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Energy Demand Prediction Based on Deep Learning Techniques

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Abstract
The development of renewable resources and the deregulation of the market have made forecasting energy demand more critical in recent years. Advanced intelligent models are created to ensure accurate power projections for several time horizons to address new difficulties. Intelligent forecasting algorithms are a fundamental component of smart grids and a powerful tool for reducing uncertainty in order to make more cost- and energy-efficient decisions about generation scheduling, system reliability and power optimization, and profitable smart grid operations. However, since many crucial tasks of power operators, such as load dispatch, rely on short-term forecasts, prediction accuracy in forecasting algorithms is highly desired. This essay suggests a model for estimating Denmark's power use that can precisely forecast the month's demand. In order to identify factors that may have an impact on the pattern of a number of unique qualities in the city direct consumption of electricity. The current paper also demonstrates how to use an ensemble deep learning technique and Random forest to dramatically increase prediction accuracy. In addition to their ensemble, we showed how well the individual Random forest performed.

Keywords
Deep Learning, Energy Prediction, Random Forest.

I. INTRODUCTION

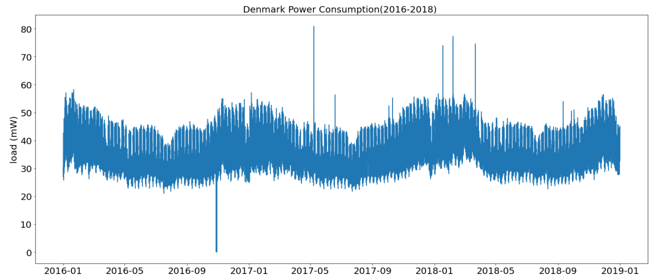
As economic expansion picks up, so does the need for electrical energy [1], [2], [3]. Energy plants produce hazardous exhausts and lose efficiency when there is a sudden need for more energy. Additionally, the estimation of electrical energy consumption or load forecast is becoming more significant with the development of renewable energy sources and smart grids. Load forecasting, which aims to predict future load demand, comprises predicting the future behavior of the electrical load. future will see the development of a single house, a grid, an area, and maybe a full country. The prediction horizon is the span of time across which this forecast is conducted in one or more phases.

Short-term load forecasting (STLF), with lead durations of half an hour to a day, is typically required for programming and energy transfer scheduling, unit allocation, and choices about load imbalance. Thus, some improvement in STLF accuracy can lead to lower power system costs and improved power management effectiveness. Forecasting with a longer horizon is also beneficial for maintenance and power management methods. Operating costs are drastically reduced when accuracy is increased by 1% [4]. In order to change the prediction inaccuracy even slightly is interesting. An underestimated or overestimated power might cause issues with supply and demand equilibrium.

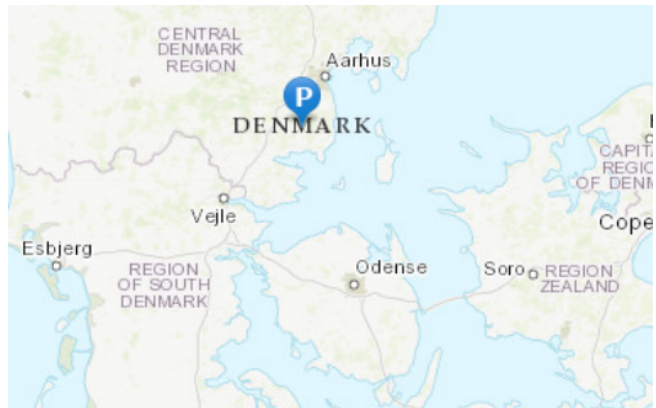
With the help of cutting-edge and clever computer technology, such as power prediction, the smart grid is designed to adjust supply in real-time to match demand. Strong ties exist between the spinning reserve and supply management. After then, estimating is part of load prediction. the spinning reserve, which is important when demand increases unexpectedly or generators fail or break down. Whenever the forecast is accurate, the spinning reserve can quickly make up for any errors. The load profile forecast over longer time horizons is used to determine the capacity to contribute to a whole network in order to avoid an emergency. Forecasting load electricity demand is crucial for modern smart energy management systems [[5]. In both the long-term planning for new transmission and generation facilities as well as the management of short-term load, it is crucial. Improved cost and energy efficiency decisions are also made possible by an accurate projection.

The number of apps for load forecasting is increasing daily. This is why the field of forecasting electricity consumption has received a lot of attention in the literature [6], [7]. Some of the literature predicts that weather variables like temperature, humidity, rainfall, or season may help to influence energy consumption [8]. While other studies made their estimates using socioeconomic and population factors [9]. Although generic characteristics can be used to estimate power use a different prediction model can lead to a better outcome. Based on the original data acquired from Data from Kaggel Western Europe Power Consumption forecasting model is created for a specific Denmark power consumption. Fig. 1 displays the site's location The National Aeronautics and Space Administration (NASA) released the Power data access viewer data and how electrical energy is consumed.

The structure of this essay's content is as follows. The background material for various load consumption prediction models is given in Section II. The approach is explained in Section III. The computational findings and discussion are covered in Section IV. The work is concluded and future work is discussed in section V.



(a)



(b)

Fig. 1. (a) electrical energy consumption distribution (b) Site location of Denmark

II. RELATED WORK

The challenge of predicting power usage has been addressed in earlier studies using a variety of prediction techniques, ranging from statistical to machine learning-based methods [10]. The majority of this research make the more predictable assumption that electricity usage follows a regular pattern[11]. In reality, however, customer behavior influences the how actual usage pattern evolves over time. Because there are so many variables at play, including the temperature, occupancy rates, and capabilities of the heating system, this behavior is too unpredictable to predict. In order to address this problem, a fresh research trend has emerged that uses Deep Learning (DL) approaches for prediction and demand forecasting. In [11], a brand-new pooling-based DL model was put forth with the goal of employing deep learning to uncover the uncertainty of the household load forecasting model. In comparison to the RNN, Support Vector Regression (SVR), and Autoregressive Integrated Moving Average (ARIMA) models, the proposed model produced better accurate results. Rahman at el. (2017) presented two deep RNN techniques to forecasting the usage of electricity over a medium- to long-term horizon. Also, they presented a method for dealing with missing data. As compared to the traditional Multi-Layer Perceptron (MLP) neural network, the results showed that the proposed models had a lower relative error [12]. Another well-liked approach is random forest (RF), which relies on training [[13], [14]]. The improvement in RF comes from its nonlinear estimating suitability and reduced sensitivity to parameter values. All AI-based methodologies call for the best possible architectural layout and parameter optimization, which hybridization can successfully handle. ANN was recently used by to forecast the energy analysis certificates of residential structures in Italy.

Ahmad et al. (2017) anticipated energy consumption using the weather, time, and building consumption[15]. Lee et al. (2017) used a large data analytics technology to calculate the environmental consumption level by country[16]. Li et al. (2017) used Autoencoder to anticipate future energy consumptions and extract the building's energy demand [17]. Wang et al. (2018) Studied a recent RF short-term electricity estimate for commercial buildings with regard to their envelope, climate and time when forecasting the hourly electricity load in buildings, the study shown that RF outperformed regression trees and SVM. Deep Neural networks can also be used in a number of other ways[18]. Kim et al.(2019) State Explainable Autoencoder was used by to forecast household electricity usage using data collected over a five-year period [19].

Polson et al. (2020) proposed DL-EVT, a mix of deep learning with extreme value theory, to address the abrupt peaks, troughs, and fast pricing shifts in energy markets brought on by variations in supply and demand brought on by intraday limitations. The levels' peaks and troughs aren't captured by this method [20]. Huang et al .(2021) constructed a hybrid model using deep neural networks to predict short-term electricity prices[21].

III. The proposed approach

The suggested strategy consists of two primary models that, when combined in two steps as shown in Figure (2), can manage the energy consumption pattern throughout the day. The historical data collected by smart meter and smart sensor in the first stage is preprocessed using data analytics. The utility then employs the suggested Deep Learning (DL) prediction to make use of this standardized data to forecast the consumer's hourly load usage.

Understanding how crucial data analysis and preparation are really for time series is necessary before talking about the forecast. The outcome of the forecast may depend on them. Preprocessing data into to the correct format is therefore the primary problem in predicting.

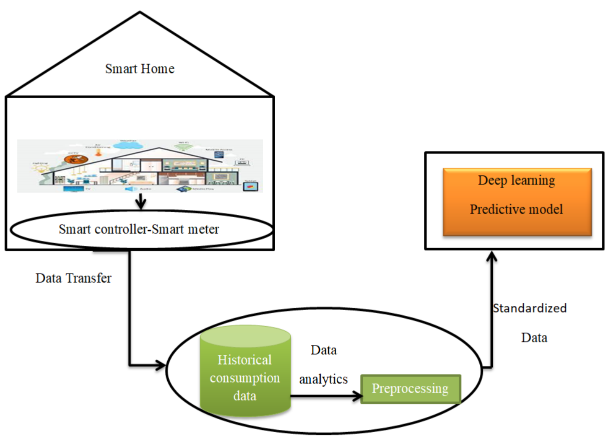


Fig. 2. shows the proposed model's general flowchart.

A. Historical data description

Data from Kaggel Western Europe Power Consumption were gathered from 2016 to 2018 in order to anticipate Denmark's overall electricity load. The National Aeronautics and Space Administration (NASA) released the Power data access viewer data for latitude 55.9562° north and longitude 10.0320° east where the weather information was acquired. To achieve error-free prediction, all the data gathered from the two sources were preprocessed. data on the total amount of electricity used from 2016 to 2018. Attributes such as date-time, temperature, pressure, humidity, air density, wind speed, wind direction, and load were finally taken into account (total energy consumed).

B. Data analytics process

The historical data acquired from smart meters and smart sensors is first grouped in a matrix, where each row contains an observation for one (24-hour) day. This is the data preparation stage. Each column also conveys a different input/output feature. The proposed model takes into account the following input features: the month item, which is coded as a binary value of 8 digits for the entire dataset; the day item; the outside temperature; and the preceding load consumption value. Also, the final column shows the output of the actual load consumption. The data are modified to have a mean of zero and a standard deviation of one, standardizing each feature column.

The standardization method can reduce the reliance on arbitrary scales and usually enhances the performance of the model. The dataset is then split into sets for training and testing with percentage of 80% and 20%, respectively.

C. Model for deep learning prediction

LSTM stands for long short-term memory and is a unique type of recurrent neural network (RNN). Using memory units capable of updating the previous hidden state, this model preserves long-term memory. Each neuron receives feedback from it. The output of an RNN depends not only on the weight and input from the current neuron, but also on the input from the primary neuron. Long-term sequences of temporal relationships can be understood because to this functionality. Explosive and vanishing gradient issues are issues with traditional RNN training that are resolved by its own memory storage unit and gate mechanism. Input, output, forget, and cell status gates are the four crucial components of the LSTM model's internal structure. Fig. 3 shows how an LSTM cell-block is constructed.

The cell's function is parameterized by the following equations:

$$f_t = \sigma(W_f.X_t + U_f.h_{t-1} + b_f) \quad (1)$$

$$i_t = \sigma(W_i.X_t + U_i.h_{t-1} + b_i) \quad (2)$$

$$\tilde{c_t} = tanh(W_c.X_t + U_i.h_{t-1} + b_c) \quad (3)$$

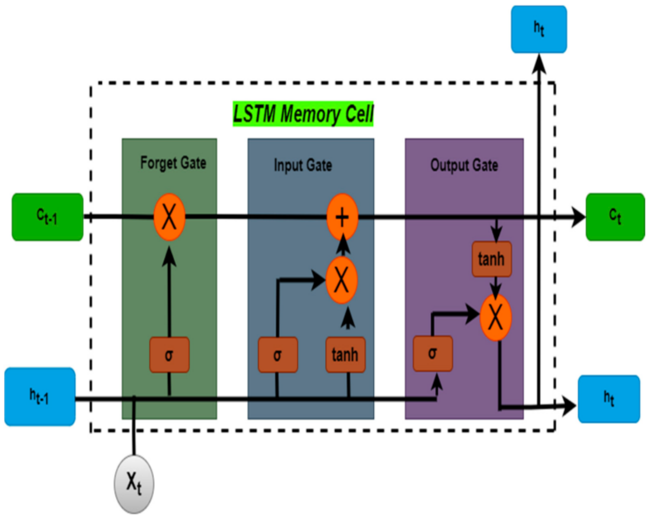


Fig. 3. a block diagram of long short-term memory

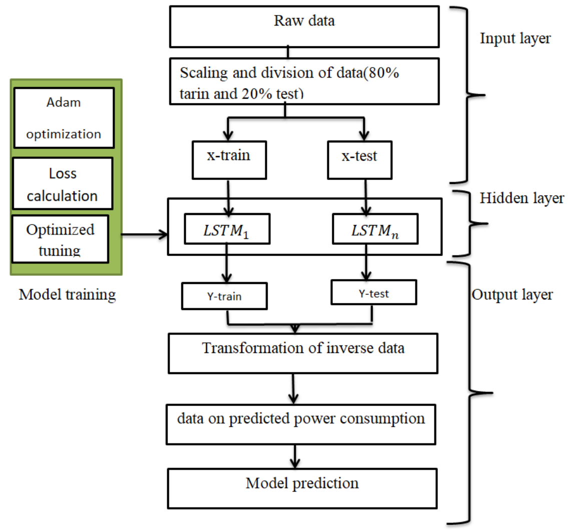


Fig. 4. the framework for LSTM power consumption forecasting.[22]

$$c_t = f_t.c_{t-1} + i_t.\tilde{c}_t \tag{4}$$

$$O_t = \sigma(W_t.X_t + U_o.h_{t-1} + b_o) \tag{5}$$

$$h_t = O_t.tanh(c_t) \tag{6}$$

The prediction strategy framework using the LSTM model is shown in Fig .4. Three major parts make up this model:
• Preprocessing of the initial data occurs mostly at the input layer;

• The training of the data and parameter optimization are done using the hidden layer;

• Using the model that was developed in the hidden layer, the output layer predicts the data.

The dataset from method was utilized to test the prediction performance by calculating the root-mean-squared Error using a multivariate LSTM method (RMSE). X and Y parameters are used to access data used for training and testing. deal with LSTM model data preprocessing. The neurons used in the input layers are also what supervised learning uses and defines. Adam optimizer is chosen as the gradient in the Mean Square Error (MSE)-based model. test the accuracy and data loss of a model after fitting it. In order to count all of the epochs and determine the training loss, the model runs. After updating the model's internal states, a final model is created. Covers the forecasting of multivariate data. For purposes of evaluation, the RMSE is calculated as the squared difference between the actual and predicted values. increased independence, prediction is more effective than bagging. It is also quicker since every tree is trained using a subset of features. In contrast, Bagged decision trees select to partition variables in a greedy manner that minimizes errors. Therefore, even Bagging can maintain a number of structural similarities, and their predictions are in fact tightly connected. Predictions from the sub models should therefore be uncorrelated or just weakly linked in order for the ensemble of predictions from multiple models to perform well. In order to learn the sub-trees and reduce the connection between all sub-tree predictions, RF alters the method. The learning algorithm is permitted to choose the optimum split point for each variable when selecting a split point. The RF algorithm modifies this function to assess only a random subset of features. The following are the RF steps:

1. Create a random subset within the sample (bootstrapping).

2. Choose a random set of features for each node's best split inside the decision tree.

3. For each subgroup, create a model decision tree.

4. Average final forecasting results and the sum of all decision trees' forecasts.

IV. Result and Discussion

A. Results of Energy Consumption Prediction Using Deep Learning and RF Models:

This section discusses a variety of experimental findings for all versions of models created using LSTM and RNN enhancement. A comparative analysis was also carried out using a dataset on power energy consumption to show how well the suggested model performed in comparison to rival benchmarks. Implementing a reliable power energy consumption prediction system with low prediction error and high accuracy is the main goal of this effort. The suggested model combines LSTM and RNN, two deep learning models that are effective at forecasting how much energy will be used in the short term. Table I lists the parameters for the deep learning recurrent neural network prediction algorithm. In terms of RF, this machine learning model is really good at forecasting how much energy will be used. Using the gridsearchcv package, we selected the ideal parameter for this model to obtain the best maximum depth as Table II. In this study, the Mean Square Error (MSE), coefficient of determination are the statistical measures chosen to evaluate the accuracy of the deep learning recurrent neural network predictive model over two states of the art in residential energy consumption (R2). Equations (7) through (8) define the various statistical measurements [23].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2 \tag{7}$$

$$R2 = 1 - \frac{\sum_{i=1}^{N}(X_i - Y_i pred)^2}{\sum_{i=1}^{N}(X_i - Y_i mean)^2} \tag{8}$$

where N is the number of data points in the test dataset, xi is the actual energy consumption at time step i, Yi is the predicted energy consumption.

TABLE I.
DEEP LEARNING MODELS EVALUATION METRICS

Method	Parameters	Time resolution	MSE	R2_Score
RNN	Activation function=" tanh" Alpha=0.7 Epochs=10 Batch_size=70	Hourly	0.012	0.94
LSTM	Activation function="tanh" Alpha=0.5 Epochs=10 Batch_size=70	Hourly	0.008	0.95

TABLE II.
RANDOM FOREST MODEL EVALUATION METRICS

Method	Parameters	Time Resolution	MSE	R2_score
RF	Max_depth=10	Hourly	3.33	0.913
	Max_depth=12		2.3	0.946
	Max_depth=18		0.8	0.975
	Max_depth=25		0.52	0.986
	Max_depth=30		0.51	0.987
	Max_depth=35		0.51	0.987
	Max_depth=40		0.51	0.987

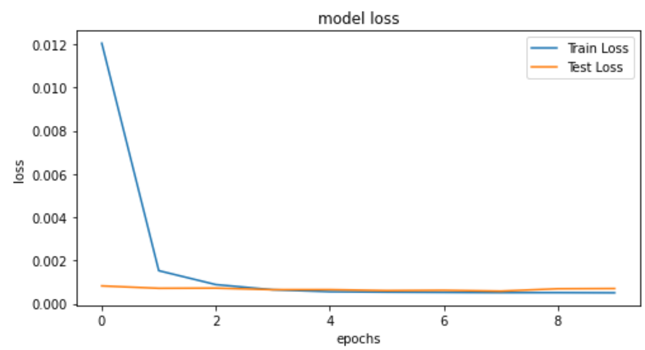


Fig. 5. loss curve of LSTM model

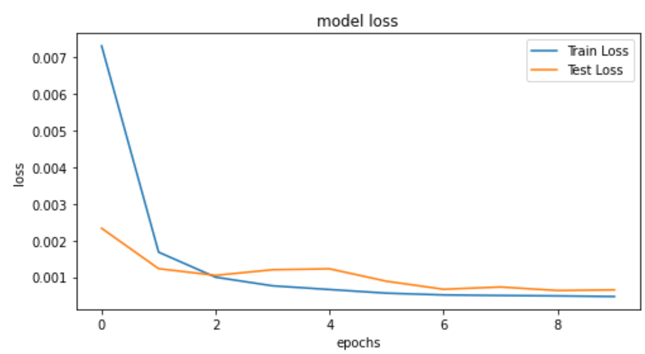


Fig. 6. loss curve of RNN model

As shown the fig. 5,6, compared to the orange line which represents validation loss, the blue line reflects training loss. The total number of epochs is shown on the X-axis, and the training and testing losses for each period are shown on the Y-axis. As shown in fig 3, the maximum validation loss is 0.001 and the highest training loss is 0.012, both of which decrease as the number of epochs rises. According to Figure 4, the highest training loss is 0.008 and the highest validation loss is 0.00025, both of which decrease as the number of epochs rises. Based on the aforementioned findings, we opt for the 70-piece batch size with the highest accuracy and lowest loss.

V. CONCLUSION

In this study, two models for predicting and managing residential load usage in smart grids are introduced. The first model seeks to predict the load demand consumption using a deep learning (DL) model that can automatically train and extract the model parameters from the historical data, utilizing deep RNN, LSTM units, and accurately predict the load demand consumption. The other proposal is called random forest, and when comparing deep learning and RF models, deep learning came out on top in terms of mean square error. At the same time, RF was preferred based on the R2 Score because it had the highest accuracy (98%), which was achieved when predicting electrical energy consumption. To improve accuracy, future research will compare one deep learning model and support vector machines.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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