Thesis End-Sem Report:

Deep learning based performance prediction of a renewable energy integrated smart Microgrid

Abstract:

In regions like India where high elevated temperatures exists almost throughout the year, ensuring the efficient operation of electronic systems in Electric Vehicle (EV) charging stations is crucial. In this paper, the power of deep learning models is utilized, including Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Gated Recurrent Unit (GRU) to forecast crucial parameters such as VRFB Power Flow, Grid Power Flow, Solar Power Grid Flow, and VRFB State of Charge (SOC) across diverse weather conditions under various weather conditions. The implementation of these Deep Learning models has demonstrated substantial enhancements in prediction accuracy and overall system performance. This improved accuracy helps us to predict the crucial parameters of the EV charging stations even when the weather is unpredictable and helps us maintain a balance among these elements, making sure that their combined demand always stays around 500W of Glazing Load Demand. A comparative analysis has been done among the Deep Learning models in terms of performance metrics such as correlation coefficient (R^2), mean absolute error (MAE) and root mean square error (RMSE). It has been observed that almost all the deep learning models exhibit high accuracy R^2 of 0.99 in Sunny, Cloudy and Prolonged Cloudy conditions and an average accuracy R^2 of 0.75 in worst case weather condition. These prediction results will be useful to gauge the EV station parameters accurately in any weather condition and will be economically beneficial and can optimize the cost spent.

1.**Introduction:**

In the EV charging station that has been discussed in [1], a solar photovoltaic (PV) source has been installed on its rooftop. This initiative is designed to promote the usage of green energy and encourage sustainable transportation methods. To provide a reliable long-term energy storage solution and to ensure energy security [1] integrates Vanadium Redox Flow Battery (VRFB) into the system. This setup enables efficient energy management and usage optimization. In this paper the utilization of Deep Learning models including Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Networks (RNN) is implemented.

These advanced models enable us to predict VRFB Power Flow, Grid Power Flow, Solar Power Grid Flow, and VRFB State of Charge (SOC) with a high degree of accuracy under various weather conditions. In this paper four weather conditions are namely Cloudy, Sunny, Prolonged Cloudy, and even the worst possible weather conditions. The predictive accuracy of deep learning models, including MLP, RNN, GRU, and LSTM, is compared using key performance metrics such as R^2(Correlation Coefficient), RMSE (Root Mean Square Error), and MAE (Mean Absolute Error).

The datasets to train these deep learning models are extracted from the graphs of VRFB Power Flow, Grid Power Flow, Solar Power Grid Flow, and VRFB SOC from [1]. The graphs have been interpolated to produce 17000 data points to train and validate each deep learning models. The interpolation process is carried out to make more precise predictions, thus enhancing the system's performance under diverse weather conditions. This study signifies a remarkable step in completely utilizing the potential of Deep Learning for real-world applications. It showcases how these models can effectively improve renewable energy management and predictive analysis within the domain of EV charging stations, thereby supporting the transition to sustainable and environmentally friendly transportation methods.

2. **Overall schematic of the proposed work:**

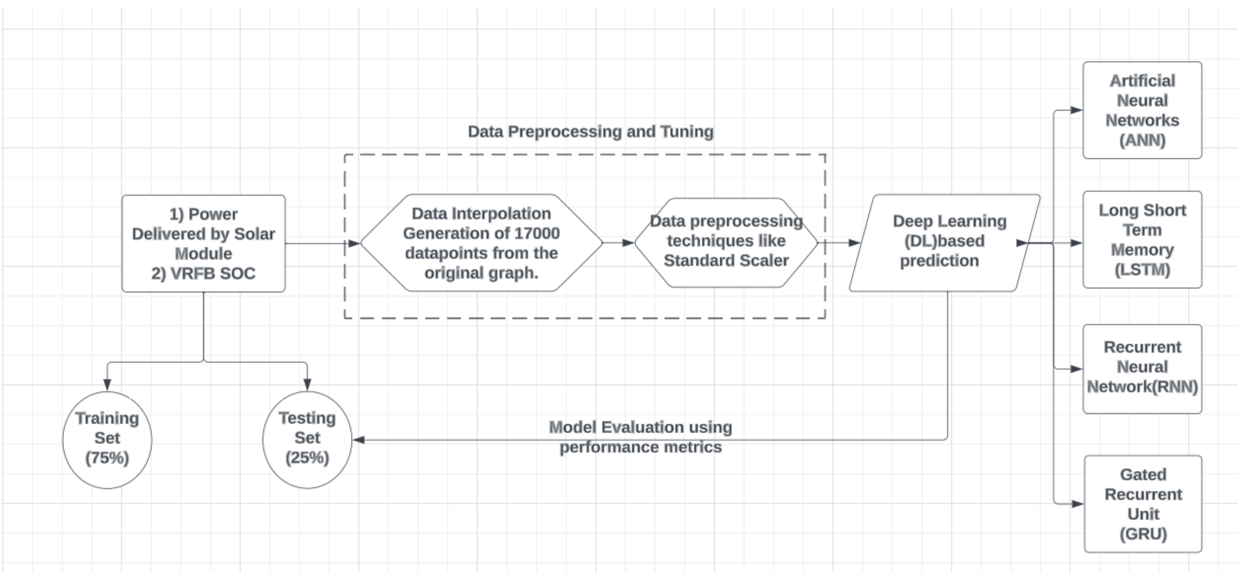

Figure 1: Flow diagram for the DL-based prediction of the Power Delivered by Solar Module and VRFB SOC.

Figure 1 shows the proposed work flow of this paper i.e. prediction of the Power Delivered by VRFB Power Flow, Grid Power Flow, Solar Power Grid Flow, and VRFB SOC under different weather conditions using DL algorithms. The efficiency of these algorithms are evaluated using performance metrics like R^2, RMSE and MAE (Mean Absolute Error). The data is primarily extracted from the graphs given in the [1]. To efficiently train the DL models data interpolation has been done to generate 17000 data points for each graph under different weather conditions. After collecting the data, preprocessing is done. In this dataset Standard Scaler is used as the preprocessing technique to ensure consistent scales of data and aiding in algorithmic convergence and performance. Each dataset is now divided into training and testing dataset of 75% and 25% of the total data respectively. The training dataset is used to train the DL models and testing dataset is used to validate the efficiency of the DL models using various performance metrics. In this paperR^2, RMSE and MAE is used as performance metrics. An efficient algorithm gives R^2close to 1. MAE is defined as Mean Absolute Error i.e. the average difference between experimental and predicted values. RMSE is defined as Root Mean Squared Error i.e. the degree of deviation between the predicted and experimental value. Both MAE and RMSE should be as low as possible for an efficient algorithm.

3. Simulation and Modelling of DL models:

Considering the data driven model for prediction of Power delivered by Solar Module and VRFB SOC during different weather scenarios four different DL models have been implemented in this paper and their performance is analyzed using appropriate error metrics.

Multi-Layer Perceptron (MLP) is a type of Artificial Neural Network (ANN) used extensively in deep learning domain. It's designed by its feedforward architecture which means that data flows in a single direction, from the input layer through one or more hidden layers to the output layer. Each MLP layer contains interconnected artificial neurons also known as perceptron. In each layer the neurons processes the input and applies an activation function on it. These activation function includes sigmoid function, tanh (hyperbolic tangent) and rectified linear unit (ReLU). The presence of multiple hidden layers is helpful in training the MLP. The number of hidden layers and number of neurons in each layer are the hyper parameters of this model and they significantly influence the network's capacity to train and validate the data.

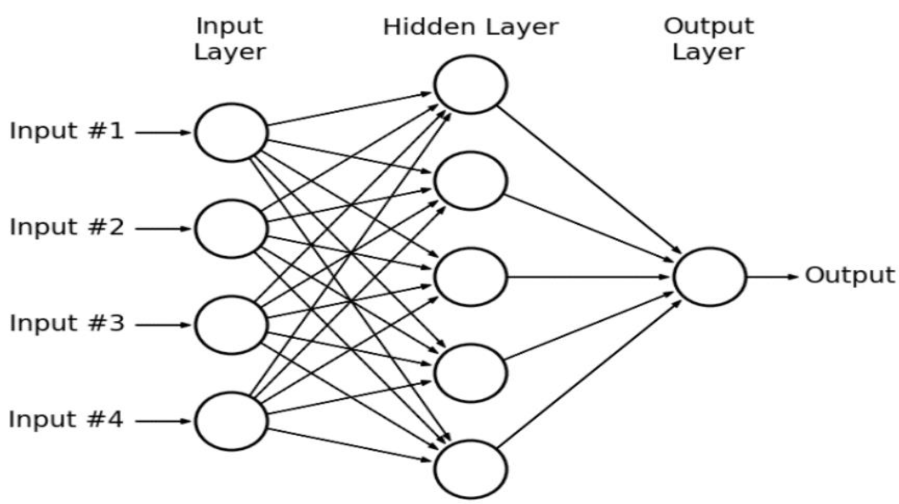

Figure 2: represents an example of a basic Multi-layer Perceptron

Recurrent neural network (RNN):

Is a class of artificial neural networks designed to handle sequential data by maintaining the internal hidden state that uses the information from previous time steps . RNN's have connections that cycle back to previous connections to maintain a form of memory. This recurrent architecture makes RNN well suited for task that involve time series data. However RNN's have limitations such as vanishing or exploding gradient problem. As a result more advanced architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have been developed to rectify these issues and have become widely used for sequential data modeling.

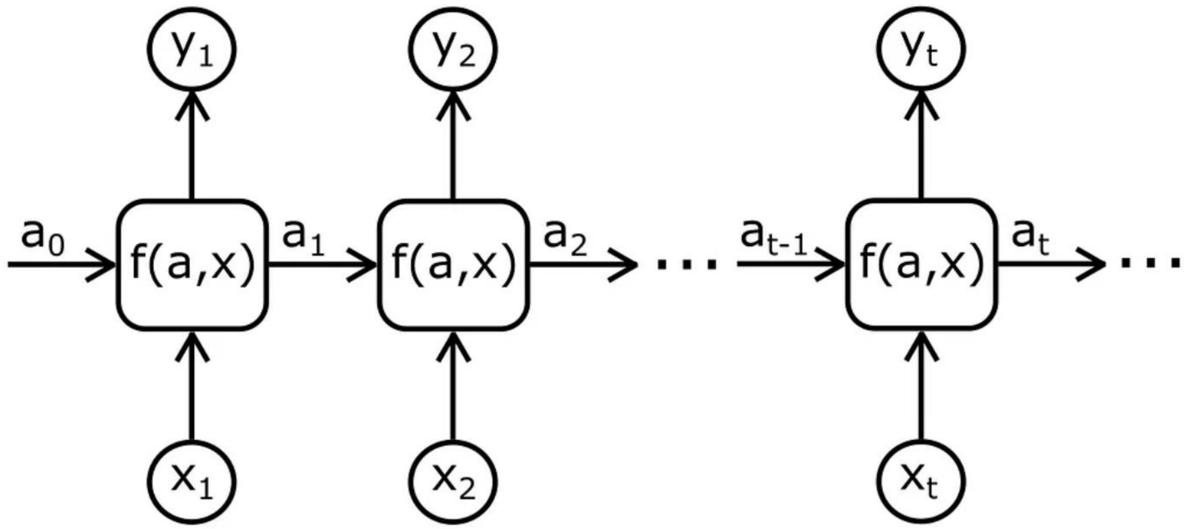

Figure 3: represents the basic architecture of RNN.

Long Short-Term Memory (LSTM):

Is an advanced form of RNN architecture to overcome the problem of Vanishing gradient and capture long sequences of data. LSTM consists of gated cells selectively store and retrieve information. These gates include input gate, output gate and the forget gate. The input and output gate manages the flow of information into the memory cell. The forget gate is used to decide what information needs to be retained or forget. The input gate decides what information needs to be passed and output gate decides what information needs to be revealed as output.

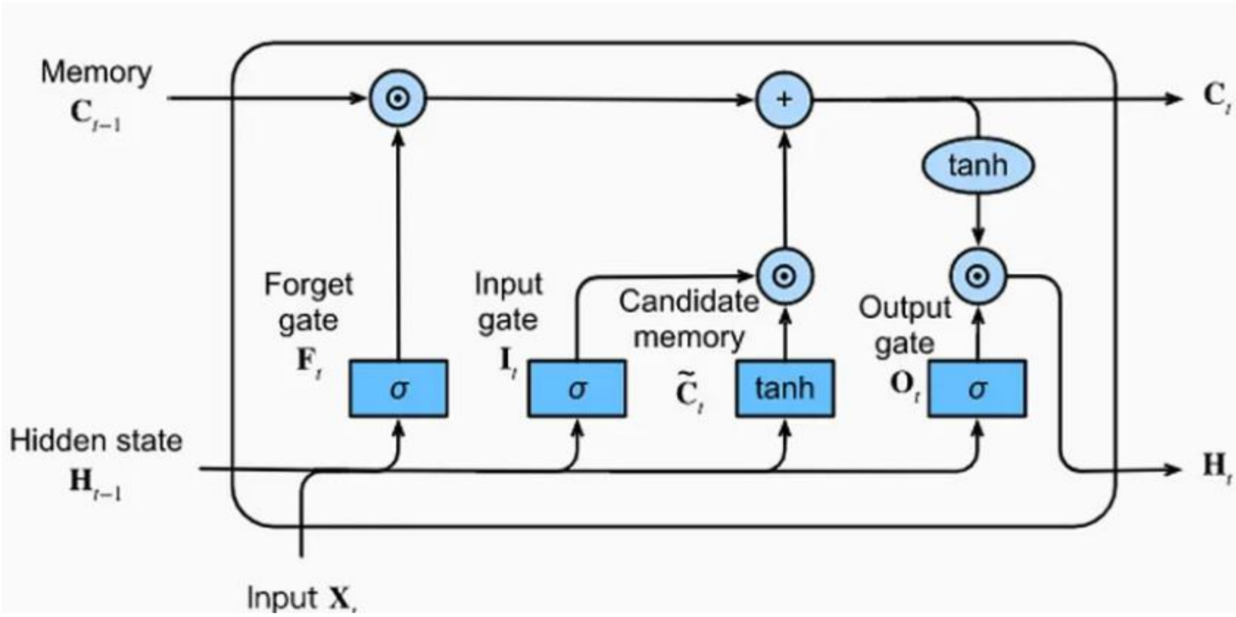

Figure 4: represents the basic architecture of LSTM.

Gated Recurrent Unit (GRU):

Similar to LSTM , GRU is an advanced form of RNN architecture to overcome the problem of vanishing and exploding gradient problem. Similar to LSTM , GRU has 2 gates namely update gate and reset gate. The update gate determines what information from the previous time slots needs to be passed further and the reset gate determines which information needs to be forget or reset.

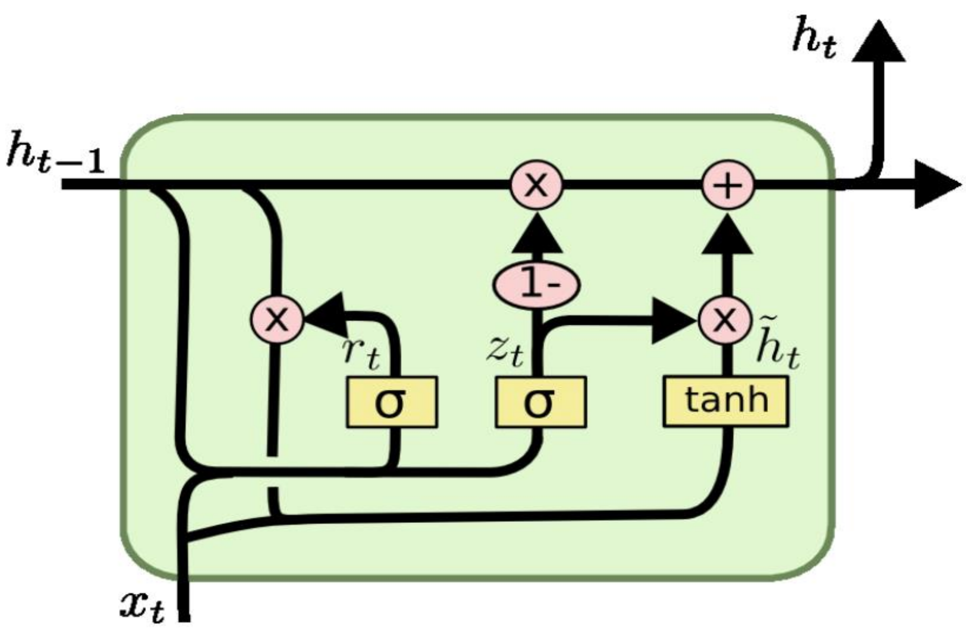

Figure 5: represents the basic architecture of GRU.

4. **Simulation Results and validation :**

In this paper, for the first time deep learning models is used to predict the Power delivered by VRFB Power Flow, Grid Power Flow, Solar Power Grid Flow, and VRFB State of Charge SOC. Taking the case of Sunny weather condition Figure 6 depicts the graph between actual and predicted values obtained by using Multi-Layer Perceptron (MLP) model. The models are trained on Google Colab platform where each model is ran for 300 epochs. When the MLP model is trained on Sunny weather conditions the below results were obtained:

<u>For MLP</u>:
R-squared: 0.998

RMSE: 0.037

MAE: 0.024

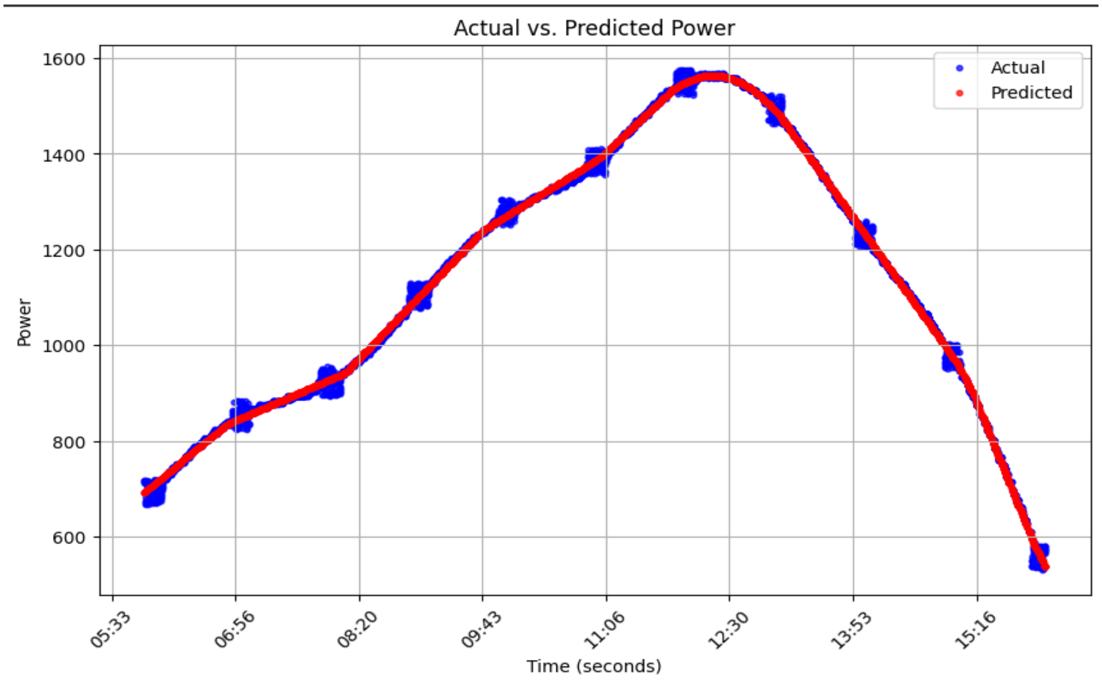

Figure 6: represents the graph between actual vs predicted values obtaining using the MLP deep learning model in Sunny weather condition.

Similarly we obtain graphs for LSTM , RNN , GRU as shown in Fig 7,8,9.

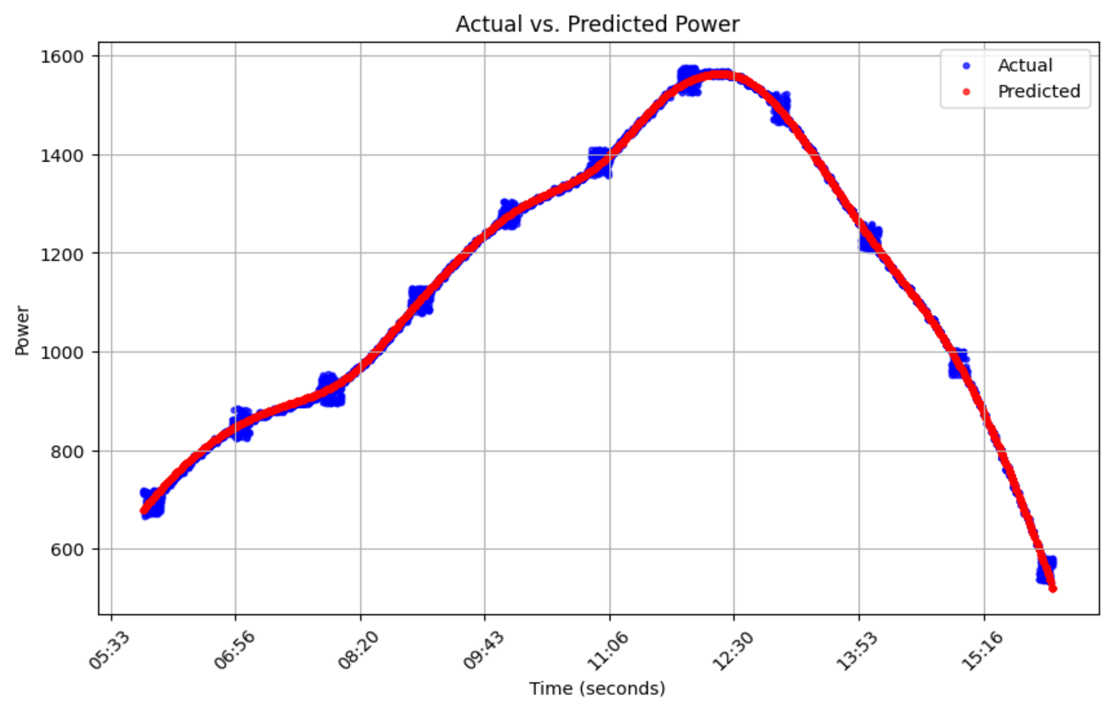

Figure 7: represents the graph between actual vs predicted values obtaining using the LSTM deep learning model in Sunny weather condition.

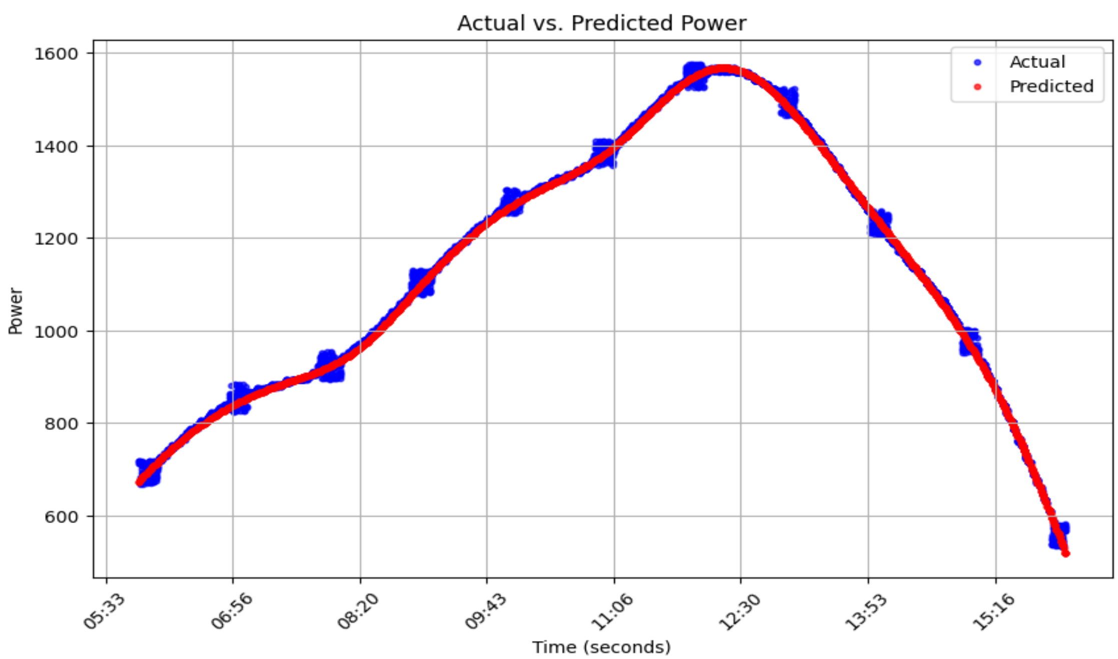

Figure 8: represents the graph between actual vs predicted values obtaining using the GRU deep learning model in Sunny weather condition.

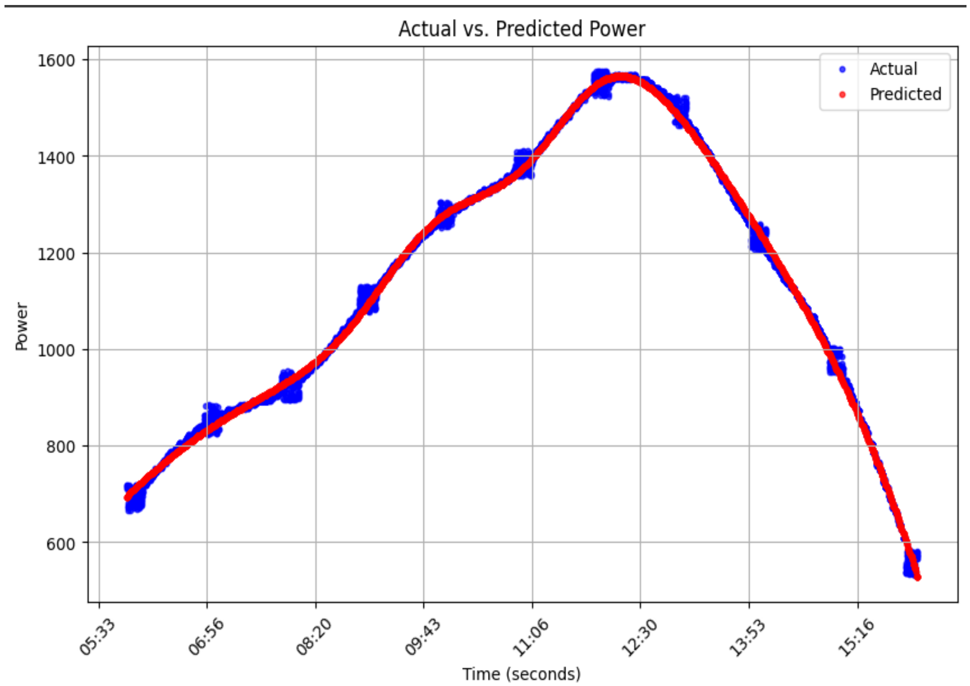

Figure 9: represents the graph between actual vs predicted values obtaining using the RNN deep learning model in Sunny weather condition.

For LSTM:
R-squared: 0.998

RMSE: 0.036

MAE: 0.022

For GRU:
R-squared: 0.998

RMSE: 0.039

MAE: 0.025

For RNN:
R-squared: 0.997

RMSE: 0.0046

MAE: 0.032

Now taking the case of VRFB Power Flow in the Sunny weather condition Figure 9 depicts the graph between actual and predicted values obtained by using Multi-Layer Perceptron (MLP) model.

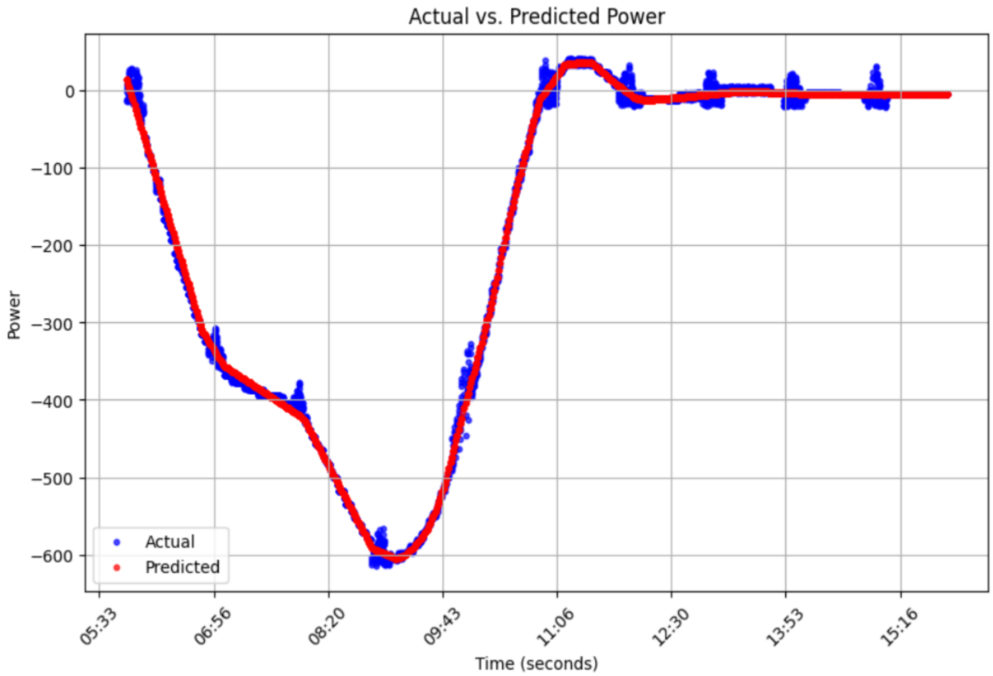

Figure 10: graph between actual vs predicted values of the VRFB Power flow in Sunny weather condition is depicted using MLP algorithm.

The MLP deep learning algorithms gives a R^2: 0.99, RMSE: 0.04 and The MAE is: 0.02 in the Sunny weather condition while predicting the VRFB Power Flow.

The DL models are also used to predict the Grid Power Flow. Figure 11 shows how the MLP is used to predict the Grid Power Flow in Sunny weather condition.

The MLP deep learning algorithms gives a R^2: 0.99, RMSE: 0.02 and The MAE is: 0.01 in the Sunny weather condition while predicting the Grid Power Flow.

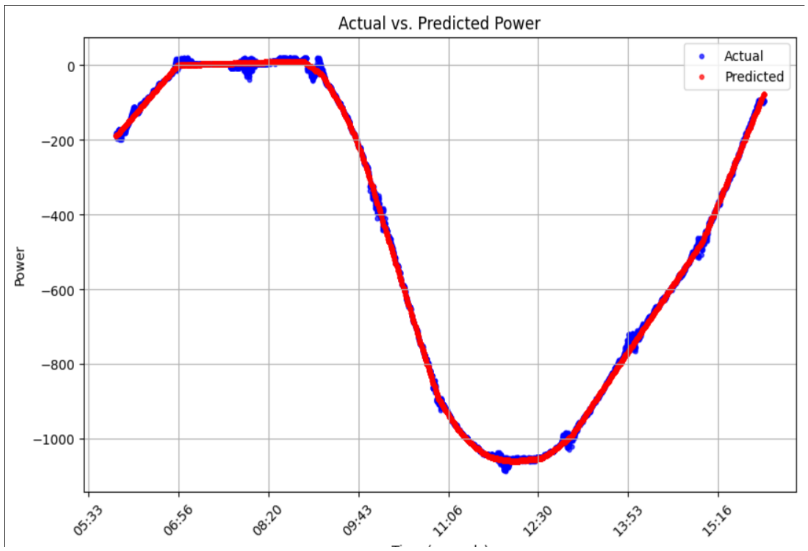

Figure 11: graph between actual vs predicted values of the Grid Power flow in Sunny weather condition is depicted using MLP algorithm.

Figure 12 depicts how DL models were used to predict the VRFB SOC in the Sunny weather conditions.

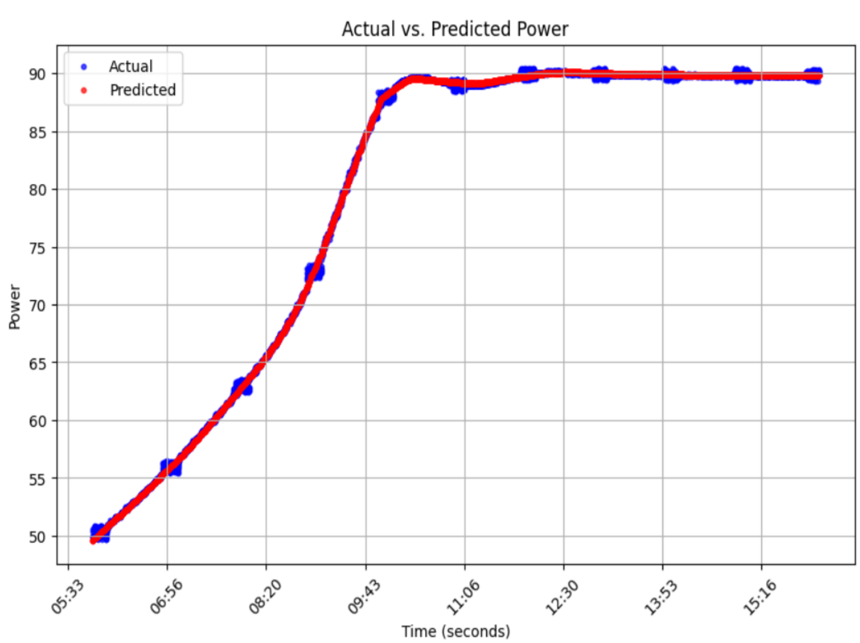

Figure 12: graph between actual vs predicted values of the VRFB SOC in Sunny weather condition is depicted using MLP algorithm.

The MLP deep learning algorithms gives a R^2: 0.99, RMSE: 0.017 and The MAE is: 0.01 in the Sunny weather condition while predicting the VRFB SOC.

5.Conclusion:

In this paper the use of DL models to predict crucial EV parameters like VRFB Power Flow, Grid Power Flow, Solar Power Grid Flow, and VRFB State of Charge SOC .The DL algorithms namely MLP, LSTM, RNN and GRU are trained based on the practical dataset provided in [1] where data interpolation has been done to generate 17000 data points for each dataset. The DL models were trained and validated on the Google Colab platform, utilizing the dataset comprising 17000 samples. For training and testing the DL models the dataset has been split into 75% training consisting of 12750 data points and 25% testing consisting of 4250 data points. The entire process was carried out on a personal computer equipped with a 16GB RAM and an Intel i7 processor. Data preprocessing has been done on the dataset as it is an important part that needs to be done before model prediction and analysis. Standard scaler from the sklearn library has been used as the preprocessing technique. A comparative analysis has been done with respect to performance evaluation metrics such as R^2, MSE and RMSE. The coefficient of determination R^2 indicates the amount of variation in the experimental and the predicted results. A R^2score of close to 1 is preferred and considered to be a good DL model. In this paper all the DL models namely MLP, LSTM, RNN and GRU predicts a R^2 of almost 0.99 for Sunny , cloudy and prolonged cloudy and an average R^2 of 0.75 in the case of worst case weather condition. Other metrics such as RMSE and MAE gave an average error of 0.004 and 0.03 respectively. The high accuracy and low error rate provided by these models help us make smart decisions about how to use energy more efficiently and economically in a complicated energy environment. This leads to a more sustainable and cost-effective use of resources.

References:

[1] Nawin Ra, Aritra Ghosh, Ankur Bhattacharjee, IoT-based smart energy management for solar vanadium redox flow battery powered switchable building glazing satisfying the HVAC system of EV charging stations, Energy Conversion and Management, https://doi.org/10.1016/j.enconman.2023.116851.

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