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Energy Demand Rise forecasting by integrating AR, ARMA, ARIMA, LSTM

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Abstract : Although in today's world, energy consumption has a minimal direct impact on technological advancement, technical advances have resulted in a rise in energy demand. In the long term, energy demand is both positively and bilaterally linked to technical growth. With numerous developments in technology and innovation, small villages have begun to grow into communities, so this growth has given rise to electricity consumption, collectively dubbed as sustainable energy. Renewable resources have given an upliftment to smart grid projects for the supply and production of electrical energy, transforming cities into metropolitan cities. Consequently, various problems are faced during power generation and power delivery due to numerous changes in technology and innovation, such as forecasting an increase in energy demand in rural or urban areas based on hourly-time series. Lack of computational distribution and utilization poses a threat to energy consumption. To address this problem, considering disparate machine learning models such as AR, ARMA, ARIMA for regression, and LSTM (a deep neural network for RNN) to remove errors and analyzing the discrepancy between the real and expected values. Using the corresponding models, we are able to minimize the error at each stage and achieve an accuracy of 93.92 percent in the proposed system. Thereupon avoiding a major hurdle and obtaining the nearest value of the predicted time series with the actual computed value by integrating respective models.

Keywords: Energy Demand Rise, Energy Consumption, Recurrent Neural Networks, Auto Regression, Auto Regressive Moving Average, Auto Regressive Integrated Moving Average, Long Short-Term Memory.

1. Introduction

Observing rural and urban areas' rise in energy consumption depending on hourly-time series with examining their errors to remove the difference between actual and the predicted value using machine learning models. Inspecting the referred dataset for energy consumption, it mainly focuses on predicting electrical consumption better than the already present forecast in the data given. The metrics used for comparison are Mean Absolute Percentage Error or MAPE. TSO Red Electric Espaa contains four years of electrical consumption, generation, pricing, and weather data. In the present scenario due to the advancement of rural areas and increasing population, there is still a scarcity of electricity as a part of consumption and rating provided to each densely populated area or areas which are on the path of development. By integrating just a few models, the proposed system can reduce errors in prediction values and achieve higher accuracy with precision.

The AR (Auto-Regressive) model has played an important role in giving an accuracy up to 84% in forecasting crime rates in a city evaluating a year's forecast and 80% as the time-lag increases for more than 1 year[1]. The design of the model is said to be dependent on past patterns as identified in the dataset, there is more scope for increasing its accuracy.

The time series analysis of household electricity consumption with ARIMA (Auto-Regressive Integrated Moving Average) and ARMA (Auto Regressive Moving Average) models is more suitable for forecasting periods in monthly and quarterly duration. It appeared that the ARMA model was suitable for daily and weekly analysis. To be more specific, for hourly analysis, the increase in energy demand, using LSTM (Long Short Term Memory) that is an RNN (Recurrent Neural Networks), based on a deep learning algorithm where it refers to the sequence of data-points in a time-lag studied, it was found very advantageous in duration as Moving average in between the data-point sequences is considered[3].

Also by predicting time series data for a satellite orbiting with higher precision, it gave an exact elliptical path for satellite time duration passing over a particular area [4]. Subsequently in LSTM it was found to give good results regarding power grid systems in the field of smart grid systems where it has been known that the power usage data were collected every five minutes of a day for all regions with respect to working organizations/industrial areas. It has been favorable for balancing heavy-level power distribution boards [2].

In proposed work, to integrate the respective four models and at each stage, to reduce the error considering MAPE value and in the last, LSTM model will consider hyper-parameter tuning of the dataset with a respective number of epochs and loss function for removing dead nodes and obtaining refined gradient with more best-fit features to obtain values closest to the forecasted value. The paper is divided in five parts. Literature survey is given in part 2. Proposed system and result analysis id explained in part 3 and 4 respectively. Conclusion of proposed system is given in section 5.

EEG recordings are widely used in the diagnosis and study of a variety of neurological illnesses, including depression. In this work, the LSTM (Long-short term memory) model is utilized to forecast depression trends for the following time instants based on the extracted characteristics, which has been proven to be highly useful [11]

We explore a variety of changes at tiny intervals in a dynamic market. Nonlinear models aid in the improvement of prediction accuracy. Because of the range of elements involved, ARIMA models are highly good at dealing with nonlinearity [9].

Also the suggested method provides a unique technique to improving the ARIMA model for time series forecasting by using a mean of estimate error. The experimental findings show that the suggested technique can increase performance in the time series data forecasting process [12].

Nowadays, time-varying complexity and non-linearity are key concerns. To address this issue, the ARIMA model is the ideal alternative because it is designed for linear time series forecasting. In this case, the usage of neural networks also aids in optimizing the convergence rate and forecast accuracy [10].

The authors propose using a linear auto-regressive (AR) model to examine the patho-physiologic processes that influence heart rate (HR) dynamics. This study used parametric models that were novel in this field to see if there was a better appropriate HR dynamics modeling framework. It has also adopted beneficial legislation for the installed application [14].

2. Literature Review

The in depth survey has been carried out to understand common methods used energy demand prediction. Some of selected literature papers show the following results.

As discussed by the author [1] Autoregressive Model is used to predict the future crime forecasting in an urban region (California). Based the training and test result it was conclude that one year ahead forecasting accuracy is 84% and two year ahead forecasting accuracy is 80%. It has also been observed by author [7] n^{th} order time varying parameter is used to fit AR model in non-stationary time series with finite length. This method helps in achieving result without no variance, mean and auto covariance errors. AR model is used with Phasor Measurement Units (PMU) data to predict the state of power supply. It is observed [8] that bus voltage is quadratic when the load is in-creased linearly at constant power factor and prediction is based on 3 prior estimations. ARMA and ARIMA models are used to forecast household electricity consumption. Also, which Model is best for which time period is analyzed based on the Root Mean Square Error (RMSE). Based on the model used we found out the power consumption series btw Dec 2006 to Nov 2010 and found for ARMA lowest RMSE for daily and weekly is 0.29 and 0.18 respectively. For ARIMA, lowest RMSE value for monthly and quarterly is 0.9 and 0.2 respectively [3]. Combination of LSTM-ARIMA algorithms is used to predict time series of a meteorological satellite telemetry parameter. LSTM-ARIMA yields high accuracy and strong reliability prediction results. By combining different weights of LSTM and ARIMA least value of RMSE is found that is 0.064 for 50-50 % weight [4]. ARIMA used for supermarket analysis [15] The author concludesthat ARIMA plays an important role in supermarket sales analysis. Power used in every 5 min window frame of a day is collected and LSTM Model is used to forecast future power series based on past data. LSTM Model is used to predict time series of weekday, holiday over summer and winter season [2]. It is shown how to efficiently generate a rational model of a wide-sense stationary time series. In pattern classification systems, the autoregressive parameters that characterize the ARMA model estimate can be used as decision variables. These factors can be used to determine if a member(s) of a specific signal class is present inside a noise corrupted measurement signal, for example[13]. Paper presents an Automatic Seasonal non–Stationary homogenous forecasting model to predict best time series of raw data. We find best model based on minimum Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) [6]. Analysis of electricity demand in Spain just after the Economic Crisis (2013-17). The report describes the energy demand surge situation that occurred in Spain between 2013 and 2017, causing a big difficulty for the distribution board and paving the path for increased development in sustainable energy consumption solutions [5].

3. Proposed System

The increase in energy consumption has paved the way for the growth and development of sustainable energy usage, and as we have progressed further into innovation and technology, discovered numerous solutions, such as the time series algorithm, which has been created in such a manner that now we can construct a pattern in future time based on previous inputs and anticipate the outcome of the future known for supervised learning. The time series algorithms have been highly effective in forecasting the future outcome in order to discover a solution considering real-time problem and thus solving it before its cause or yet to occur with collectively all error values to assess for the reason.

The proposed system is as shown in Figure 1 below.

In this implementation, exploring time series algorithms such as AR, ARIMA, ARMA, and LSTM for computing the predicted value that is closest to the forecasted value by lowering its error percentage with the corresponding model at each stage using the MAPE value, which is Mean Average Percentage Error as the output of each model. Thus, when it compares the MAPE value to the initial anticipated MAPE value and strive to minimize the MAPE value, the data-point sequences in a time lag consideration begin joining as a statistically observable feature in the representation. This is accomplished by temporarily creating a dataset with refined values that is 80 percent training dataset and 20 percent testing dataset that is in other words, it is preprocessing the dataset collectively called as chunks of dataset to be fed to the respective models.

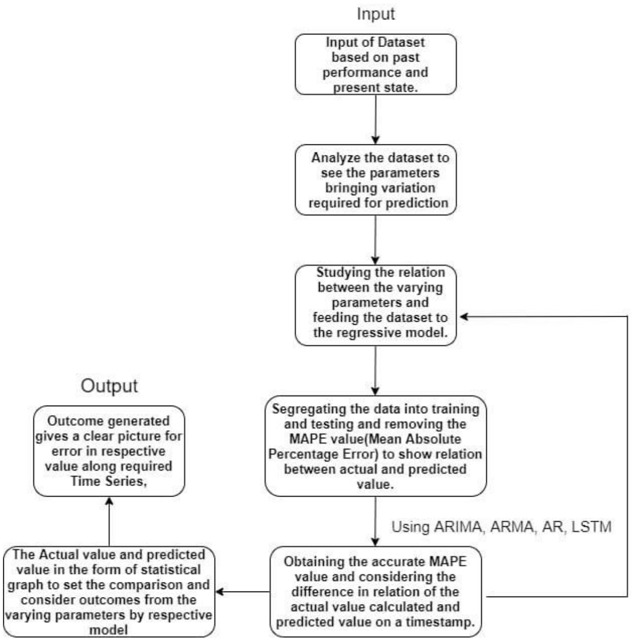

Figure 1 Flow chart of Proposed System

The relevant models play a significant part in the proposed system, taking into account their MAPE, mean absolute error, and root mean squared error values.

1.) ARIMA, ARMA, AR: (Auto regressive integrated Moving Average), (Auto-regressive Moving Average), (Auto Regressive).

The ARIMA, ARMA, and AR models are time series models used in statistical modeling to predict the recurrence of an event based on previous events. They build a pattern in data-points mapped based on previous inputs and forecast the type of the data-point sequence in the future outcome using the dataset feed. ARIMA forecasts using several points of time-lagged observations of time series. Each lagged data-point value is composed of a weight added to a previous input point, and so these weights fluctuate depending on how near they are to being accomplished. Whereas AR and ARMA differ in the weights of data-point selection in the previous values and how they act when each time-lagged to be regarded with respective moving average and thus statistically exhibiting their behavior. Thus, according on their mean absolute error, root mean square error, and MAPE values, ARIMA, ARMA, AR will display varied features.

2.) LSTM (LONG SHORT TERM MEMORY): LSTM is an artificial recurrent Neural Network based on deep learning architecture; in this case, we are using LSTM model to refine more error as compared to AR, ARIMA, ARMA and reaching closest MAPE value to the anticipated MAPE value computed, thus with minimal error %. In this step, refine the dataset one more by constructing a temporary dataset. Following that, divide the dataset into training and testing, with 80 percent of the data to be trained. Also discuss hyper-parameter tuning of the dataset with the appropriate number of epochs and collective loss functions. This refines the dataset by removing dead nodes and picking the optimum gradient feature to attain high precision accuracy.

Below figure shows the respective proposed System.

Step 1: Refinement of the dataset

Step 2: Calculating Reference MAPE Value of the forecasted value

Step 3: Segregation of data into training and testing

Step 4: Feeding of data to the respective models

Step 5: Comparison of MAPE values of respective model and reducing error with hyper parameter tuning

Step 6: Obtaining Highest Precision values with minimized error and closest accuracy to the reference MAPE of forecasted value.

3.1 Data Set

This dataset comprises electricity consumption, generation, price, and weather data for Spain for a four-year period. Data on consumption and generation was obtained from ENTSOE, a public data site for Transmission Service Operators (TSOs). The Spanish TSO Red Electric Espaa provided the settlement pricing. The dataset is distinctive as it comprises hourly data on electricity usage as well as TSO projections for use and prices. Preprocessing of the dataset is done in-order to achieve chunks of data-points based on the time-lagged look-back error by temporary creation of dataset and thus obtaining various features and shapes in the dataset favorable for feeding it to the respective models as shown in figure 2.

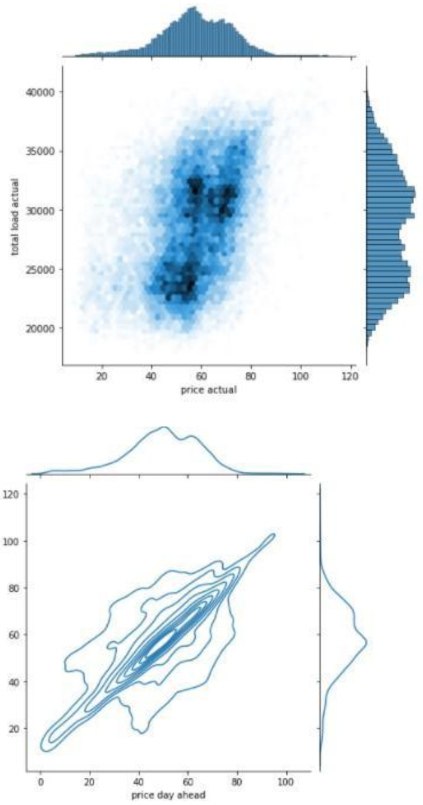

Figure 2 The statistical analysis done on the dataset.

4. Experimental Results

4.1 Preprocessing

Here the dataset has been pre-processed and segregated, considering 80% for training and 20% of validation of data-set. The dataset consists of varying parameters such as (Total Load Actual) that is the real value of consumption and (Total forecasted value) that is the prediction made. Considering a temporary creation of dataset it is refined into following features, shapes, training samples to feed the respective models (Screen shot-1) to be added after this.

4.2 Evaluation Metrics

Here in the implementation, considering MAPE value (Mean Average Percentage Error) for each model to be calculated in-order to get error percentage and remove accuracy depending on the Error. We are also considering Mean Absolute Error and Root Mean Squared Error for each model to keep metric of errors between paired observations. Considering the Implementation the MAPE value is calculated as:

MAPE= ((Total actual value-Total forecasted value)/Total Actual Value)*100

$$mean\ absolute\ error = \sum_{i=1}^{n} \frac{|yi - xi|}{n}$$

Where , yi = prediction

xi = True value

n = Total no of data points

$$root\ mean\ square\ error = \sqrt{\frac{\sum_{i=1}^{N}(observed - predicted)^2}{n}}$$

4.3 Result Analysis

Calculated value for the respective MAPE value of original forecasted value is 1.096023073723821

As seen in the below analysis figure 3, lookback value is 25 for each set of unit time for time-step

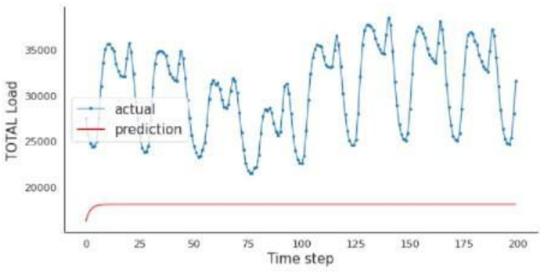

Figure 3ARIMA Model

Test Mean Absolute Error: 10816.58865487927

Test Root Mean Squared Error: 11722.24334395776

Testing MAPE: 35.88114074618695

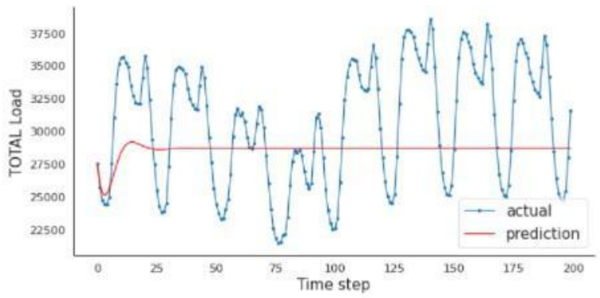

Figure 4 ARMA Model

Test Mean Absolute Error: 3862.9291367806095

Test Root Mean Squared Error: 4521.711458398291

Testing MAPE: 13.815133603588034

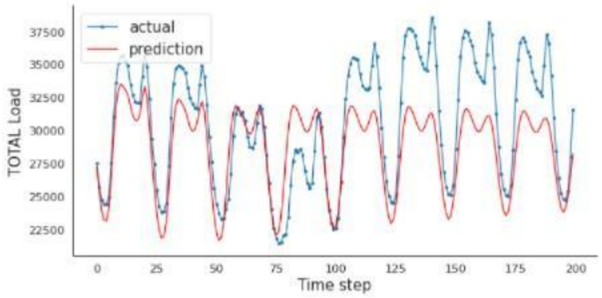

Figure 5 AR Model

Test Mean Absolute Error: 3729.264425078766

Test Root Mean Squared Error: 4391.073081234284

Testing MAPE: 13.333375085466773

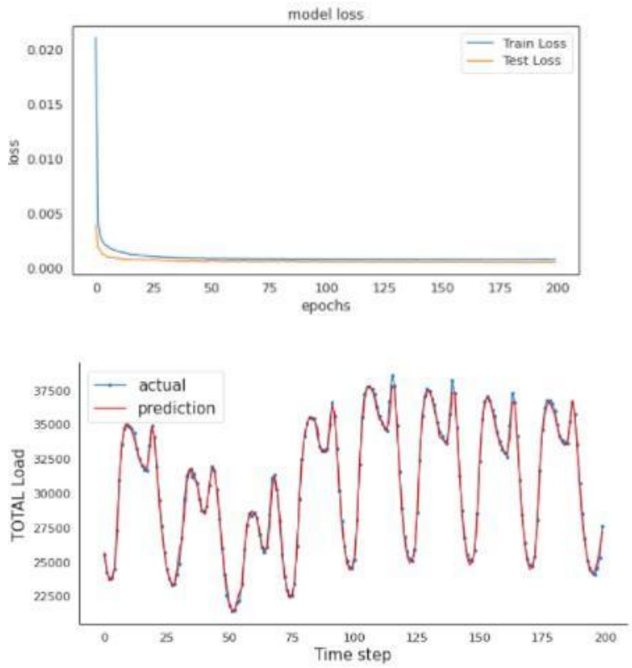

Figure 6LSTM Model

Test Mean Absolute Error: 331.18379167044407

Test Root Mean Squared Error: 533.2132495535183

MAPE: Test MAPE: 1.166855731137757

Considering Epoch value set to 200, we remove dead nodes and obtain best gradient feature and thus with reduced Error, achieved the forecasted MAPE value that is 1.096023073723821 and considering the LSTM model the test MAPE value is closest to the original reference MAPE value. Above analysis done as at each stage the MAPE value is reducing and thus the data-point sequence of the predicted value get aligned with the actual in the last step with respective MAE and RMSE.

The results are compared with state of art systems as shown in Table 2 below.

Implementations	Accuracy
Auto-Regressive Model for Predicting Crime Rate [1]	84%
Prediction of Satellite Time Series Using LSTM-ARIMA [4]	High Precision -(As mentioned by author)
Time Series Analysis of Household Consumption with ARIMA and ARMA [3]	Best suitable model for estimation for short duration time series.-(As mentioned by author)
Proposed System Using ARIMA, ARMA, AR, LSTM.	93.92%

Table 2 Result comparison

5. Conclusion

We were able to obtain high precise accuracy with the respective models utilized by implementing this project, which may be advantageous in the future for many applications such as sustainable energy, efficient power grid distribution system, and prediction-based real-time solution for time-series analysis. The proposed approach attained the highest accuracy when the MAPE was taken into account. In contrast to the predicted MAPE value. The time series method is not only confined to prediction-based issues, but it also provides variation in every entity or event as the sole constant changing that can be monitored and gather information about an event that is going to occur. With this, I'd want to point out that different real-time problems may be handled using time as a real unit.

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