is proved that the smaller the numbers of hidden neurons required for the Online Sequential-Extreme Learning Machine algorithms, it will speed up the classification process. Also, from the above observed that the algorithm the support vector machine has the largest time duration required when compared to Online Sequential-Extreme Learning Machine. However, for the classification algorithms, it has been proved that Online Sequential-Extreme Learning Machine with the radial basis function nodes generate the largest classification accuracy. On the other hand, it has also been proved that the time duration required, support vector machine with radial basis nodes has the slowest speed while Online-Sequential Extreme Learning Machine with the sigmoid function has the fastest speed.

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