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Predicting Energy Usage Of Electrical Appliances Using Machine Learning

Cigiri Rashmi, Chinthalapally Sree Harika, Chennoju Chandana, Chava Nuthana

1 (Information Technology, Assistant Professor, Malla Reddy Engineering College For Women
Email: *rashmi.cigiri@gmail.com)*
2 (Information Technology, Malla Reddy Engineering College For Women, Medchal
Email: *sonyreddy80162@gmail.com)*
3 (Information Technology, Malla Reddy Engineering College For Women, Medchal
Email: *chennojuchandana@gmail.com)*
4 (Information Technology, Malla Reddy Engineering College For Women, Medchal
Email: *chavanuthana1503@gmail.com)*

Abstract:

The correct analysis of energy consumption by home appliances for future energy management in residential buildings may be a difficult downside because of its high impact on the human close surroundings. during this project, a prediction methodology is given for energy consumption of home appliances in residential buildings. The aim of the project is that the daily power consumption prediction of home appliances supported classification in step with the hourly consumed power of all home appliances getting used in residential buildings. the method consists of 5 stages: knowledge supply, knowledge assortment, feature extraction, prediction, and performance analysis. completely different machine learning algorithms are applied to knowledge containing historical hourly energy consumption of home appliances employed in residential buildings. we've divided knowledge into different coaching and testing ratios and have applied different quantitative and qualitative measures for locating the prediction capability and potency of every formula.

I. INTRODUCTION

The sensible grid has emerged may be a new sort of power generation grid with main focus to regulate and manage electricity in additional economical, reliable and intelligent means. sensible grids area unit thought of handiest and reliable intelligent grid that options bound automation devices, protecting equipment's, communication protocols and a lot of significantly customers' response. These architectures and technologies facilitate in minimizing the energy gap between the generation facet and demand and permit property generation and distribution of electric power. Besides the opportunities offered by sensible grid, developing AN intelligent and sensible system for managing home energy system isa difficult task.

II. LITERATURE SURVEY

Smart load node for nonmottled underneath sensible grid paradigm: a brand new home energy management system.This article presents a unique approach for economical operation of non-smart family appliances underneath sensible grid surroundings exploitation the projected sensible load node (SLN). In world state of affairs, there area unit such a lot of non-smart masses presently in use and embedding appliance specific intelligence into them to create them as sensible masses are going to be dearer compared to the projected SLN, that may be a common resolution for every kind of non-smart masses. This makes the projected cheap SLN, that neither needs any infrastructural amendment within the electrical wiring of a house nor any constructional amendment in home appliances at the producing stage and at the patron finish, as a possible resolution for intelligent operation of non-

smart home appliances underneath sensible grid surroundings. The SLNs, that area unit placed in a very home like distributed wireless sensing element nodes, kind a home space network (HAN).

III. METHODOLOGY

A. Data Description

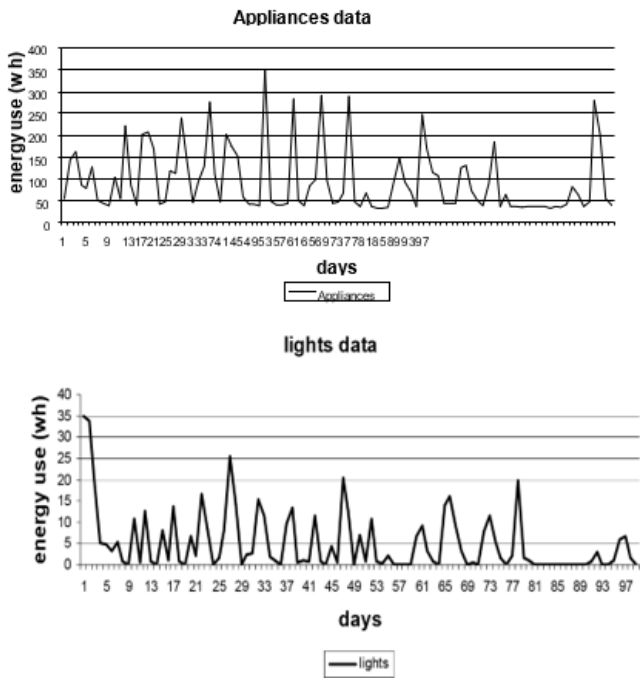
The experiment dataset was ready by combining 2 sorts of info. One was environmental information, like: temperature, humidity, wind speed, dew point, and visibility. different was energy use info for lights and appliances. Temperature and humidness information were collected by victimisation wireless detector network (ZigBee), that contained four.5 months information for every ten minutes slot, which implies hourly half dozen information and one hundred forty four information daily.

Attribute Name	*Unit*
Date time year-month-day	hour:minute:second
Appliances, energy use	Wh
lights, energy use of lights	Wh
T1, Temperature in kitchen	°C
T2, Temperature in living room	°C
T3, Temperature in laundry room	°C
T4, Temperature in office room	°C
T5, Temperature in bathroom	°C
T6, Temperature outside the building	°C
T7, Temperature in ironing room	°C
T8, Temperature in teenager room	°C
T9, Temperature in parents room	°C
T_out, Temperature outside (from weather station)	°C
RH_1, Humidity in kitchen	%
RH_2, Humidity in living room	%
RH_3, Humidity in laundry room	%
RH_4, Humidity in office room	%
RH_5, Humidity in bathroom	%
RH_6, Humidity outside the building	%
RH_7, Humidity in ironing room	%
RH_8, Humidity in teenager room	%
RH_9, Humidity in parents room	%
RH_out, Humidity outside (from weather station)	%
Pressure (from weather station)	mm Hg
Wind speed (from weather station)	m/s

B. Data mental image

Figure a pair of show the visual illustration of appliances and lights energy use information severally. From these there's a transparent indication of uncertainty in energy use prediction into an occasional energy house. These information area unit solely a couple of specific home. The spikes of the road graphs show that the demand of power fluctuates in time varied. it's owing to several correlative things; like: presence of family individuals, temperature, outside temperature, light-weight condition into and out of doors the rooms, weather, humidness etc. light-weight energy use comparatively less than the appliances, as a result of lights remains turned off most of your time in day time. But, appliances would like a lot of energy use as a result of some family appliances, like: icebox, Air condition, blower, electrical cooking utensil, area heater, different electronic stuffs, etc stay in use terribly oftentimes in whole day.

Fig. 1. Daily average energy use data by home appliances



C. Data preparation

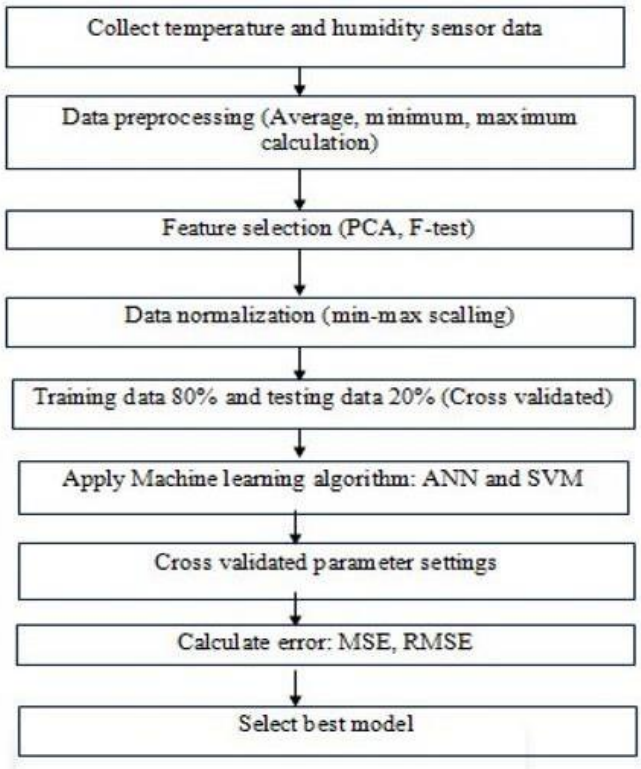
Though the data set was collected from on-line repository [1], it required to try to to some major information pre-process before getting ready our experiment information. Such as, the most information set contained energy usage statistic information for every ten minutes interval. How ever

we've calculated some derived attributes, like; daily average, daily minimum, daily most, weekday use, weekend use, first light use, afternoon time use, already dark use, night and time of day use. of these attributes area unit ready so as to spot the various patterns of electrical energy use in several times during a day. These analyses facilitate to spot correlations among the predictor attributes and also the target attribute (label). Moreover, we've done five differing types of study, like first light use, afternoon time use, already dark use, night and time of day use. So, dataset area unit ready consequently for these 5 sorts of experiments. Table II shows the PCA analysis results for selecting correlative feature attributes as predictors. Here Positive (+) suggests that robust correlation and Negative (-) suggests that comparatively less correlative.

TABLE II. ATTRIBUTE RELATIONSHIP SUMMARY AFTER PCA

Attributes	*Appliance*	*Lights*
T1	Positive (+)	Negative (-)
T2	Positive (+)	Negative (-)
T3	Positive (+)	Negative (-)
T4	Positive (+)	Negative (-)
T5	Positive (+)	Negative (-)
T6	Positive (+)	Negative (-)
T7	Positive (+)	Negative (-)
T8	Positive (+)	Negative (-)
T9	Positive (+)	Negative (-)
T_out	Positive (+)	Negative (-)
RH_1	Positive (+)	Positive
RH_2	Negative (-)	Positive
RH_3	Positive (+)	Positive
RH_4	Positive (+)	Positive
RH_5	Positive (+)	Positive
RH_6	Negative (-)	Positive
RH_7	Negative (-)	Positive
RH_8	Negative (-)	Positive
RH_9	Negative (-)	Negative (-)
RH_out	Negative (-)	Positive
Pressure	Negative (-)	Negative (-)
Wind speed	Positive (+)	Positive

D. Model Flow Chart



IV. PROPOSED FRAMEWORK

Support Vector Regression (SVR) works very good to identify patterns of dataset with numeric feature values. It has the ability to perform computationally effective analysis to reveal knowledge from input dataset. As our experiments are related to time series data analysis for pattern recognition and future value prediction, we choose SVR to apply with different types of kernel tricks, like; radial, polynomial, and sigmoid. Different kernel tricks help to identify and learn those hidden patterns and train the model with these knowledge such that model can produce good predictive results with minimum error rate. Table III show the cross validated information of SVR analysis with three different kernel techniques for appliance energy use prediction. All the parameters are cross validated and only the best combinations are tabulated with their

error performances.

TABLE III. CROSS VALIDATED RESULT SUMMARY OF SVM MODEL WITH DIFFERENT KERNEL FOR APPLIANCES

kernel	*Kernel parameters*					*MSE*	*RMSE*
	gamma	*cost*	*Epsilon*	*degree*	*Coef0*		
radial	0.01	2	0.0001	----	----	1.32%	11.49%
polynomial	0.01	2	0.0001	2	0	1.56%	12.51%
sigmoid	0.01	2	0.0001	----	0	1.54%	12.42%

Table IV shows the fine tuned SVR parameters with three different kernels for lights energy use prediction. Here polynomial and sigmoid kernels very slightly outperformed radial bias function .

TABLE IV. CROSS VALIDATED RESULT SUMMARY OF SVM MODEL WITH DIFFERENT KERNEL FOR LIGHTS

kernel	*Kernel parameters*					*MSE*	*RMSE*
	gamma	*cost*	*Epsilon*	*degree*	*Coef0*		
radial	0.01	2	0.0001	----	----	0.39%	6.25%
polynomial	0.01	2	0.0001	2	0	0.37%	6.07%
sigmoid	0.01	2	0.0001	----	0	0.37%	6.11%

Table V and VI show the actual vs Predicted values of energy usage of home appliances and lights respectively using support vector regression model. The predictors were chosen by using PCA analysis to feed input data into SVR model. There are five types of predicted values, like; morning, afternoon, evening, night and midnight time prediction of energy usage by home appliances and lights. In some cases of light energy prediction, some predicted values are produced in negative amount. This is because the previous inputs pattern contained many zero values, which means no lights were used. So the model predicts some negative energy values which could be treat as "0", as the energy use amounts can not be negative ever; either zero or some positive values.

TABLE V. ACTUAL VS PREDICTED VALUES OF APPLIANCES USING SVR

Attributes	*Date*	*Actual Value*	*Predicted value*	*Difference*
Appliances, T1, RH_1, T2,T3, RH_3, T4, RH_4, T5, RH_5, T6, T7, T8, T9, T_out, Windspeed	4/20/2016 morning	0.168	0.108	0.060
	4/20/2016 afternoon	0.284	0.069	0.215
	4/20/2016 evening	0.034	0.051	-0.017
	4/20/2016 night	0.038	0.006	0.033
	4/21/2016 midnight	0.052	0.163	-0.111
	4/21/2016 morning	0.135	0.225	-0.090
	4/21/2016 afternoon	0.262	0.240	0.022
	4/21/2016 evening	0.884	0.152	0.733
	4/21/2016, night	0.078	0.112	-0.034

TABLE VI. ACTUAL VS PREDICTED VALUES OF LIGHTS USING SVR

Attributes	*Date*	*Actual Value*	*Predicted value*	*Difference*
Lights, RH_1, RH_2, RH_3, RH_4, RH_5, RH_6, RH_7, RH_8, RH_out, Windspeed	4/20/2016 morning	0.063	0.007	0.057
	4/20/2016 afternoon	0.333	0.001	0.333
	4/20/2016 evening	0.000	-0.038	0.038
	4/20/2016 night	0.010	-0.079	0.089
	4/21/2016 midnight	0.041	0.009	0.032
	4/21/2016 morning	0.008	-0.019	0.027
	4/21/2016 afternoon	0.036	-0.002	0.038
	4/21/2016 evening	0.000	-0.106	0.106
	4/21/2016 night	0.000	-0.140	0.140

V. CONCLUSIONS

Smart meter supply associate intelligent thanks to get info of consumers regarding the consumption of voltage. during this project hybrid machine learning approach is used to forecast social unit electrical appliances consumption and peak demand consumption. quicker k- medoids agglomeration methodology is employed to divide the total knowledgeset into completely different clusters supported mean consumption data that later employed by support vector machine uncontrolled neural network to forecast the electrical appliances consumption and peak demand consumption severally. Our planned methodology achieves best accuracy in prediction electrical appliances consumption and far reduced share error in prediction peak demand consumption compared to many state-of- the-art methodology. The experimental results valid the effectiveness of our planned approach. In future, additional studies and economical techniques ar required, to grasp the explanation behind the height consumption by appliances in specific amount of your time and to shift the height time so as to save lots of a lot of energy.

V. REFERENCES

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