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Deep Learning-Based Models for Wind and Solar Curtailment Forecasting

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***Abstract* –** Renewable Energy Resources (RESs) power curtailments, mainly wind and solar, have become a significant problem in many countries due to the rapid rise in renewable energy capacity and a sharp reduction in the cost of their power plants. These curtailments lead to the deteriorating economic viability of renewable energy. Modelling and predicting RES power curtailments are essential to better managing and can provide more apparent perspectives to increase the efficiency of future RES performance. However, the prediction of RES power curtailments is a complex problem because it is not only influenced by the volatile renewable power generation but also by the power generation of other units, imports, load demand and power exchange. In this study, using different Machine Learning (ML) and Deep Learning (DL) approaches, we aimed to predict wind and solar curtailments employing historical training data on power generation. A comprehensive learning-based data analysis was performed based on time-series renewable power curtailment reports obtained from California ISO (CAISO). The prediction models are trained based on ten input features for nine years, including load demand, imports, the output power of nuclear units, thermal power plants, small and large hydro units, biomass and geothermal, solar farms, wind turbines, and historical wind and solar curtailments. To find the best possible prediction methodology, different ML-based models, including Stochastic Gradient Descent (SGD), K-Nearest Neighbours algorithm (KNN), Support Vector Machines (SVR), Regression Trees (RT), and Random Forest (RF), are employed. Also, among the several deep learning methods, we utilize Deep Neural Network (DNN) as a fundamental deep learning model and Long Short-Term Memory (LSTM), and the Gated Recurrent Unit (GRU) to consider the time-series characteristics of the data. The learning results demonstrated that the GRU method outperformed all utilized models and could achieve a better forecasting performance. The results indicated the effectiveness of the proposed approach in predicting wind and solar curtailments.

***Keywords*:** Power Curtailment; Renewables; Solar Forecasting; Renewable prediction; LSTM; GRU; Deep learning; California ISO

1. Introduction

A swift rise in renewable energy capacity and a sharp reduction in the cost of their power plants, mainly wind and solar, contribute to curtailment becoming a significant problem in many countries [2]. Curtailment usually occurs due to the lack of rapid ramp-up/down-generating units in power grids. This curtailment can be defined as a reduction in the output of a generator from what it could produce on an involuntary basis, given available resources [3]. For example, snowpacks send much water to hydroelectric power plants in spring, leaving less capacity for renewable energy sources. In such conditions, due to the lack of flexibility of conventional generation systems, energy production from RESs is sometimes curtailed by independent system operators (ISOs). In the case of wind energy, power is generated from the wind turbines at any time of the day, even sometimes higher at night, with the lowest energy consumption leading to curtailing energy generation during the night. Therefore, the curtailed energy presents a significant amount of the total wind energy capacity [4].

Curtailment is not always a "bad" thing. For example, wind operators can provide upward reserves when a part of accessible energy is curtailed [5]. However, whenever grid support services are not drawn from wind power, curtailment is simply a loss of clean energy. In this situation, curtailment is a "bad" thing, not only for generators and investors but also for transmission system operators and regulators, due to the lack of system flexibility or appropriate market design. Increasing grid flexibility and using technological advance devices such as low-cost battery storage could prevent some future solar curtailment [6]. Policy and grid planning practices can influence where, when, and how much solar is curtailed. For example, the California Energy Imbalance Market (EIM) resulted in some shifting of solar curtailment from California to Arizona [6].

A shift in thinking toward managing curtailments rather than preventing them could enhance the value of delivered and curtailed solar output to the grid [6].

CAISO has one of the highest solar shares in the USA. Through the third quarter of 2022, solar accounted for 45%, and wind accounted for 25% of all new electricity-generating capacity added to the US grid; this means solar and wind energy produces almost 70% of the total electricity-generated capacity [1]. According to some recent reports, in 2022, the amount of renewable power curtailments in CAISO increased more than five times from 461,054 Megawatt hours in 2018 to 2,432,659 Megawatt hours in 2022 [1]. Thus, modelling and predicting RES power curtailments are essential and can provide more apparent perspectives concerning future renewable energy systems' performance and efficiency.

In this study, using ML and DL techniques, we aimed to predict wind and solar curtailments employing historical training data on power generation (renewables, thermal, small/large hydro, nuclear), demand, imports, and historical wind and solar curtailments. The target variables are considered one hour ahead of wind and solar curtailments.

ML and DL techniques can provide comprehensive models to predict wind and solar curtailments, so they can be employed in the planning and operation of energy systems to increase the utilization of RES. In this context, the excellent performance of the LSTM and GRU networks based on related literature for time series solar and wind power forecasting motivates our study of applying these networks to hourly wind and solar power curtailment prediction. Also, to find the best possible predicting approach, other well-implemented approaches, including DNN as a fundamental DL model and different ML-based models, are employed to forecast wind and solar curtailment. A comprehensive learning-based data analysis was performed based on time-series renewable power curtailment reports obtained from CAISO, and it was utilized as input for training and forecasting procedures.

The rest of this paper is organized as follows: Section 2 presents the literature review. Section 3 examines the data gathering and deep learning approaches. The results and discussion are presented in Section 4. Finally, the paper is concluded in Section 5.

2. Literature Review

Curtailment of renewable generation, particularly wind and solar energy, is discussed by many researchers. Li et al. [7] discussed the leading causes, calculation process and strategies to reduce curtailed electric power and estimated the worldwide Curtailed Electric Energy (CEE), especially in China. Different CEE calculation methods are adopted in different countries [3, 7-9]. L. Bird et al. [10] reviewed international experience with the curtailment of wind and solar energy on bulk power systems. It examines levels and the causes of curtailment, curtailment methods and using different techniques to reduce renewable energy curtailment. Y. Yasuda et al. [9] investigated global curtailment trends using an objective and quantitative tool named the C-E map, a correlation map between curtailment ratios and wind (or solar) energy shares. The C-E map helps to quickly and visually understand the historical trend of curtailment in the given countries/areas and compares the current status and trend between several countries. A. Alkhalidi et al. [4] proposed several energy storage systems to use curtailed energy better, which eventually decreases energy costs and reduces carbon emissions. L. Bird et al. [3] summarized curtailment experiences of different utilities and grid operators in the United States. The authors also discussed various reasons for curtailment, methods of implementing curtailments, compensation curtailed generators, and other strategies to mitigate curtailment.

On the other hand, the design and operation of power systems can be improved through effective and practical renewable energy sources forecasting models [11]. ML methods have been widely and recently used to predict the output power of photovoltaic and wind farms. In this regard, some papers proposed comprehensive reviews of the state-of-the-art ML-based and DL-based approaches developed to forecast the power generation from wind turbines and solar panels, along with the forecasting of load demand of consumers [12-14]. Despite the existing capabilities of forecasting the power of wind and solar resources based on meteorological and technical parameters, the prediction of wind and solar curtailments is still a challenging and complex problem. To the best of our knowledge, there have been just two recent studies on the prediction of renewable power curtailments [15, 16]. However, the study in [16] presented the prediction of wind and solar power curtailment without considering the input features to generate scenarios for a planning problem.

The paper [15] recently proposed artificial intelligent-based models to predict wind and solar power curtailments using different ML-based algorithms.

Based on the studies examined in a very recent and comprehensive review of DL-based approaches to forecast wind and and solar power generation, many studies demonstrate that LSTM has higher efficiency over RNN under all circumstances. circumstances. Because the LSTM has intrinsic memory to resolve vanishing gradient issues arising in the RNN [12]. However, in terms of computational or training time, GRU exhibits more efficiency than LSTM. Overall, considering training training time and estimation accuracy, the GRU model yields a satisfactory result for forecasting solar irradiance [12, 17]. 17].

Based on related literature for time series solar and wind power forecasting, in this study, we examined three practical and well-implemented DL-based approaches named LSTM, GRU, and DNN and different ML-based approaches to find the best possible methodology for hourly wind and solar power curtailment prediction.

3. Data analysis and deep learning approaches

In this study, 9-year historical data of wind and solar curtailments from 2014 to 2022, including 10,353,432 points, were taken from CAISO [6] and were utilized as input for training and forecasting procedures. The historical curtailment data was recorded for all 24 hours during the day in 5-minute intervals, which are grouped by one-hour intervals to increase consistency. A year-round curtailment distribution for the aggregate solar and wind curtailment from 2015 to 2022 is shown in Fig. 1. As it is evident from Fig.1, the amount of curtailment has increased significantly during this period. The amount of maximum curtailed power has soared from 50,000 MWh in 2015 to 600,000 MWh in 2022, which this curtailed power can unlock potential benefits and affect the revenue of renewable energy projects. The prediction models are developed using recurrent neural networks and feed-forward Artificial Neural Networks (ANNs), and data sequences are investigated using two effective and well-implemented methods: LSTM [18] and GRU [19]. Accordingly, the best method with the least Mean Absolute Error (MAE) is selected to forecast wind and solar curtailment. Eq. (1) demonstrates the MAE, where y_i denotes prediction, x_i denotes actual values, and n denotes the total number of data points.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{1}$$

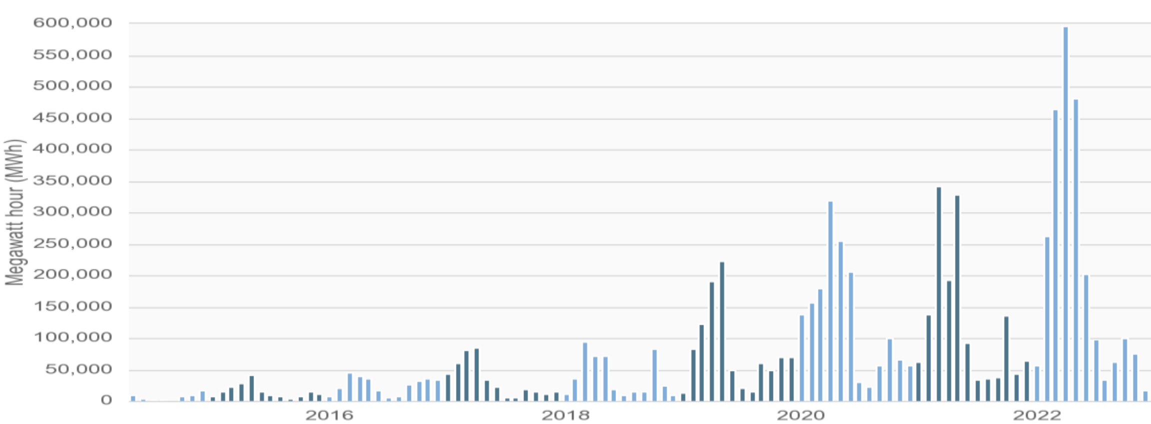

Fig. 1: Wind and solar curtailment totals from 2015-2022 [1]

3.1. Deep Neural Network (DNN)

DNN structure comprises several hidden layers in addition to the input and output layers [20]. An ANN with two or more hidden layers is named DNN. To generate the output, DNN investigates the input data using mathematical manipulation. The advantages and disadvantages of DNNs are similar to ANNs, but since DNNs comprise more layers than ANNs, they often need more training data to attain better results than ANN [21]. The rectified linear unit (ReLU) and dropout are used to overcome the vanishing gradient problem and over-fitting in DNN.

3.2. Long Short-Term Memory (LSTM)

LSTM developed by [18] is mainly used for sequence prediction. LSTM networks are a type of RNN with a purpose-built memory cell. Therefore, long-range dependence data might be much better discovered and utilized. Equations (1)-(5) implement a memory cell of the LSTM network.

$$I_t = \sigma(W_{xI}x_t + W_{hI}h_{t-1} + W_{cI}c_{t-1} + b_I) \tag{1}$$

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

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

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

$$h_t = o_t \tanh(c_t) \tag{5}$$

Where σ, I, f and o represent a sigmoid activation function in addition to input, forget, and output gates, respectively. The weight matrices are W with the subscripts same as gates, and b_i, b_f, b_c, and b_o are biased vectors. Also, h_t is the output of the LSTM at time t.

3.3. Gated Recurrent Unit (GRU)

The GRU model was proposed in 2014 by Cho et al. [19] on statistical machine translation. GRU networks were proposed to capture dependencies over timescales by adapting each recurrent unit. GRU units have gate units that control information flow, just like LSTMs, without separate memory cells. The GRU selects a new type of hidden unit motivated by the LSTM unit and combines the input and forget gates into a single update gate. The final model is more straightforward than the standard LSTM model and is a popular variant. There are two gates in GRU; a reset gate, r, adjusts the incorporation of new input with the previous memory, and an update gate, z, controls the preservation of the last memory. The following describes how the activation of the hidden unit at time step t is computed. Firstly, r_t is computed as follows:

$$r_t = \sigma(W_r h_{t-1} + U_r x_t) \tag{6}$$

where σ is the logistic sigmoid function, and W_r, U_r are weight matrices, respectively. The new remember $\tilde{h}_t$ is generated using r_t with a tanh layer. The function is given by:

$$\tilde{h}_t = \tanh(W(r_t^* h_{t-1}) + Ux_t) \tag{7}$$

The GRU deletes the remember gate and forget gate in LSTM and create the z_t to replace them. In which z_t is computed by following equation:

$$z_t = \sigma(W_z h_{t-1} + U_z X_t) \tag{8}$$

Finally, the hidden state value is updated by the following equation:

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

4 Results and discussions

The forecasting models are developed in Python using the “Scikit-learn” machine learning package [22] for ML-based models and the “Keras” deep learning package [23] for DL-based approaches. Different ML-based models, including SGD, KNN, SVR, RT, and RF, and three well-known DL-based approaches, including DDN, LSTM, and GRU, are utilized to find the best possible prediction methodology. The pre-processed nine-year data from 2014 to 2022, including 862,786 points, is applied to predict wind and solar curtailments. Sorted data sets of seven years from 2014 to 2020 with 690,229 points were input as training values to the machine learning and deep learning algorithms. The Keras Tuner library in TensorFlow is applied to tune hyperparameters and optimal sets for the applications. Table 1-2 presents the hyperparameter values and the MAE scores of all the developed ML and DL-based models for solar and wind curtailments, respectively. The actual outputs and curtailment peaks are considered without normalization in calculating MAE.

It should be considered that the values of MAE for “solar curtailments” are much higher than those for “wind curtailments”; because the mean solar curtailment power is much higher than those of wind curtailments. The learning results showed that all DL-based models outperformed ML-based models, and GRU was the best-performing method. For predicting “solar curtailments,” the GRU (with two layers) outperformed all utilized models, and for “wind curtailments,” GRU (with dropout) had the best performance.

Table 1. Defined parameters and nnumerical results for the ML and DL- based methods for predicting “solar curtailment”

Method	MAE [MW]	Parameters
SVM	187.01	-
RT	116.55	-
KNN	130.73	-
SGD	97.39	-
RF	113.27	-
DNN	80.47	3 hidden layers with 64,32,16 neurons, Activation function=Relu, Optimizer="rmsprop", epochs=30
LSTM (one layer)	82.71	1 layer with 256 neurons, Activation function="tanh" optimizer="rmsprop", epochs=30
LSTM (two layers)	83.30	2 layers with 128 and 32 neurons, Activation function="tanh", Optimizer="rmsprop", epochs=30
LSTM (with dropout)	79.92	2 layers with 128 and 64 neurons With a dropout layer, Dropout=0.25, Activation function="tanh", Optimizer="rmsprop", epochs=30
GRU (one layer)	79.44	1 layer with 256 neurons, Activation function="tanh" optimizer="rmsprop", epochs=30
GRU (two layers)	73.50	2 layers with 128 and 64 neurons, Activation function="tanh", Optimizer="rmsprop", epochs=30
GRU (with dropout)	78.06	2 layers with 128 and 128 neurons, With dropout layer, Droput=0.25, Activation function="tanh", Optimizer="rmsprop", epochs=30

Table 2. Defined parameters and nnumerical results for the ML and DL-based methods for predicting “wind curtailment”

Method	MAE [MW]	Parameters
SVM	10.81	-
RT	13.83	-
KNN	13.12	-
SGD	10.77	-
RF	9.73	-
DNN	8.69	2 hidden layers with 64,32 neurons, Activation function=Relu, Optimizer="rmsprop, epochs=20
LSTM (one layer)	9.22	1 layer with 256 neurons, Activation function="tanh", Optimizer="rmsprop", epochs=10
LSTM (two layers)	9.07	2 layers with 128 and 32 neurons, Activation function="tanh", Optimizer="rmsprop", epochs=30
LSTM (with dropout)	9.44	2 layers with 128 and 64 neurons, With dropout layer, Droput=0.25, Activation function="tanh" Optimizer="rmsprop", epochs=30
GRU (one layer)	8.86	1 layer with 256 neurons, Activation function="tanh", Optimizer="rmsprop", epochs=30
GRU (two layers)	8.27	2 layers with 128 and 64 neurons, Activation function="tanh", Optimizer="rmsprop", epochs=30
GRU (with dropout)	7.63	2 layers with 128 and 128 neurons, With dropout layer, Droput=0.25, Activation function="tanh", Optimizer="rmsprop", epochs=30

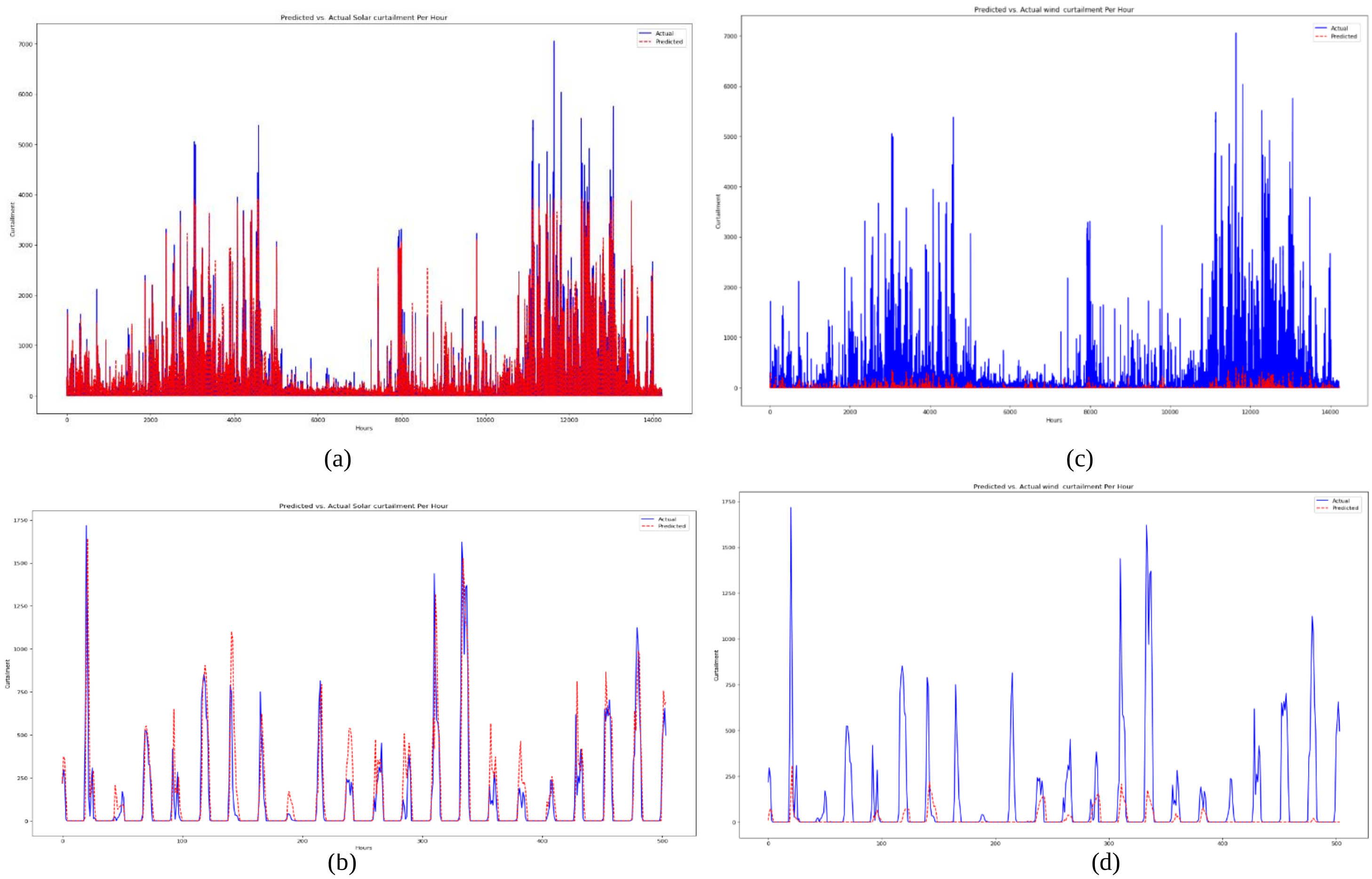

Fig. 2: GRU prediction plot with actual wind and solar curtailment data – (a) solar curtailment, (b) Three-week zoom of solar curtailment, (c) wind curtailment, (d) three-week zoom wind curtailment

Also, between ML-based methodologies, SGD resulted in better performance for prediction “solar curtailment”, whereas for “wind curtailment” RF led to better prediction. Furthermore, among other methodologies, SVM had the lowest performance in predicting “solar curtailments,” whereas for “wind curtailments,” Regression Tree resulted in the lowest performance. Fig. 2 shows the GRU plots as the best wind and solar curtailment prediction method. As shown in Fig. 2, “solar curtailment” has better predictions than “wind curtailment.” The main reason is that solar power usually follows a regular pattern for most of the year, whereas wind power is highly volatile and uncertain. This high uncertainty causes wind curtailment to be much more volatile than solar curtailment and has low correlations with input features, leading to less predicting effectiveness than solar curtailment.

5. Conclusion

As the share of wind and solar energy increases, curtailment practices and strategies to mitigate the potential for curtailment become increasingly important. A shift toward managing curtailments rather than preventing them could enhance the value of delivered and curtailed solar and wind output to the grid. RES power curtailment forecasting can provide generators with better information and enable them to participate more fully in the future market. It can also decrease uncertainty associated with renewable energies and reduce the need for curtailments due to unexpected changes. Curtailment order varies and is often based on different features like load demand, power input, and generation via renewables and other sources like nuclear or thermal. This makes curtailment prediction a very complex and challenging problem. In this study, to find the best possible prediction models, different ML-based models, including SGD, KNN, SVR, RT, and RF and three well-implemented DL-based approaches, including DNN as a fundamental DL model, and LSTM and GRU, to consider the time-series characteristics of the data was utilized. The learning results showed that DL-based approaches outperformed ML-based methods, and GRU resulted in the best prediction for both wind and solar curtailments. Also, "solar curtailments" were more effectively predicted than "wind curtailments." The main reason is that solar power usually follows a more regular pattern for most of the year, whereas wind power is highly volatile and uncertain. This high uncertainty leads to much more volatility in wind curtailment and lower correlations with input features making its prediction less effective than solar curtailment prediction. Overall, this study can be utilized by operators and ISOs to manage energy curtailment issues better and utilize more RES by effectively predicting renewable energy curtailments. This study can be extended by utilizing more effective prediction models and ensemble learning structures to deal with high volatility and uncertainty in wind power curtailment and promote the model's forecasting ability.

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