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SHORT TERM LOAD FORECASTING FOR ENERGY CONSUMPTION THROUGH MACHINE LEARNING: SVR AND LSTM-DRIVEN DEMAND FORECASTING

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Article Info

Abstract

Home Energy Management System (HEMS) has gained significant attention due to its important role in reducing energy waste. Despite its effectiveness, there are certain potential improvements, such as its ability to accurately forecast the household demand and share it with the utility company for better planning. Moreover, consumers seek ways to reduce their electricity bills due to increasing electricity prices. In this paper, we focus on predicting household energy demand accurately for optimal energy consumption, generation at reduced cost. We used K-Means Clustering, LSTM (Long Short Term Memory) and SVR (Support Vector Regression) techniques to learn the energy usage patterns from Pakistan residential energy consumption (PRECON) dataset complementing it with weather conditions and time of day. The SVR is found to be the best approach with least RMSE score. The proposed system will help consumers to make informed decisions to tradeoff between energy cost and comfort by shaping up their energy consumption habits during peak and off-peak hours. The utility companies may use the energy demand information to optimally manage the generation resources to lower energy cost, avoid transformer/feeder/grid overloading and reliable electricity supply to the consumers. The proposed system will reduce energy waste and improve overall energy efficiency by addressing the challenges faced by HEMS and providing consumers with valuable insights.

Keywords:
Home Energy Management System (HEMS), Machine Learning, Energy Demand Forecasting, Long Short Term Memory (LSTM), K-Means Clustering, Support Vector Regression (SVR), Artificial Intelligence, Energy Efficiency, PRECON Dataset.

Introduction

To create intelligent spatial zones, smart buildings take advantage of the rapid advancement of computer and communication technologies. Generally, people view smart buildings as being automated, which use micro-controllers and two-way communication devices to automatically govern a building's operation. According to the UN Environmental Program Report, The buildings are consumed 40% of the energy consumption [1]. This presents a significant challenge for energy management systems. The program, however, encourages data scientists to develop innovative approaches for predicting energy use [2]. The climate conditions, infrastructure, and energy costs impact energy consumption patterns. Therefore, it is difficult to estimate the total energy consumption of residential buildings using standard approaches [3].

Various machine learning techniques have been used to predict energy consumption levels in the last decade, including supervised and unsupervised methods [4]. Unsupervised learning strategies like clustering are popular in machine learning and data mining where objects exhibiting similar patterns under observation are categorized into multiple groups [5]. As a method for categorizing medium voltage consumers, [7] advocated grouping residential homes according to their power use trends and evaluated different clustering methods which resulted in eight standard load profiles. Based on comparable power usage patterns, [8] divided consumers into groups based on k-means and hierarchical clustering. Moreover, an analysis of power utilization characteristics was conducted in [9]. The literature indicates that potential significant perspectives of energy consumption prediction are not included while employing the clustering techniques.

In this paper, we developed and evaluated three machine learning models using K-Means Clustering, LSTM (Long Short Term Memory) and SVR (Support Vector Regression) techniques with Google Collab. The Pakistan residential energy consumption (PRECON) dataset is used for these model evaluations by complementing it with weather conditions and time of day.

Due to the use of Energy and Pollution, There will be some environmental factors take place such as Solid waste disposal, climate change, air pollution, thermal pollution and water pollution. Urban air pollution is done to the use of Fossil Fuel Combustion.

The importance of forecasting is evident in many aspects of our lives, and knowing what to do next plays a huge role in your decision-making. An electricity load forecast is a method for estimating consumption and peak demands on hourly, daily, weekly, and annual basis [12]. The electricity load forecasting (ELD) has gained a lot of attention due to its relevance to power system operations and planning. There has been a growing interest in ELD among power grid companies, smaller power systems like solar systems [10], wind power systems [11], and researchers due to the diversity of systems involved in forecasting that make it difficult and complex. Moreover, emphasis on energy conservation has increased in recent years. In order to forecast demand, past information is crucial, but it must be processed correctly with reference to time horizon and granularity (aggregation).

Electrical demand estimation is a technique used to evaluate solar power system benefits in relation to the electricity bill as a mean of successfully reducing the electricity charges attributed to solar installation. It is non-trivial task due to the variable nature of electricity consumption patterns over time, including variations in demand for electricity. As a result, making forecasts as accurate as possible is one of the goals of maintaining an effective electricity supply chain by developing a ”one-trip” model and a ”multi-phase” model (performed over time) to facilitate online estimation and adaptation.

1. Literature Review

Energy Consumption forecasting basically plays an important role in the development of home energy management systems. The systems are used in the planning, efficient operations and in the optimization of the energy resources. The forecasting is basically consisting of three different parts. The first one is Short term forecasting in which we use data of hours to days. The second one is Medium Term forecasting where data consist of weeks to months and the last one is Long Term Forecasting where we use data up to years.

In this research paper, our focus is one STLF (Short Term Load Forecasting). The STLF is a broad field in the literature. The STLF is firstly defined in the 1987 by the authors of [14] and also demonstrate its importance in the implementation of Home Energy Management System (HEMS). This research [14] also demonstrates the externals factors such as weather condition, time and economy conditions. To explain the STLF they discuss firstly the technique of ARIMA. ARIMA is basically helpful to controls the external factors of Weather conditions.

The STLF is basically study and main area of research in the field of Electrical Engineering but with the advancement of technology, Machine Learning (ML) techniques and AI Models it become the big field in the computer sciences and data sciences. In [15], they used Deep Neural Networks (DNN) to solve the problem of STLF. Where they will train the models in two ways, the one is pre-trained restricted Boltzmann Machine and second one is untrained restricted Boltzmann Machine. They train the DNN by providing the consumer data with also providing the weather data for better results. The use MAPE and RRMSE to compare the results of model with shallow neural network (SNN), double seasonal Holt–Winters (DSHW) and autoregressive integrated moving average (ARIMA) models.

In [13], this research use three different models to get solve the problem of STLF. The first one is Support vector regression, the second one is Multiple Linear Regression Model and the last one is Artificial Neural Network. In [13], three different techniques are used for results comparing. The first one is Mean Error (ME) the second one is Route Mean Square Error (RMSE) and the last one is Mean Percentage Error (MPE).

However, in the development countries there is a vacuum for the studies that focus on the Load or Energy Consumption. PRECON is a mission that is a one-step which tries to fulfill this gap. The Short Term Load Forecasting is a new topic for developing countries like Pakistan, India etc. This paper presents the demand forecasting from residential dataset of PRECON by using short term load forecasting technique.

2. Methods

In this paper, this research uses weather, time of day and electricity usage data to predict household electricity demand. The PRE- CON dataset is prepared by Lahore University of Management Sciences (LUMS) and is available on an average per minute and per hour basis, in kilowatt (KW) load and kilowatt hour (KWH) unit formats for all appliances in the target houses. The data comprise of one year 2018-2019 and is collected from houses in Lahore. PRECON dataset is used which includes consumption (appliances level) data at 1 minute interval for 42 houses over the period of one year. As the weather in Lahore varies throughout the year, there is an impact of high degree of seasonal variation in the dataset. Three machine learning algorithms are used in this prediction method: k-Means, SVR, and LSTM. In the functional specification, power factors, voltages, currents, and goal output demands are taken into account. The data is complemented with weather and time of day features. The Python is used for predictive modeling in

Google Collab's Machine Learning Studio. The base data is evaluated and pre-processed followed by model training and testing.

2.1 Support Vector Machine (SVM)

Support Vector Machine is abbreviation of SVM. SVM is basically a Supervised Machine Learning (ML) Algorithm basically used for classification and Regressions problems. In our research we will use SVR (Support Vector Regression) because our problem is regressive. In Regression techniques, we basically work on minimizing the error, in our research we focus on one error named as Route Mean Square Error (RMSE) for both training data and testing data with our all house consumption and individual level appliance consumptions.

2.2 Long Short Term Memory (LSTM)

LSTM is stands for Long Short Term Memory. The LSTM is based on AL (Artificial Intelligence) and DL(Deep Learning). The LSTM is basically a Recurrent Neural Network (RNN), it will basically designed to overcome the limitation if traditional RNN Algorithms. The LSTM used memory cells and Gating Mechanism to control the flow of Information. The three main gates are included named as: Input Gate, Forget Gate and Output Gate. These gates decided which information we need to add in the network, which information needs to removed and which information we need to pass through the Network.

2.3 K-Means Clustering

K-Means Clustering basically an Unsupervised Learning Algorithm, it will basically use to group data into different clusters. This algorithm make clusters of different points in a way that points in the clusters are more similar to each other. In this research we basically used K-Means Cluster algorithm to make different clusters of data on the basis of similarities but due to high number of attributes in the datasets we are not be able to make clusters correctly and the accuracy of the algorithm not be satisfied for further work, so we will used SVR and LSTM to solve this research problem.

2.4 Tools and Languages

In this research, we use python as a primary language for developments. And also we use different tools to finalize our research as follow: Excel for ABC Classification because data in .csv format, Google Digital Collab for development and Google Drive for dataset storage. It is worth mentioning that Jupiter Notebook and Python are the platforms and languages used to implement the machine learning models, which are installed using Python 3.6 and Anaconda.

2.5 Data Collection and Analysis

We used energy data from 10 household buildings in the PRECON dataset and complemented it with weather data of Lahore, Pakistan's most densely populated city. The energy consumption data in PRECON dataset include various columns referring to different appliances. The abbreviations for each appliance are given in the table (1) below, with the names of the columns representing the abbreviations.

Table 01: Appliances Name with Abbreviations for Dataset

Sr.	**Appliance Name**	**Appliance Short Name (Abbreviation)**
1.	*Light Consumption of Iron*	*Iron_KW*
2.	*Light Consumption of Microwave Oven*	*MV_KW*
3.	*Light Consumption of Window AC*	*W_AC_KW*
4.	*Light Consumption of AC*	*AC_KW*
5.	*Load of Light Consumption without UPS*	*Non_UPS_KW*
6.	*Freezer & Water Dispenser Light Consumption*	*Freezer_WD_KW*
7.	*Light Consumption of Freezer*	*Freezer_KW*
8.	*Light Consumption of Refrigerator*	*Refrigerator_KW*
9.	*Light Consumption of Water Pump*	*WP_KW*
10.	*Light Consumption of Water Dispenser*	*WD_KW*
11.	*Light Consumption of UPS*	*UPS_KW*
12.	*Light Consumption of Servant Room*	*Servant_KW*
13.	*Light Consumption for Laundry*	*Laundry_KW*
14.	*Light Consumption of Lounge Room*	*LR_KW*
15.	*Light Consumption of Bed Room*	*BR_KW*
16.	*Light Consumption of Kitchen*	*Kitchen_KW*
17.	*Light Consumption of Study Room*	*SR_KW*
18.	*Lounge Room AC*	*AC_LR_KW*
19.	*Dining Room AC*	*AC_Dr_KW*
20.	*Drawing Room AC*	*AC_DR_KW*
21.	*Bed Room AC*	*AC_BR_KW*
22.	*Master Bed Room AC*	*AC_MBR_KW*
23.	*Study Room AC*	*AC_SR_KW*
24.	*Guest Room AC*	*AC_GR_KW*
25.	*AC & Refrigerator*	*AC_Ref_KW*
26.	*AC & UPS*	*AC_UPS_KW*
27.	*Washing Machine & Refrigerator*	*Ref_WM_KW*
28.	*Overall Light Consumption of House*	*Usage_KW*

Table 2: Extracted Features Abbreviations

SR.	**Abbreviation (Short Name)**	**Abbreviation Description**
1.	*Cloudiness*	*It's used to represent the Cloudiness at that time when data collected in this research*
2.	*Daytime*	*Its shows that the time at which data is collected means Evening time, Morning Time or Night Time Etc. in this research*
3.	*Season*	*Its shows that in which season data is collected like summer, winter, fall etc. in this research*
4.	*dayType*	*Its shows that in which day data is collected is belong to Weekday or Weekend in this research*

5.	*Date*	*Represent the date and time with day, month, year, hour and minutes in this research*
6.	*QV2M*	*Its used to represent the Humanity in this research*
7.	*T2MDEW*	*Its used to represent the Temperature with Dew Point in this research*
8.	*T2M*	*It's used to represent the Temperature in this research*
9.	*Hour*	*It's used to represent the Hour in this research*
10.	*Year*	*It's used to represent the Year in this research*
11.	*Month*	*It's used to represent the Month in this research*

2.6 Data Preprocessing (Data Cleaning and Data Resampling)

We use Python to preprocess the original dataset. The preprocessing done by using following steps: The first one is Data Cleaning and second one is Data Re-sampling. In Cleaning of data is also divided into two steps the first one is removing unwanted columns and second one is handling missing values in the dataset.

In the process of removing unwanted columns, we remove the data columns which are not necessary. The removing of unwanted columns is done by using pandas function name as drop. The drop is worked by writing columns name's as parameter with mentioning axis as 1 (The 1 refers to the column).

$$\text{df\_name} = \text{df\_name.drop}(\text{“ColumnName”}, \text{axis} = 1)$$

The null values in the dataset is known as missing values, we use different methods to handle missing values such as dropping the null values rows, replacing the null values with 0's, and using with different imputations such as mean, median and mode functions. In the 1st method of dropping null values, we drop the rows having null values. For this purpose pandas a library of python provide a function of dropna. The 2nd method of replacing null values, we used 0's to replace the null values. For python provide a function of fillna for this purpose. In the last method, we use different Imputations such as mean, median and mode. The mean use the values of data points in the columns and take average of these data points to fill the missing value. The Median function the missing values is replace by median of the column and in the Mode function the missing value is replaced by the mode of the data points in that column.

Table 3: Python Code to handle Missing values

This code will be used to replace the missing values with 0's in all the dataset.	***Dataframe = data frame. replace(0, NumPy. Nan)***
This code will be used to replace the missing values by using interpolate method, the interpolate method work by	***Dataframe = data frame. interpolate()***

replacing missing value to average of two data points.	

Times series data must needed data reshaping so it's easy for analysis and modeling. In this research, we use dataset of PRECON which is recorded on the interval of one minute so we will reshape on the scale of hour. In other words, the data is in kilo watt so we convert into kilo watt hour for better results. This is done by using a pandas function by the name of resample () with passing date time index attribute as parameter.

3. Results

In our research, we applied three different techniques to generate results from the energy consumption dataset. The two techniques are statistical techniques name as LSTM (Long Short Term Memory) & SVR (Support Vector Regression) and the one is clustering based technique name as K-Mean Clustering. After applying the techniques we will compare their results to give findings accuracy of the method by using a method of RMSE (Route Mean Square Error).

SVR is a machine learning algorithm which may the extension of Support Vector Machine (SVM). The SVM is basically used to solve the classifications problems while the SVR is used to solve the Regression problems. SVR use the same mechanism as used by SVM. In this research, we basically use a time series data so we use SVR to solve this problem. The SVR is worked by minimizing the prediction error to find relationship between the Input Features and the target value. To perform this research we use 10 houses data to predict results. The Results showed in the table (4) represent that the SVR performed more accurately on the Individual Level Compliance data as compare to the Total Consumption of the house by comparing their RMSR Value's.

LSTM is basically a Recurrent Neural Network algorithm which will be used mainly to solve the Time Series Problems. The RNN is trained using parameters as input in this Model. The results are getting through this model, by training them up to 10 epochs/iterations and 100 steps per epoch. The RNN consist of 18 input signals, they work on a sequence of arbitrary length. To perform this research we use 10 houses data to predict results. The Results showed in the table (4) represent that the LSTM performed more accurately on the Individual Level Compliance data as compare to the Total Consumption of the house by comparing their RMSR Value's.

K-Means Clustering belongs to unsupervised learning algorithms. This algorithm used to make clusters in the provider dataset on the basis of similar features. The cluster is denoted by K. It will use centroids to make clusters which will be the average of all the data points in that area. In this research, we want to make cluster of houses on the basis of Meta data provided by PRECON dataset. But when we applied the K-Means clustering technique on the Meta data, the algorithm generate 42 clusters for the 42 houses. So from this we result that we cannot be able to apply clustering on this dataset.

3.1 Training Results for LSTM and SVR

Apply LSTM and SVR for getting RMSE value in the regressive problems so found that the model give best results on individual appliance level as compared to total consumption. Also find that the SVR give best perform than LSTM than we will use SVR as a Final Algorithm for our Research (Scenario)

Table 4: Results for Training dataset

House No	*RMSE Training (Total Consumption) For SVR*	*RMSE Training (Mean of Individual Appliances) For SVR*	*RMSE Training (Total Consumption) For LSTM*	*RMSE Training (Mean of Individual Appliances) For LSTM*
H1	*0.09943871*	*0.0120581*	*0.35*	*0.074*
H2	*0.0423898*	*0.0065595*	*0.23*	*0.05*
H3	*0.2506753*	*0.0296374*	*0.47*	*0.2*
H4	*0.2659138*	*0.0272903*	*0.57*	*0.166*
H5	*0.1242866*	*0.0132982*	*0.41*	*0.12*
H6	*0.2140174*	*0.0013*	*0.46*	*0.0375*
H7	*0.1827289*	*0.0101*	*0.48*	*0.0925*
H8	*0.0212782*	*0.0082838*	*0.16*	*0.0733333*
H9	*0.0634168*	*0.0285029*	*0.31*	*0.116*
H10	*0.0837544*	*0.0148565*	*0.28*	*0.0933333*

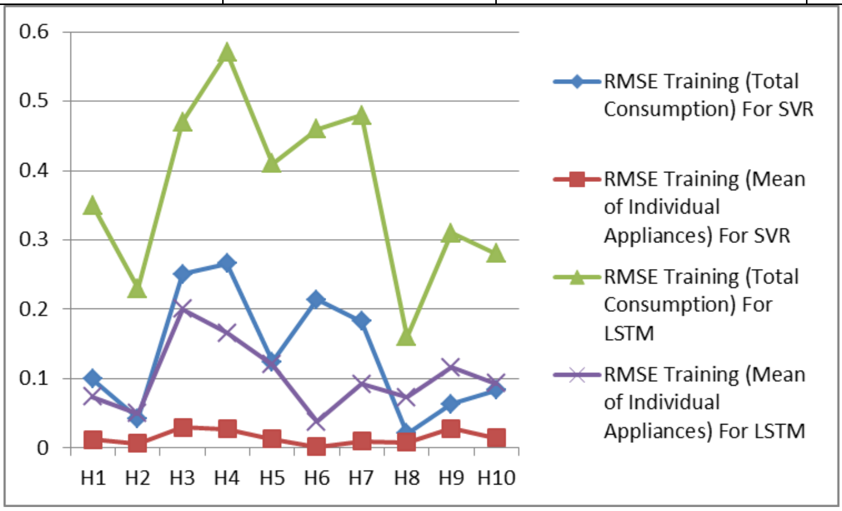

Figure 1: Results for Training data-set

3.2 Testing Results for LSTM and SVR

The SVR model gives the best results on individual appliance level as compared to total consumption when applying regressive models. The SVR is used as our final algorithm (scenario).

Table 5: Results for Testing dataset

House No	*RMSE Testing (Total Consumption) For SVR*	*RMSE Testing (Mean of Individual Appliances) For SVR*	*RMSE Testing (Total Consumption) For LSTM*	***RMSE Testing (Mean of Individual Appliances) For LSTM***
H1	*0.04020784*	*0.0069573*	*0.22*	*0.054*
H2	*0.02044634*	*0.0023516*	*0.16*	*0.03*
H3	*0.11535549*	*0.0125869*	*0.33*	*0.0866666*
H4	*0.13885567*	*0.0155319*	*0.41*	*0.102*
H5	*0.04451989*	*0.0074204*	*0.24*	*0.083*

H6	*0.22734274*	*0.0091659*	*0.29*	*0.1175*
H7	*0.10469950*	*0.0080053*	*0.41*	*0.075*
H8	*0.06341681*	*0.0285029*	*0.22*	*0.1133333*
H9	*0.09860069*	*0.0126900*	*0.38*	*0.104*
H10	*0.07080921*	*0.021043*	*0.28*	*0.1166667*

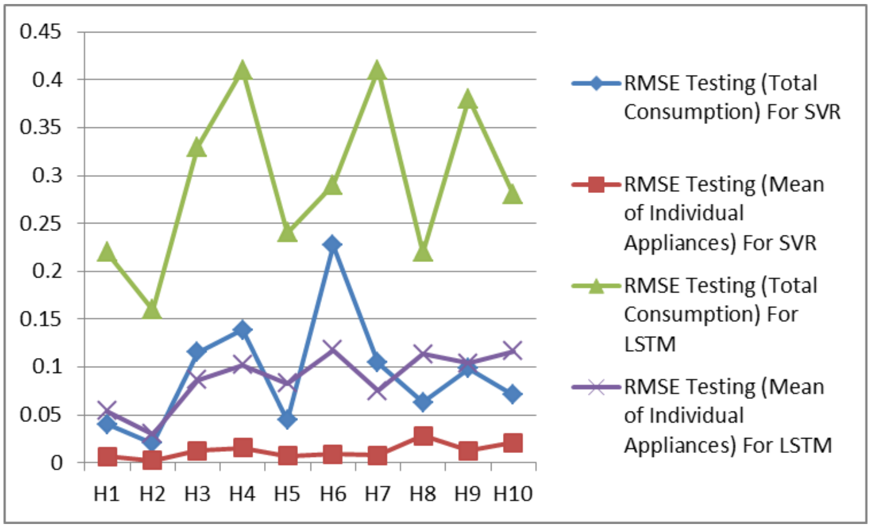

Figure 2: Results for Testing data-set

3.3 Bill Estimator

In order to demonstrate the impact of accuracy in energy consumption prediction, its transformation into electricity charges is important which is done using bill estimator developed by LESCO (Lahore Electric Supply Company).

3.4 Energy Advisor

Using rule based AI; energy advisor will help consumers to better manage their electricity bills. As a basic level model, three rules in energy advisor are implemented to Shift Peak and Off-Peak Hours consumption.

1. Total Units = 1350.8567468209706
2. Peek Rate = 24.33 (Supposed)
3. Off-Peak Rate = 18.01 (Supposed)
4. Original Price = 31336.4054769538 PKR
5. 25/75 = 30068.919555976387 PKR
6. 50/50 = 30491.414862968857 PKR
7. 75/25 = 30913.910169961335 PKR

4. Discussion

In the real world, model parameters predicting short-term energy consumption will be heavily influenced by utility needs and factors such as risk appetite, supply demand, and cost. This is of course a challenge that becomes increasingly important as the smart grid grows and as all parties reaps the environmental and economic benefits of improved short-term energy demand.

5. Conclusions

There are various limitations that prevent power consumption profiling as limited accuracy, limited range of parameters and short-term historical data. The results show how these features affect the energy consumption prediction. To make our dataset more useful, we may use feature generation techniques to identify relevant attributes from existing data, such as data type, date, weather, and cloud etc. There is also a general research strategy that can be applied to any data set regardless of its geographic location. We used the most commonly used methods, support vector regression (SVR) and LSTM, which produced predictions with lower RMSE values.

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