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Smart Meter Firmware for Monitor and Control the Electrical Appliances Consumption

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ABSTRACT

Smart cities can improve our daily life by offering a wide range of intelligent services, like currently, power distribution firms are in charge of obtaining readings to determine the final consumer's energy usage. Field personnel contractors undertake this job, which exposes them to dangers to their physical integrity from the environment or social circumstances. The information on a residential building's monthly electric energy bill does not distinguish between the consumption patterns of household loads and appliances. Consumers might efficiently reduce a device's electrical energy usage if they were able to recognize the ones that consume more based on historical consumption data or baseline consumption. In light of the energy provider and user, the electricity information for each piece of equipment can aid in managing the supply and demand of the electrical system. The goal of this project is to provide a web application for monitoring and controlling smart energy metre readings and appliance usage. Its architecture is based on a centralized concept, and user contact takes place via a web interface. Typically made inside the user interface provided by a Cloud platform, a customized data visualization dashboard. The ambition of this project is to automate data gathering on electricity usage and to do analysis that can visualize and detail specific indicators to reduce the price of electricity consumption. It offers permission for linked smart metres, data gathering and archiving, device and software management, warnings, and other features. Analytics module that enables trend tracking, warnings based on rules, comparison report generating, etc.

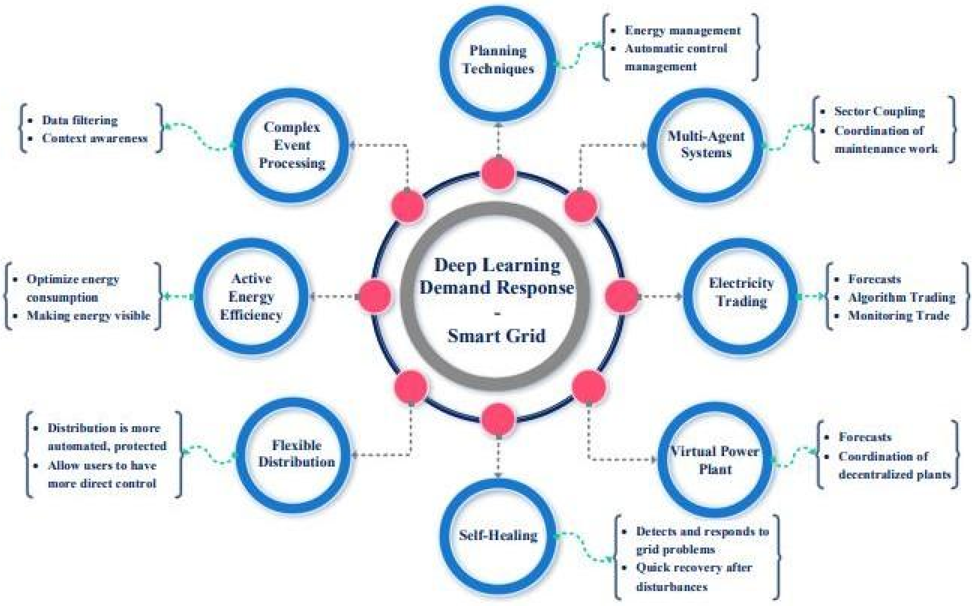
Keywords: Long-term load forecasting, clustering, smart meter, household consumption.

1. INTRODUCTION

A vital resource for human life is electricity. It is used in homes for heating, cooking, ironing, and other crucial daily activities. It is used by businesses to run production and plant machinery. Additionally, it is used in offices for routine tasks like running air conditioning and powering computers. It is produced using a variety of energy sources, such as thermal, coal, nuclear, and hydro. An adequate supply of electricity contributes to a nation's economic stability and growth. This leads to an increase in the Gross Domestic Product and a variety of economic activities. Due to its effects on the economic and financial spheres, energy consumption has recently become one of the biggest issues. Numerous factors in Saudi Arabia contribute to higher energy use in non-residential buildings. There are numerous issues in the CoC that lead to higher consumption. One of the main issues is extreme weather, which leads to summer temperature increases and increased energy use from frequent air conditioning use. During the winter, depending on the type, size, duration of use, and wattage consumed per hour, the heat results in increased energy consumption through repeated use of the heater. Energy consumption will inevitably rise as the number of devices increases because they generally place a heavy burden on the grid. Devices and servers abound in the CoC. Consumption of energy will rise as the population grows. Compared to the weekend, the workday involves more energy consumption because there are more lectures, which is true of the entire day. The devices have numerous uses outside of the time of the practical examinations. Another factor for the increase in consumption is the number of cafeterias present at the college, each of which has a variety of appliances like microwaves, coffee makers, and refrigerators. Multiple devices must be present around us, and their quality is crucial for the best performance. However, low-quality devices will not function properly. In the world of electric power, the quality of devices is crucial because poor quality equipment, regardless of how outdated or weather-related, will increase energy consumption. The energy consumption of the devices is influenced by their quality; the lower the quality, the more energy is consumed.

2. SCOPE OF THE PROJECT

The grid's sustainability is maintained by load shedding during times of peak demand and effectively managing all consumption data patterns using DR models, which use consumer and their load consumption data. Therefore, creating a successful DR system depends on extracting the precise load consumption patterns from the data patterns that need to be adjusted for the current time. An efficient prediction technique must be used to design a DR system that can effectively reflect consumption patterns by forecasting future consumer usage patterns and recommending appropriate solutions.



In order to achieve forecasts with higher accuracy and lower error percentages than the aforementioned models, a hybrid model (HSBUFC) based on the stacking of bi-directional and uni-directional LSTMs followed by fully connected dense layers is developed in this work.

3. Existing System

3.1 Traditional machine learning method

The support vector machine (SVM), k nearest neighbor (KNN), random forest (RF), extreme random forest (ERF), support vector regression (SVR), artificial neural network (ANN), autoregressive integrated moving average (AIMA), and multiple linear regression (MLR) are eight traditional machine learning methods that are used to build household appliance energy consumption prediction models.

- **SVM-Support Vector Machine**

SVM is a type of generalized linear classifier used for supervised learning-based binary data classification.

- **KNN-K Nearest Neighbour**

By finding a sample's closest neighbors and assigning the average of their properties to the sample, KNN can be used to determine the properties of the sample. Giving the influence of neighbors with varying distances on the sample different weights, with the weight being inversely proportional to the distance, is another improved method.

- **RF- Random Forest**

RF is a crucial bagging-based integrated learning technique that can be applied to both regression and classification. A random forest regression model is employed in this study.

- **ERF – Enhanced Random Forest**

The RF algorithm and the ERF algorithm are very similar. It can solve the variance problem more effectively than random forests because it is made up of many decision trees and introduces more randomization. Additionally, the computational complexity is slightly diminished.

- **Support Vector Regression**

In order to solve the problem of time series forecasting, Müller et al. developed a modified version of the SVM known as SVR. Over the years, it has drawn more and more attention, particularly in the forecasting of electricity demand. Finding a hyper plane function that can identify patterns in the provided time series data is the main goal of SVR. This model has the benefit of minimizing the upper bound of the generalized error rather than the learning error. Because previous research has shown that an SVR-based model can produce satisfactory results across various electricity demand forecasting, SVR was chosen as a benchmark model. In this study, the experimentally determined values for the SVR hyper parameters, penalty factor and gamma, were 100 and 0.001, respectively.

- **Artificial Neural Networks**

A mathematical model known as an ANN is created to mimic the functions and operations of the human brain. The primary goal in this context is typically to find a relationship that can automatically map input to output during the network's training phase, which is used to iteratively train the network to reduce forecasting error. The benefit of using ANN is that it can be used with multivariate models and can describe non-linear relationships between output and input from given historical data. The most popular network structure used in this study was a back-propagation ANN, which combines a back-propagation algorithm with a feed forward multi-layer perceptron; the momentum and learning-rate parameters were experimentally determined to be 0.2 and 0.3, respectively.

- **Autoregressive Integrated Moving Average (ARIMA)**

The most popular statistical technique for time series analyses, ARIMA, can forecast and model complex patterns in uni-variate time series data. The three significant components of the ARIMA model function are p, d, and q, which stand for the moving average, integration, and autoregressive factors, respectively. The general ARIMA (p, d, q) model is expressed as follows:

where p denotes the number of autoregressive terms and Fp denotes the order p autoregressive parameter. Yt stands for the actual value in the given time series data, _q is the order p's autoregressive parameter, q is the number of forecasting errors, which are lagged in the forecasting equation, et is a random perturbation or white noise, and lambda stands for a constant value. BO stands for the backshift operator.

- **Multiple Linear Regression (MLR)**

As a benchmark model, MLR, one of the most popular statistical regression models, was also used. Modelling the relationship between a dependent variable and a number of independent variables is the goal of the MLR. In MLR, it is assumed that the relationship between the vector of regressors and the dependent variable is linear. For forecasting purposes, the equation of linear regression maps the forecasting model to the observations in the provided time series, represented by the x and y values. The MLR model can be expressed as follows:

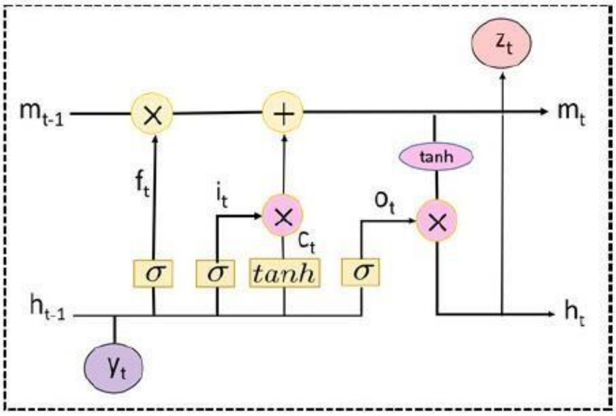
$$y = \varepsilon + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \ ,$$

With additional observations x, the resulting model is applied to forecast the value of y.

4. PROPOSED SYSTEM

In order to produce forecasts with higher accuracy and lower error percentages than the aforementioned models, a hybrid model (HSBUFC) based on the stacking of bi-directional and uni-directional LSTMs followed by fully connected dense layers was developed.

There is discussion of the architectures of the unidirectional and bidirectional LSTMs. Bi-directional LSTMs use the forward and backward passes to recognise underlying patterns in energy consumption data using past and future inputs.



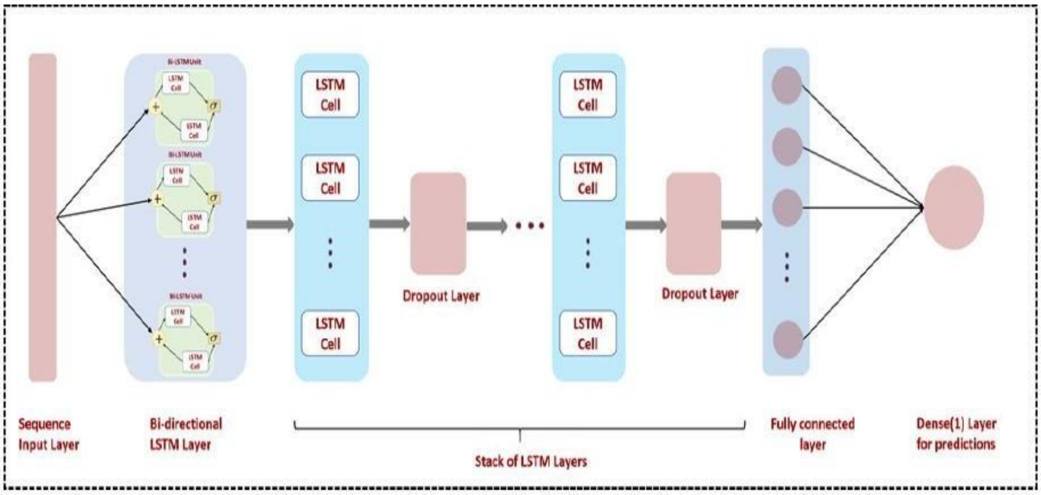
A. UNI-DIRECTIONAL LSTMS (OR LSTMS)

Recurrent neural networks of the LSTM variety are typically designed to process, examine, and forecast sequence data. Based on the input from the current time step and the output from the previous time step, the RNN model makes predictions. LSTMs can perform better with long-term dependency tasks like energy forecasting because they have memory cells to accumulate steps over prediction sequences in addition to the ability to use information from the recurrent connections to the outputs of previous time steps. Additionally, LSTMs can be used to control the information that is passed through and circumvent the issue of vanishing gradients thanks to the inclusion of gates and more complex recurrent units.

B. BI-DIRECTIONAL LSTMS

Over uni-directional LSTM models, bi-directional LSTM is a development. The bi-directional LSTMs process the inputs from past inputs to future inputs in the forward pass and from future inputs to past inputs in the backward pass. The information from both past inputs and future inputs is preserved through the combination of hidden states from the forwarding pass and backward pass through two different hidden layers. The single identical output layer receives the output from these hidden layers. As a result, the context and data patterns from both past and future inputs can be preserved by the bidirectional LSTMs with less delay. It has been demonstrated that bi-directional LSTMs outperform uni-directional LSTMs in a variety of applications, including speech recognition.

C. PROPOSED MODEL ARCHITECTURE



The structure of the hybrid stacked bi-directional uni-directional LSTM with fully connected dense layers that has been proposed (HSBUFC) model. Three different layer types make up the HSBUFC model: a bidirectional LSTM layer, stacked unidirectional LSTM layers, and fully connected layers/dense layers. Bi-directional LSTMs use both forward and backward dependencies, as was covered in the earlier section. During the feature learning process, the initial layer of the bi-directional LSTM extracts the temporal long-term dependencies of the energy consumption values in two directions. After learning from the extracted detailed and complex features, LSTM layers that are effective in forward dependencies are then used in the top layers, which receive the outputs from the lower layer.

Advantages

• By precisely predicting monthly residential electricity usage, which makes up the majority of total electricity usage, the proposed model is anticipated to support effective power-system planning.

• This accurate deep learning-based forecasting model could also be applied to other problems associated with analysing time series and optimising energy processes, energy conservation, and sustainable use of energy resources.

5. Model Description

5.1 Forecaster Web App

The overall systems for measuring, collecting, and analyzing electricity usage are included in the Forecaster Web App. By enabling two-way communications between the system of the utility provider and the metre, the FWA system goes beyond Advanced Metre Reading (AMR) Technology. Demand-response actions, remote service blocking, or disconnects are made possible by this.

Device configurations in the monitored households

House	Devices
0	Coffee machine, washing machine, radio, water kettle, fridge w/ freezer, dishwasher, kitchen lamp, TV, vacuum cleaner
1	Fridge, dishwasher, microwave, water kettle, washing machine, radio w/ amplifier, dryier, kitchenware (mixer and fruit juicer), bedside light
2	TV, NAS, washing machine, drier, dishwasher, notebook, kitchenware, coffee machine, bread machine
3	Entrance outlet, Dishwasher, water kettle, fridge w/o freezer, washing machine, hairdrier, computer, coffee machine, TV
4	Total outlets, total lights, kitchen TV, living room TV, fridge w/ freezer, electric oven, computer w/ scanner and printer, washing machine, hood
5	Plasma TV, lamp, toaster, stove, iron, computer w/ scanner and printer, LCD TV, washing machine, fridge w/ freezer
6	Total ground and first floor (including lights and outlets, with whitegoods, air conditioner and TV), total garden and shelter, total third floor.
7	TV w/ decoder, electric oven, dishwasher, hood, fridge w/ freezer, kitchen TV, ADSL modem, freezer, laptop w/ scanner and printer

5.2 Smart Metered Dataset Annotation

Training Dataset

The dataset includes information on a single residential customer's electrical consumption over the course of five months, from 11 January 2016 to 27 May 2016. The study used data with an hourly resolution. The first three years were used as training data for all three architectures, and the final year served as testing data. The anticipated electricity use over the next 60 hours was calculated for each architecture.

Input Variable	Description	Values
Hour of Day	Hour of the day for the first prediction	[1,24]
Month	Month of the first prediction	[1,12]
Day of the week	Day of the week for the first prediction	[1,7]
Day of the Month	Day of the Month for the first prediction	[1,31]
Weekend Flag	Flag which is set if the day of the first prediction is a weekend	[0,1]

Testing Data

A real-world dataset of appliance energy consumption is used to construct and assess the proposed hybrid model. Data from each home appliance's smart metre.

5.2.1 Pre-processing

The Mean or Median of the entire column must be used in this module to replace any missing data. The NULL values and redundant values from the dataset are removed, and feature variables of the type "Soil Nutrients" are used instead.

5.2.2 K-means Clustering

K-means clustering's popularity can be attributed to its ease of use and generally positive performance. K-means is a simple option for quick clustering because it is implemented in many software programs, both proprietary and open source. The K-means algorithm's greedy design approach can result in suboptimal solutions due to unfavorable initial starting conditions and converge in local optima; this issue can be resolved by repeatedly running the algorithm.

5.2.3. Fast Fourier Transform Feature Extraction

Since the information from smart metres can be viewed as signals, it may be beneficial to use methods that make use of time series data, such as periodicity or autocorrelation. There are several other methods for analyzing time series besides the Fast Fourier transform (FFT), which is a frequency domain analysis technique for signals.

5.2.4 HSBUFC Classification

The HSBUFC model has three different kinds of layers: Bidirectional LSTM layer is the first layer, followed by stacked

uni-directional LSTM layer and fully connected/dense layer. Bi-directional LSTMs use both forward and backward dependencies, as was covered in the earlier section. During the feature learning process, the initial layer of the bi-directional LSTM extracts the temporal long-term dependencies of the energy consumption values in two directions. After learning from the extracted detailed and complex features, LSTM layers that are effective in forward dependencies are then used in the top layers, which receive the outputs from the lower layer.

5.2.5 Prediction

The Pythagorean formula determines the "ordinary" distance between two points that one would measure with a ruler in this module, known as the Euclidean distance or Euclidean metric. Euclidean space (or even any inner product space) becomes a metric space by using this formula as distance. The Euclidean norm is the name of the associated norm. The metric is referred to as Pythagorean metric in older literature.

The length of the line segment that connects points p and q is the distance in Euclid between them: p.q The distance between two points in Euclidean n space with coordinates p = (p, p,..., p) and q = (q, q,..., q) is determined by the following heterogeneous value difference metric.

5.3 Performance Analysis

The result is counted as a True Positive (TP) in this module; if the same result is mistakenly classified as a negative it is False Negative (FN). The outcome is counted as a True Negative (TN) if the valid diagnosis is CHD absent and it is correctly classified as negative; if the same outcome is incorrectly classified as positive, it is counted as a False Positive (FP).

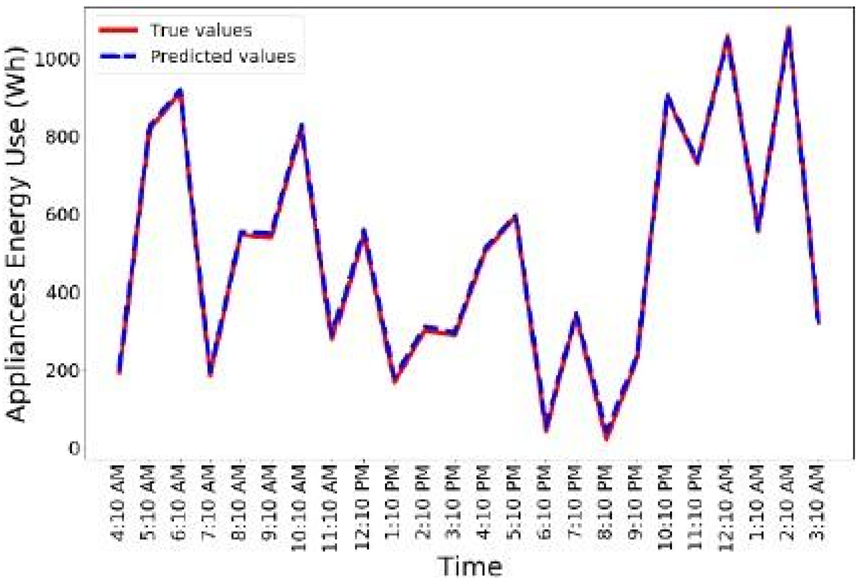
$$Accuracy\ (\%) = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\%$$

$$Sensitivity\ (\%) = \frac{\mathrm{TP}}{TP+\mathrm{FN}}\ x\ 100\%$$

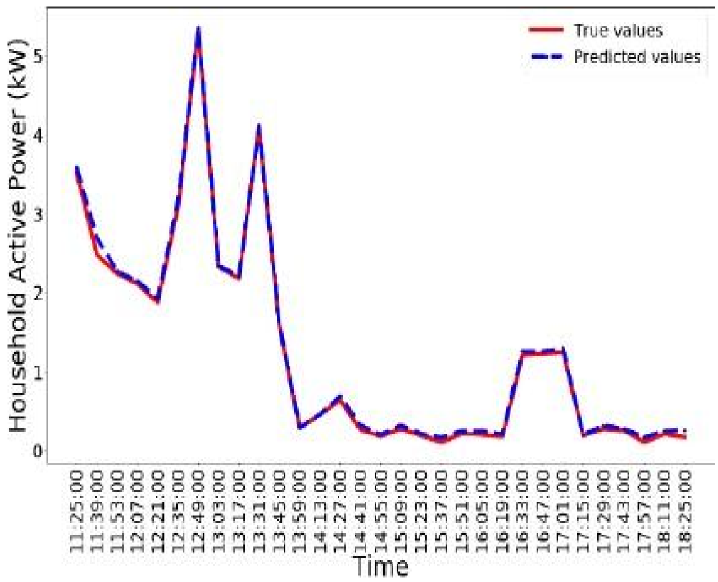
$$\mathrm{Specificity}\ (\%) = \frac{\mathrm{TN}}{TN+\mathrm{FP}}\ x\ 100\%$$

Result Analysis

Using the proposed HSBUFC model, several experiments were conducted in this section with the aim of obtaining high accuracy energy forecasting in smart buildings and comparing the performance of the proposed model to that of other baseline models and widely used hybrid deep learning models. Among the baseline models are neural networks, linear regression, ELM, stacked LSTM models, and bi-directional LSTM models.



Graph 1: study 1actual v/s predicted values for appliances energy use.



Graph 2: Case study 2 actual v/s predicted values for global active power.

In the testing dataset, the actual and predicted values for the energy use of appliances on a random day are plotted in Graph 1. The dependent axis in the figure shows how much energy is used by the appliance, while the independent axis in the figure shows what time of day it is. The graph shows that the predicted values and actual energy consumption values agree very well. The proposed hybrid deep learning prediction model's high accuracy and low error are demonstrated by this. On a subset of records from Case Study 2's records, Graph 2 shows the real and predicted values using the proposed forecasting model for global active power. The suggested model performs with nearly perfect accuracy at both the spikes and troughs in the example.

CONCLUSION

Enhancing the predictability of energy consumption at the building level will have a significant impact on the production and scheduling of energy resources as well as the effective use of renewable energy sources. In this project, a novel hybrid deep learning model was put forth that enhances the benefits of uni-directional LSTMs, bidirectional LSTMs, and stacking of RNNs on the accuracy of energy consumption forecasting. Bidirectional LSTMs are used to accurately forecast energy consumption values and identify the underlying patterns in both directions of energy consumption. The accuracy was achieved despite the high uncertainty and stochasticity of each household's load demand. Two real energy consumption datasets from distinct residential smart buildings were used to show off the superior accuracy performance. In the suggested hybrid deep learning model, over fitting was avoided by using dropout regularisation and early stopping. The proposed model has been compared with a number of commonly used hybrid models, such as CNN-LSTM, ConvLSTM, the LSTM encoder-decoder model, other invariants of stacked LSTM models, and our proposed ensemble AREM model from prior research. Bidirectional training is advantageous, as evidenced by the superior performance of our suggested model in case studies and multi-step forecasting. Short-term energy forecasting is not the only application of the suggested model.

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