HOUSEHOLD ENERGY CONSUMPTION PREDICTION

A PROJECT REPORT

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I. INTRODUCTION

With the rise of technology, there is a constant increase of electricity consumption in the household. Sometimes this increase can cost us heavy bill charges due to which we are unable to manage our household expenses. The energy performance in buildings is influenced by many factors, such as ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting and HVAC systems, occupancy and their behavior. This complex situation makes it very difficult to accurately implement the prediction of building energy consumption.

Thus in order to solve this problem and save electricity from getting wasted, smart electricity meters are introduced due to which a lot of data is available that can be processed and used for our benefit. The goal of our project is to create a Predictive Model that can analyze and predict the electricity consumption in household by implementation of supervised and unsupervised learning algorithms. With the help of supervised learning algorithms like Support Vector Machine (SVM), Logistic Regression and Linear Regression, accuracy is determined by feeding dataset with a categorical target variable for classification whereas for unsupervised learning algorithms like K – Means Clustering, Isolation Forest, and Local Outlier Factor (LOF), data need not be fed by a target attribute as they learn with experience. Machine learning algorithms predict a single value and will not be feasible to be used directly for multi-step forecasting. So, we will implement two strategies recursive method and the direct method that will be used to make multi-step forecasts with machine learning algorithms. Our model would be helpful for the electricity department to plan the electricity demand better for a specific residential area and conserve energy. It could also be helpful within the household in planning expenditures. Our project reviews recently developed models for solving this problem, which include elaborate and simplified engineering methods, statistical methods and artificial intelligence methods.

Previous research work concerning these models and relevant applications are introduced. Based on the analysis of previous work, further prospects are proposed for additional research reference.

II. Literature Survey

[1] Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines, 2015.

Electricity generation, transmission and distribution facilities require an investment of billions of dollars. Therefore, forecasting electricity consumption is very important for the investors and companies. Adequate capacity planning requires accurate forecasts. The analysed results indicate that the LS-SVM model can be used effectively for Turkey’s long-term net electricity consumption forecast. In addition, a successfully trained ANN model is a powerful forecasting tool as well.

Therefore, the recommendations presented in this article are useful for policy makers and energy planners.

[2] Modelling of Residential Lighting Load Profile Using Adaptive Neuro Fuzzy Inference System (ANFIS), 2016.

Most practices currently adopted in modelling the presence of people in residential houses do not reflect the complexity of the impact occupants have on lighting loads. Hence the needs to contribute a methodology, that will be able to look into such characteristics. This study entailed the use of adaptive Neuro Fuzzy inference system (ANFIS) for estimation and prediction of lighting load usage profile for energy and demand side management initiatives.

Results obtained showed a better correlation analysis and root mean square error (RMSE) in contrast to the regression method model. This shows that ANFIS model has good prediction accuracy capability.

Based on the result obtained from the research work, it can be deduced that the ANFIS model is a better modelling tool for the prediction of lighting load demand profile DSM & EE (energy efficiency) project - middle income earner category, other income groups investigation such as low income are is still on – going.

[3] Deep learning for estimating building energy consumption, 2016.

In this paper, we investigate two newly developed stochastic models for time series prediction of energy consumption, namely Conditional Restricted Boltzmann Machine

(CRBM) and Factored Conditional Restricted Boltzmann Machine (FCRBM). The assessment is made on a benchmark dataset consisting of almost four years of one minute resolution electric power consumption data collected from an individual residential customer. The results show that for the energy prediction problem solved here, FCRBM outperforms ANN, Support Vector Machine (SVM), Recurrent Neural Networks (RNN) and CRBM.

[4] Energy consumption prediction using people dynamics derived from cellular network data, 2016.

The paper proposed the following technical solution:

a) A highly parallelized feature extraction algorithm, which characterizes diversity, regularity and general human dynamics, derived from telecommunication data and aggregated by the square grid areas, including innovative second-order features in time and frequency domains;

b) A feature selection algorithm (32 features for the final models are selected out of >3,000 features), thus reducing the computational complexity of the model;

c) A non-linear regression modelling and prediction based on ensemble of decision trees, which are bootstrapped and aggregated;

d) A model generalization strategy, as opposed to data overfitting, including strict separation of the test set from the training set (the test set is the next week after the training set with the dependent variables taken with 7-days shift to the future), random splits, bootstrapping and bagging techniques.

[5] A Prediction Approach for Demand Analysis of Energy Consumption Using K-Nearest Neighbor in Residential Buildings, 2016.

The main aim of this paper was to facilitate the energy suppliers to make decisions for the provision of energy to different apartments according to their demand. In this paper, they have utilized K-Nearest Neighbors classifier for daily energy consumption prediction based on classification. The process consists of five stages namely data collection, data processing, prediction, and validation and performance evaluation. The historical data containing hourly consumption of 520 apartments of Seoul, Republic of Korea has been used in the experimentation. The data has been divided into different training and testing ratios and different qualitative and quantitative measures have been applied to find the performance and efficiency of the predictor. The highest accuracy has been observed for 60-40% training and testing ratio giving 95.9615% accurate results. The effectiveness of the model has been validated using 10-Fold and 5-Fold cross validation.

[6] Energy consumption forecasting based on Elman neural networks (ENN) with evolutive optimization, 2017.

It proposes a method for predicting energy consumption by using ANN and the GA to improve the accuracy of these models. The main objective of this paper is to provide a methodology to analyse historical energy consumption, and perform the daily prediction with such models. Furthermore, a comparison is made between ANNs and identifies if the energy consumption forecasting can improve with external information or it depends entirely on historical consumption. This paper deals with energy efficiency in public and distributed buildings analysing a new proposed model of ANN with previous forecasting methods for energy consumption applied. proposed methodology which follows has been developed in four stages. The first stage is data capture and preparation. Once the data have been compiled, the second stage is the ANN forecasting model. The next stage is genetic optimizing. And the final phase involves the analysis review and the use of the optimized ENN.

[7] K-Shape clustering algorithm for building energy usage patterns analysis and forecasting model accuracy improvement, 2017.

In this paper, a clustering method based on k-Shape algorithm is proposed, which is a relatively novel method to identify shape patterns in time-series data. In the experiment, clustering is performed for each individual building according to its hourly consumption. The novelty of this paper is that a new k-Shape algorithm is applied to detect building-energy usage patterns at different levels, and the clustering result is further utilized to improve the accuracy of forecasting models. Ten institutional buildings covering three different typologies are used as case studies and a set of hourly and weekly energy consumption data is further analysed in this paper. The experimental results reveal that this proposed method can detect building energy usage patterns in different time granularity effectively and also proves that the forecasting accuracy of SVR model is significantly improved by utilizing the results of the proposed clustering method.

[8] Household Electricity Consumption Prediction Under Multiple Behavioural Intervention Strategies Using Support Vector Regression, 2017.

This paper has proposed an optimal SVR model for predicting household consumption under multiple intervention strategies. The improved model is designed to incorporate energy related behaviours, personality traits, demographic/building features and the weather data, into behavioural interventions to predict electricity consumption for the households. In particular, the interaction effect between behaviours and other variables has been introduced to the household electricity consumption prediction.

The study has developed a behaviour- based RBF SVR model that is capable to predict household electricity consumption under multiple intervention strategies. The proposed model is able to act as a decision-making tool to choose the most appropriate intervention strategy for different households as it can predict the electricity savings accurately through each strategy.

The result shows that the proposed model has the best and robust performance on the next month prediction and time-series forecasting.

[9] Short-Term Residential Load Forecasting based on LSTM Recurrent Neural Network, 2017.

In this paper, they proposed a long short-term memory (LSTM) recurrent neural network (RNN) based framework, which was the latest and one of the most popular techniques of deep learning, to tackle this tricky issue. The proposed framework was tested on a publicly available set of real residential smart meter data, of which the performance is comprehensively compared to various benchmarks including the state-of-the-arts in the field of load forecasting.

As a result, the proposed LSTM approach outperforms the other listed rival algorithms in the task of short-term load forecasting for individual residential households.

[10] Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks, 2017.

The main objectives of this paper are: (a) Develop and optimize novel deep recurrent neural network (RNN) models aimed at medium to long term electric load prediction at one-hour resolution; (b) Analyze the relative performance of the model for different types of electricity consumption patterns; and (c) Use the deep NN to perform imputation on an electricity consumption dataset containing segments of missing values. The proposed models were used to predict hourly electricity consumption for the Public Safety Building in Salt Lake City, Utah, and for aggregated hourly electricity consumption in residential buildings in Austin, Texas. For predicting the commercial building's load profiles, the proposed RNN sequence-to-sequence models generally correspond to lower relative error when compared with the conventional multi-layered perceptron neural network. For predicting aggregate electricity consumption in residential buildings, the proposed model generally does not provide gains in accuracy compared to the multilayered perceptron model.

[11] A Smart Forecasting Approach to District Energy Management, 2017.

The aim of each individual ANN was to predict electricity consumption and the aggregated demand in sub-hourly time-steps. The inputs of each ANN were determined using Principal Component Analysis (PCA) and Multiple Regression Analysis (MRA) methods. The accuracy and consistency of ANN predictions were evaluated using Pearson coefficient and average percentage error, and against four seasons: winter, spring, summer, and autumn. The lowest prediction error for the aggregated demand was about 4.51% for winter season and the largest prediction error was found as 8.82% for spring season. The results demonstrated that peak demand can be predicted successfully, and utilized to forecast and provide demand-side flexibility to the aggregators for effective management of district energy systems.

[12] Building power demand forecasting using K-nearest neighbours model – practical application in Smart City Demo Aspern project, 2017.

In this study, they had applied a forecaster based on the KNN technique to predict daily load curves of three different smart buildings participating in SCDA project, achieving convincing forecast accuracy. Without any manual setup or parametrization, their forecaster turned out to be significantly more accurate than the forecast done using individual load profiles obtained for each building.

[13] Forecasting Energy Consumption Time Series using Machine Learning Techniques based on Usage Patterns of Residential Householders, 2018

This investigation presented a comprehensive review of machine learning techniques for forecasting energy consumption time series using actual data. Real-time data were collected from a smart grid that was installed in an experimental building and used to evaluate the efficacy and effectiveness of statistical and machine learning techniques. Well-known artificial intelligence techniques were used to analyze energy consumption in single and ensemble scenarios. An in-depth review and analysis of the 'hybrid model' that combines forecasting and optimization techniques was presented. The comprehensive comparison demonstrates that the hybrid model is more accurate than the single and ensemble models. Both the accuracy of prediction and the suitability for use of these models are considered to support users in planning energy management.

[14] A Deployable Electrical Load Forecasting Solution for Commercial Buildings, 2018.

This paper presented a practical solution, which can be readily deployed, by considering various real-life issues. Load forecasting algorithms was developed using Non-linear Autoregressive model with eXogenous input (NARX) neural network and Support Vector Regression (SVR) to forecast the power consumption for day ahead, week ahead and month ahead at 15 minute granularity. Missing values, outliers in the power consumption data were treated using simple but effective techniques based on the thorough understanding of the power consumption time-series data. Autoregressive features, temperature and some efficacious contextual information, which were completely pertinent to this problem, are being derived to model this heterogeneous time series that consists of disparate patterns on weekdays, weekends and holidays. The novelty of the solution lies in the fact that it extensively models all the variations and produces accurate long term predictions at high granularity (15 min).

[15] A Prediction Methodology of Energy Consumption Based on Deep Extreme Learning Machine and Comparative Analysis in Residential Buildings, 2018.

In this paper, they have proposed a methodology for the energy prediction having four layers, i.e., the data acquisition layer, the pre-processing layer, the prediction layer, and the performance evaluation layer. They have performed different operations on the data in each layer of the proposed model.

In the prediction layer, the deep extreme learning (DELM) approach for the improved performance of the energy consumption prediction is used. The DELM takes the benefits of both extreme learning and deep learning techniques. The DELM increases the number of hidden layers in the original ELM network structure, arbitrarily initializes the input layer weights and the initial hidden layer weights along with the bias of initial hidden layer, uses the technique for hidden layers (excluding first hidden layer) parameters calculation, and finally uses the least square technique for output network weights calculation. The trial and error method to set the best number of hidden layers, a suitable number of neurons in the hidden layers, and a compatible activation function.

[16] Day-ahead forecasting approach for energy consumption of an office building using support vector machines, 2018.

This paper presents a Support Vector Machine (SVM) based approach for energy consumption forecasting. The proposed approach includes the combination of both the historic log of past consumption data and the history of contextual information. By combining variables that influence the electrical energy consumption, such as the temperature, luminosity, seasonality, with the log of consumption data, it is possible for the proposed method by find patterns and correlations between the different sources of data and therefore improves the forecasting performance.

[17] Data-driven heating and cooling load predictions for non-residential buildings based on Support Vector Machine Regression and NARX Recurrent Neural Network: A comparative study on district scale, 2018.

In this paper, the performance of a NARX RNN of varying depth was compared to a e-SVM-R using a RBF and a polynomial kernel to predict thermal loads with the goal to provide progress for the current discussion on the superior performance of SVMs in comparison to ANNs. Adding more depth to the NARX RNN introduced a Deep Learning component that can be used to investigate possible performance improvements. In order to improve generalizing propositions, the test case includes detailed measurement data of 98 buildings within the heating system and measurement data of 47 buildings within the cooling system. Thus, possible differences between heating and cooling load prediction accuracy were investigated, which was motivated by different time series characteristics occurring frequently.

[18] Forecasting Residential Energy Consumption Using Support Vector Regressions, 2018.

In this study, Support Vector Regression (SVR) is used for the prediction of fifteen households' residential electricity consumption. These households are anonymous residents in London Ontario, with a home-installed smart meter for electricity measurement. Support vector regression (SVR) is a version of SVM, which is a non-linear regression model that looks at the extremes of data sets and draw a decision boundary (or a hyperplane) to solve function fitting problems.

The prediction model is designed to work with SVR on both hourly and daily data granularities for every household. It was analysed that, more variability in electricity consumption has been seen in weekends other than weekdays.

Because of the stochasticity for single residential customers, daily data granularity achieves better prediction results than hourly data for all the 15 households.

[19] Using Recurrent Artificial Neural Networks to Forecast Household Electricity Consumption, 2019.

The paper presents a model based on an Elman recurrent neural network for the prediction, one hour ahead, of the intensity of the electric current supplied to the residential users located within a particular area of the town of Palermo (Italy). The model takes as inputs weather data as well as data related to the electricity consumptions. Furthermore, a special input (HC index) related to the presence and use of the AC appliances in the investigated area was added to the model. The achieved results are quite interesting: the percentage prediction errors computed for a test week are respectively 1.5% for the mean error and 4.6% for the maximum error.

[20] Ensemble forecasting for electricity consumption based on nonlinear optimization, 2019.

Due to the instability and nonlinearity of electricity consumption, the performances of classical or single time series forecasting methods are limited. Based on the nonlinear optimization method, this paper proposes an ensemble forecasting method, which integrates the forecasting results of two basic classical forecasting models and two artificial intelligence models. The ensemble model displays more accurate electricity demand forecasting performance than single and average integrated models. This ensemble model can be easily employed to other time series forecasting and more verification can be made to data at different frequencies for future study.

[21] Enhancement of a Short-Term Forecasting Method Based on Clustering and kNN: Application to an Industrial Facility Powered by a Cogenerator, 2019.

In this paper, a clustering approach for the short-term forecasting of energy demand in industrial facilities was presented. A model based on clustering and k-nearest neighbors (kNN) was proposed to analyze and forecast data, and the novelties on model parameters definition to improve its accuracy were presented. The model was then applied to an industrial facility (wood industry) with contemporaneous demand of electricity and heat. An analysis of the parameters and the results of the model was performed, showing a forecast of electricity demand with an error of 3%.

[22] Electricity consumption prediction for buildings using multiple adaptive network-based fuzzy inference system models and gray relational analysis, 2019.

This study proposes a method to predict the electricity consumption of public buildings by using an adaptive network-based fuzzy inference systems (ANFISs) and weather conditions. ANFIS combines the interpretability of fuzzy inference systems and the learning ability of neural networks.

Gray relational analysis (GRA) is used to analyse the relationship between weather conditions and electricity consumption. In this study, a multi-ANFISs approach is introduced to estimate the electricity consumption by weather conditions and human activities.

An alarm system was also developed using the estimation errors. The results show that the proposed multi-ANFISs achieves a greater performance with less number of parameters, and the GRA can evaluate the magnitude of relation between the factors and a specific output.

[23] Operational supply and demand optimization of a multi-vector district energy system using artificial neural networks and a genetic algorithm, 2019.

This paper demonstrated two district energy management optimization strategies; one that optimizes district heat generation from a multi-vector energy centre and a second that directly controls building demand via the heating set point temperature in addition to the heat generation. Several Artificial Neural Networks were used to predict variables such as building demand, solar photovoltaic generation, and indoor temperature.

These predictions were utilized within a Genetic Algorithm to determine the optimal operating schedules of the heat generation equipment, thermal storage, and the heating set point temperature.

Optimizing the generation of heat for the district led to a 44.88% increase in profit compared to a rule-based, priority order baseline strategy. An additional 8.04% increase in profit was achieved when the optimization could also directly control a proportion of building demand. These results demonstrated the potential gain when energy can be managed in a more holistic manner considering multiple energy vectors as well as both supply and demand.

[24] Deployment of data-mining short and medium-term horizon cooling load forecasting models for building energy optimization and management, 2019.

In this study, data-mining techniques comprising three forecasting algorithms for accurate and precise cooling load requirement prediction in the building environment, with the primary aim and the objective of improving the load management were applied.

Forecasting intervals were divided into two basic parts: i) 7-day ahead prediction; and ii) 1-month ahead prediction. To assess the prediction performance, four performance evaluation indices are applied, which are: i) coefficient of correlation (R); ii) mean absolute error (MAE); iii) mean absolute percentage error (MAPE); and iv) coefficient of variation (CV). The model's performance was compared with the selection of different hidden neurons at different load conditions. The MAPE for 7-day ahead prediction interval by MLR, GPR and LMB-NN model is 13.053%, 0.405% and 2.592% respectively.

[25] Towards Efficient Electricity forecasting in Residential and Commercial Buildings: A novel Hybrid CNN with LSTM-AE based framework, 2020.

In this paper, a hybrid model of CNN LSTM-AEs' synergy for electricity prediction in residential and commercial buildings is proposed. CNN layers are used to extract spatial features and their output is fed into LSTM-AE, followed by a dense (fully connected) layer for final prediction. Finally, the time resolution is changed to observe if further improvement can be made using the CNN with a LSTM-AE model. For the first time, a hybrid model of CNN and LSTM-AE is developed and tested to predict residential and commercial power consumption. Two datasets used: the household electric power consumption dataset available on the UCI machine learning repository and their own commercial data.

III. BACKGROUND

After reviewing various research papers, the common or the most used Algorithms for Household Electricity Consumption Prediction are:

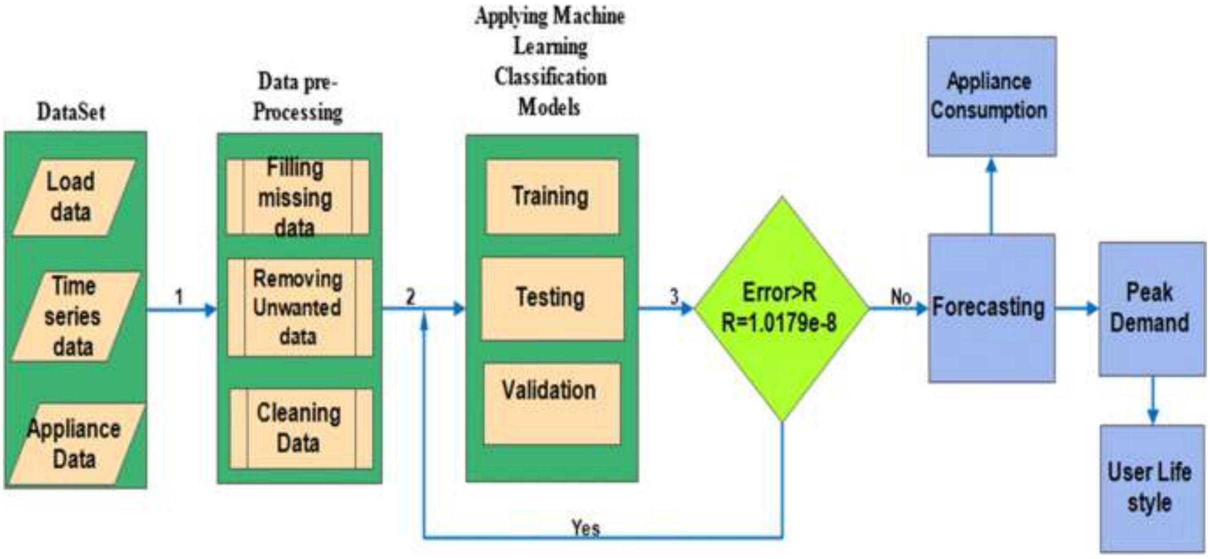
- Artificial Neural Networks – It is the most common algorithm used in this field. Various researchers have implemented it with various combinations. Like to over come some issues they have taken the hybrid of some other algorithm like Genetic algorithm, Radial Basis Function etc to improve the performance.
- Linear regression and Multiple regression systems also exists.
- Support Vector Machine and its various version like Support Vector Regression are implemented in many papers.
- K – means clustering and K – nearest neighbour algorithms.
- Various approach using Artificial Intelligence and Machine Learning Algorithms.

Gaps identified in various implementations of algorithms are:

- Generally, the reviewed papers are using raw data as datasets that is available from various electrical supply companies or smart meter that are installed in the buildings. Due to this the data is very noisy and inconsistent which result in decreasing the accuracy rate of the applied algorithms.
- Only few papers are paying attention to the effects that parameters of weather condition may have on electricity consumption because it becomes very much complicated to predict the output. Solving this type of problem requires much complex architectures, so this is one of the reason target output or accuracy is not attained.
- More tuning is required in the implemented algorithms for better performance.
- Kernel function is needed in most of the research papers for non – linear problems. It is very difficult to choose between various kernel functions as it consumes more time in deciding.

- More time – series data are used in implementation which his highly prone to less accuracy.
- Often leads to overfitting and requires more computational time.

IV. Architecture Diagram



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