Short-Term Energy Forecasting Using an Ensemble Deep Learning Approach

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Abstract Precise estimation of domestic electricity usage is essential for sustainable energy management, enabling effective energy allocation, and advancing the development of intelligent networks. To anticipate home electric power consumption from time series data, this research investigates usage of advanced machine learning models, including Recurrent neural networks. The dataset includes observations of a household's electricity use over a long period, together with details like usage patterns and time of day. To address anomalies, standardize the series, and organize the data for sequential learning, we preprocess it. The study assesses the performance of each model, finding that GRUs are better at spotting spatial-temporal patterns in the data, RNNs are better at sequential data prediction, and LSTMs are better at capturing long-term dependencies. To increase prediction accuracy, the comparison study lays the groundwork for future efforts to optimize model architectures and incorporate outside variables like weather and economic data. This study highlights how deep learning has the ability to change energy management procedures and open the door to more economical and environmentally friendly home energy use.

Keywords: Energy Management, Electric power Consumption, Computational Viability, Machine learning LSTM networks, smart sensor systems.

1 Introduction

The technique of estimating future electricity demand in a residential context using past consumption data and maybe other pertinent variables like the weather, the day of the week, and the characteristics of the household is known as "household power consumption prediction." Several statistical, ml or dl models are considered in this predictive study to comprehend and predict usage patterns of electric power. Predicting residential power consumption is primarily done to improve energy efficiency, make better energy management easier, and help smart grids function.

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Time series data, or readings of power consumption taken at regular intervals (hourly, daily, etc.), can be used by effective prediction models to increase accuracy. They can also incorporate external influences. They can identify sequences and patterns in data, techniques which are listed above are seen to be frequently taken into consideration for this kind of forecasting. Neural networks of the long-term dependency learning were created in response to the vanishing gradient issue.

Neural networks with a focus on processing sequences are called RNNs. They are trained with input data with the help of internal memory. CNNs are a category of algorithm that is well-known for its capacity to get features lineage. Although their primary application lies in picture recognition and processing, they have also been modified to handle sequences and anticipate time series by identifying spatial- temporal patterns.

2 Literature Survey

Prediction of Energy Consumption via RNN networks and Bi-Directional LSTMs' is an extensive study that uses a typical machine learning approach to measure household electric energy usage. Convolutional neural networks (CNN) and multi-layer bi-directional networks are used in this method to overcome the difficulties in predicting energy consumption brought on by elements like the weather and occupants' dynamic behavior. A three-step methodology for short-term electricity energy consumption prediction (ECP) is introduced.“High-Power Prediction of Load based on Optimized LSTM Network” suggests a forecasting model that uses the Algorithm to reduce parameters, improving the learning capacity and efficiency of neural networks. By utilizing historical data, holiday characteristics, and meteorological information, this method seeks to increase the resilience and accuracy of forecasting real-power demands, like water heaters that run on electricity and cooling devices, are scheduled for the next 24 hours."Household Power Consumption Prediction on Selective Ensemble Learning" offers a novel method for predicting the amount of electricity that a home will use via selective ensemble learning technology. Due to the complicated nature of household energy usage data, which is characterized by high volumes, wide distribution, and different types, the study tackles the difficulty of effectively estimating power consumption. To increase prediction efficiency and accuracy, the researchers suggest using a FIOES, which involves integrating basic learners (predictive models) in a predetermined order based on performance."Household Electricity Consumption Prediction with CNN-GRU Techniques" is a study that uses a hybrid deep learning strategy that incorporates techniques from GRU and CNN to forecast household energy power consumption. This method is intended to solve the difficulties associated with forecasting power usage, which can be impacted through a number of parameters including local climate and resident behavior.

3 Proposed Work

Proposed model follows the steps shown in Fig.1 involving preprocessing, training and evaluation and steps of preprocessing for data preparation is represented in Fig.2. Data is trained and tested to measure behavior of the model.Sequential compilation with mean squared error loss and Adam optimizer.Evaluation of model performance using loss and validation loss metrics over epochs to monitor learning and overfitting.

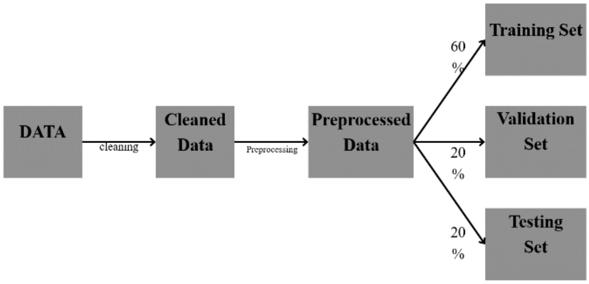

Fig 1: Data Model

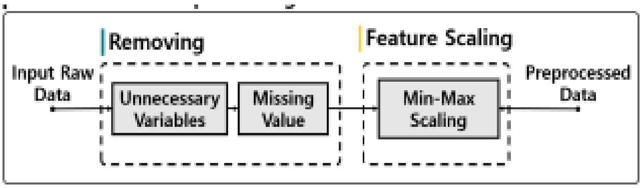

Fig 2: Data Preprocessing

Incorporating extra pertinent data to enhance the predicted accuracy of the models, such as socioeconomic variables, weather patterns, and energy costs. Developing more reliable forecasting models may result from examining how outside variables affect power usage. To better capture temporal dependencies and increase prediction accuracy, look into the application of more complex neural network architectures such as Transformer models, attention mechanisms, and GRU (Gated Recurrent Unit).Real-time Data Preprocessing and Forecasting: In order to allow these to dynamically update predictions in the upcoming data, extend the project to include real-time data processing and forecasting. This could entail creating a streaming data preprocessing pipeline. Scalability and Deployment: Investigate ways to deploy the models in the real world, such as integrating them with energy management platforms or smart home systems, and optimize them for scalability.

Derivation of Algorithms

LSTM

The model introduces a more intricate memory cell framework with the goal to resolve the problem of gradients disappearing. Combining a memory cell with gating mechanisms to regulate the movement of data is the fundamental idea of LSTM.

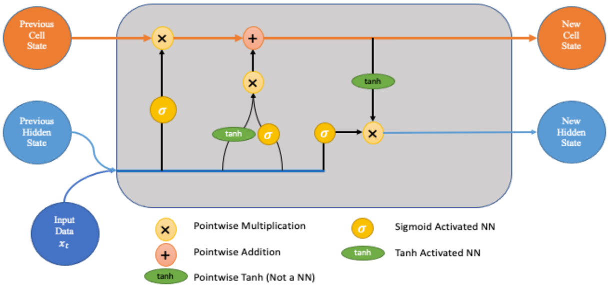

Fig 3: Mathematical equations in LSTM

A synopsis of the LSTM version equations, in figure 3, is as follows:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i)(1)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f)(2)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh\,(W_{xc}x_t + W_{hc}h_{t-1} + b_c)(3)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o)(4)$$

$$h_t = o_t \odot \tanh\,(c_t)(5)$$

Where:

i_t, f_t, o_t are the gates respectively,,c_t is the state of cell,,σ is the sigmoid, $\odot$ denotes element-wise multiplication.

GRU (Gated Recurrent Unit):

A different approach RNN derivative that provides comparable results but streamlines the design of the LSTM is identified as GRU. The initial states combine, and the forget and gates are merged into a unique update. The update and the reset gate are the two gates of GRU.

Here is an overview of the GRU update equations:

$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z)(6)$$

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r)(7)$$

$$\tilde{h}_t = \tanh\,(r_t \odot (W_{xh}x_t + W_{hh}(h_{t-1} \odot z_t) + b_h))(8)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t(9)$$

Where:

z_t *and* r_t are the gates respectively, $\tilde{h}_t$ is a new candidate activation,σ is the sigmoid function.

RNN (Recurrent Neural Network)

The logic behind processing input sequences wherein the outcome at each stage relies on the present and earlier inputs is the core of the basic RNN algorithm. In mathematical terms, an RNN utilises the current input x-t, to compute the output at step t. The earlier hidden state h_(t-1) together with a few of the biases b and weights W.

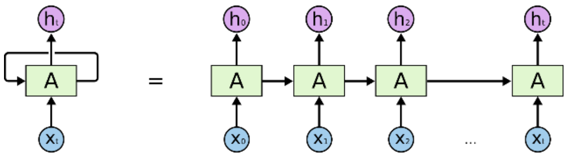

Fig 4: Mathematical approach of RNN

The following is an overview of the amended equations, of model shown in fig 4:

$$h_t = \tanh\,(W_{hh}h_{t-1} + W_{xh}x_t + b_h)(10)$$

$$y_t = softmax(W_{hy}h_t + b_y(11)$$

Where:

h_t is state hidden at time step t.
x_t is the input.
W_{hh} and W_{xh} are weights.
b_h is the basis vector.
y_t is the output at time step t.
W_{hy} is another weight matrix.
b_y is the bias vector

Bagging Model

- Aggregation: Bagging combines the predictions of multiple base models by averaging or voting to make final predictions.
- Reducing Variance: Bagging helps reduce anomalies and variance through integrating the predictions which have been trained on various information subsets.

Generic Analysis:

LSTM Model- LSTM Layer:

Input dimension: train_xshape [1] (number of time steps), train_x.shape[2] (number of features)
Number of units: 100
Activation functions: Default (often tanh for the recurrent activation and sigmoid for the input and forget gates)
Output shape: (batch_size, 100) (100 units output)
Dropout Layer:
Dropout rate: 0.1.
Dense Layer:
Number of units: 1
Activation function: None (linear activation by default)
Output shape: (batch_size, 1) (single output)

GRU Model- GRU Layer:

Input dimension: train_x.shape[1] (number of time steps), train_x.shape[2] (number of features)
Number of units: 150
Activation functions: Default (often tanh for the recurrent activation and sigmoid for the input and update gates)
Output shape: (batch_size, 150) (150 units output)
Dropout Layer:
Dropout rate: 0.1
Dense Layer:
Number of units: 1
Activation function: None (linear activation by default)
Output shape: (batch_size, 1) (single output)

SimpleRNN Model- SimpleRNN Layer:
Input dimension: train_x.shape[1] (number of time steps), train_x.shape[2] (number of features)
Number of units: 200
Activation function: Default (often tanh)
Output shape: (batch_size, 200) (200 units output)
Dropout Layer:

Dropout rate: 0.1
Dense Layer:
Number of units: 1
Activation function: None (linear activation by default)
Output shape: (batch_size, 1) (single output)

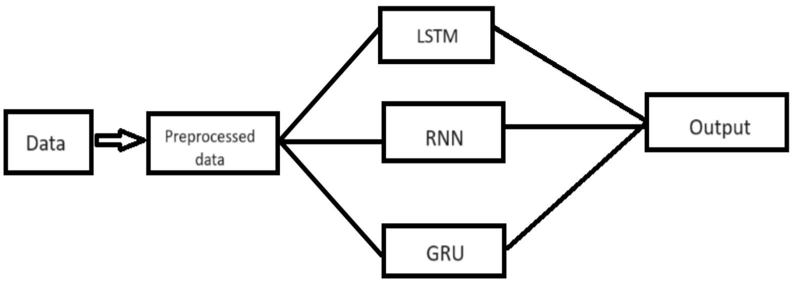

Fig 5: Process used for three RNNs

These are the three recurrent neural network (RNN) types' layouts, shown in figure 5, and configurations: Simple RNN, GRU, and LSTM. Each framework has a unique set of parameters.

3.1 Performance Metrics

Root Mean Square Error is a metric that's frequently employed for evaluating how unreliable a model is at predicting quantitative data. It is very widespread in forecasts and statistical analysis.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2} \quad (12)$$

The study employed a state-of-the-art machine learning model, specifically short-term energy forecasting. The results obtained from the developed prediction model demonstrate a high level of accuracy, with an impressive value of RMSE score of 0.6 and the combination of the models lead to greater impact on the demonstrate of the model's effectiveness in accurately predicting the future demand.

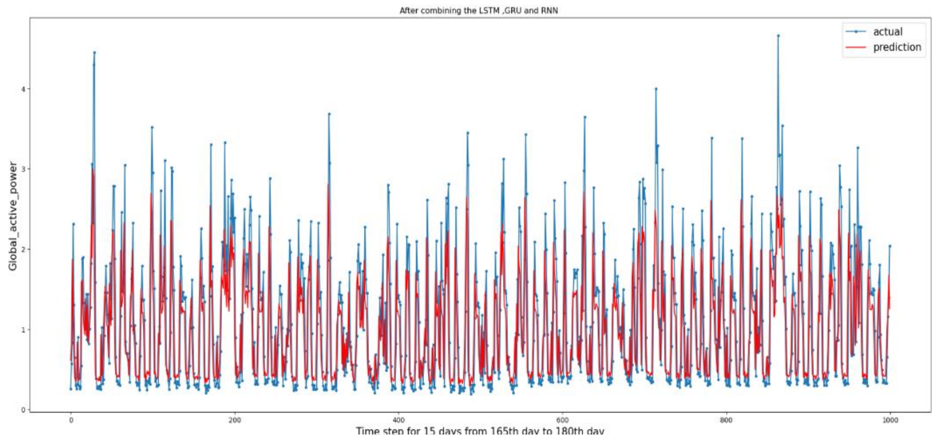

Fig.6. Actual Vs Predicted values after combining three different models

4 Conclusion

In conclusion, our study on the research paper, there are some flaws and shortcomings in the state of the research at this time. The processing of high-dimensional and multivariate time series data presents a typical difficulty to these investigations, as the intricate and dynamic nature of household energy usage patterns can greatly affect forecast accuracy. Many approaches find it difficult to successfully incorporate outside variables into their models, such as the weather, tenant behavior, and temporal fluctuations. Furthermore, standardized datasets for training and testing are conspicuously lacking. The models, making it challenging to measure and evaluate the effectiveness of various strategies. The suggested models' scalability and computing efficiency represent yet another important gap. Resolving these issues and creating more effective, scalable, and understandable models that are simple to include into smart energy systems could make a big impact on the field of predicting household energy usage.

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