Solar Energy Forecasting Based on Complex Valued Auto-encoder and Recurrent Neural Network

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***Abstract*—Renewable energy is becoming a trusted power source. Energy forecasting is an important research field, which is used to provide information about the future power generation of renewable energy plants. Energy forecasting helps to safely manage the power grid by minimizing the operational cost of energy production. Recent advances in energy forecasting based on deep learning techniques have shown great success but the achieved results still too far from the target results. Ordinary deep learning models have been used for time series processing. In this paper, a complex-valued autoencoder was coupled with an LSTM neural network for solar energy forecasting. The complex-valued autoencoder was used to process the time series with the advantage of processing more complex data with more input arguments. The energy value was used as a real value and the weather condition was considered as the imaginary value. Taking into account the weather condition helps to better predict power generation. The proposed approach was evaluated on the Fingrid open data dataset. The mean absolute error (MAE), root-mean-square error (RMSE) and mean absolute percentage error (MAPE) was used to evaluate the performance of the proposed method. A comparison study was performed to prove the efficiency of the proposed approach. Reported results have shown the efficiency of the proposed approach.**

Keywords*—Solar energy forecasting; artificial intelligence; complex-valued autoencoder; long-short term memory; deep learning

I. Introduction

Modern cities have elevated the power demand and fuel-based energy sources are polluting the globe. Renewable energy has been considered as a solution to provide power needs while reducing pollution and power production costs. Sun, wind, and water are natural clean power sources that can be considered trusted sources, but their power production was based on weather conditions. Recently, the energy produced by clean resources was integrated into the power grid. The main concern of those sources is that the generated power cannot be controlled and varies with weather conditions. Integrating clean power into the grid is a very challenging task because of the variability of the generated energy amount.

Solar power is a clean energy source that converts daylight to electricity. The main issue of this type of energy generator is that the amount of generated power is unpredictable. Generated solar power must be consumed at the same time of production because of the volatility of this energy. However, overload power causes many problems such as voltage regulation and reverse power flow. Besides, low power can cause discontinuity and can affect all devices connected to the grid. Subsequently, for the safe integration of the solar power generator into the grid, it is important to predict the grid power need and integrate the solar power at its stable generation period to benefit from it the maximum possible. A high-performance energy forecasting system can help to solve the problem. Mainly there are two energy forecasting systems, physical models and artificial intelligence models. Physical models are based only on whether conditions generate a forecast based on wind speed or solar power curves based on light availability. Those models were not very accurate because many other conditions must be taken into account such as solar panels' conditions and temperature. However, artificial intelligence models have been efficiently and flexibly used for energy forecasting. Those models do not need to explicitly scale the physical process of power generation. In effect, it builds a relationship between the input and output through processing data and reducing the error with the target values.

Energy forecasting has been widely studied to manage energy production costs by predicting clean power generation. Many averaging techniques were deployed for energy forecasting such as Autoregressive Integrated Moving Average (ARIMA) [1], simple moving average (SMA) [2], and weighted moving average (WMA) [3]. The averaging techniques have achieved low performance and the predicted results were different from the expected. Methods such as simple exponential smoothing (SES) [4] were used for forecasting but the achieved results were not convincing.

Recently, the deep learning technique [5] has achieved great success in many applications. Deep learning techniques are based on deep neural networks. Convolutional neural networks [6], recurrent neural networks [7], and auto-encoder [8] were the most used deep learning models. The mentioned deep learning models have boosted the performance of many applications such as object detection [9, 31], indoor object detection [10, 29], face mask detection [11], pedestrian detection [12], traffic signs detection [30], time series forecasting [13], and many others. The outcomes demonstrated the effectiveness of deep learning models. for solving many problems and can be used to solve more problems. The ability of automatically learning features without any handcrafted engineer features has been very effective. Besides, such models mimic the biological brain's decision-making process. Considered to solve renewable energy forecasting using deep learning models. Energy forecasting is based on analyzing historical time-series records. Similar to economic time series forecasting [14], renewable energy forecasting needs deep learning models with memory such as recurrent neural networks. For better performance, we proposed to use an autoencoder to denoise and better represent the input data. Then, a long-short-term memory network was used to process the temporal information of the data for power prediction. The proposed autoencoder is a complex-valued autoencoder with real and imaginary outputs. The energy value was used as real input and the weather condition was used as an imaginary value. Combining the energy value with the weather condition helps to learn more relevant features and generate more trusted predictions.

The proposed method's key benefit is that it may be customized for various forecasting categories based on the horizon range such as short, middle, and long-range forecasting. The proposed method can apply for data forecasting for hours, days, or months. This advantage makes the model useful for many cases and not designed for a specific case.

The main contribution of this paper is the following: (1) proposing a solar power forecasting system; (2) proposing the use of a complex-valued autoencoder for data denoising and features clustering; (3) combining the complex-valued autoencoder with an LSTM neural network to process time-series data for energy forecasting; (4) validate the proposed approach on the open solar dataset.

The paper is organised as the follows: Section II presents related works. The proposed approach is described and detailed in Section III. In Section IV, the experiment and results are presented and discussed. The paper was concluded in Section V.

II. Related Works

The application of renewable energy forecasting for grid management and cost reduction makes it a significant study area. Many works have been proposed for achieving trusted predictions. For a complete overview of existing works, the readers can refer to the survey presented in [15]. Energy forecasting techniques can be categorized based on the base model. The first category is based on averaging techniques and the second category is based on deep learning techniques. In this paper, we have focused on deep learning techniques.

Abedinia et al. [16] proposed a solar energy forecasting method based on neural networks combined with the metaheuristic algorithm. The metaheuristic algorithm was used to optimize the forecasting parameters. The neural network was composed of an input layer, 3 hidden layers, and output layers to generate a prediction. The Levenberg-Marquardt algorithm [17] was used to train the suggested neural network. The Levenberg-Marquardt presents a combination between the gradient descent algorithm [18] and the Newton technique [19]. After training the neural networks, the optimized weights were optimized using the metaheuristic algorithm based on the improved shark smell optimization (ISSO) technique. The proposed method was evaluated in a real solar energy production case.

In [20], a photovoltaic power forecasting model is based on the combination of the stationary wavelet transform, an LSTM network, and a deep neural network. First, the stationary wavelet transformation was used to fix the high fluctuation and the non-stationary behavior of the input data. The stationary wavelet transformation allows the transformation of the original photovoltaic power data to wavelets which makes the data processible and manageable. Second, an ensemble of four LSTM networks was used to extract temporal features of the input data. The extracted features were reconstructed using the inverse stationary wavelet transformation. Third, statistical features were extracted from the input data by calculating many features such as the Mean, Standard Deviation, Variance, Skewness, and Kurtosis. The statistical features, the reconstructed data from the LSTM network ensemble, and the temperature data were combined and used to train the deep neural network to generate power prediction. The proposed method was evaluated for horizon forecasting but it can be adapted for multi-step forecasting based on the resolution of the available input data.

A solar energy forecasting method was proposed in [21] based on combining the LSTM network with a convolutional neural network. The LSTM network was first used for temporal features extraction and the convolutional neural network was then used for the extraction of the spatial features. Experimental results have shown that extracting temporal features and then extracting spatial features is more effective than extracting spatial features and then extracting temporal features. The proposed model was compared to existing models based on a single network either Convolutional Neural Network or LSTM network and presented superior performance.

Lin et al. [22] proposed the use of a temporal convolutional neural network for solar energy forecasting. The temporal convolutional neural network is an improved convolutional neural network used for temporal data processing. It is composed of a combination of regular convolution layers, dilated convolution layers [23], and residual connection [24]. A temporal convolutional neural network has a hierarchical architecture with several hidden layers that have the same size as the input layer. This type of convolutional neural network was designed for autoregressive prediction with a long memory. The proposed method proved its efficiency compared to regular neural networks such as multi-layer feedforward neural network, LSTM neural network, and GRU neural network.

The majority of the aforementioned techniques are intended for processing historical data for energy power forecasting. Generally, solar energy production is not stationary and not predictable and it is challenging to process it. In this work, we propose to use the weather condition as additional input data to generate more trusted predictions.

III. Proposed Method

We outline the suggested strategy for solar energy forecasting in this section, which combines a complex-valued autoencoder and an LSTM neural network. In the first subsection, the complex-valued autoencoder will be detailed. In the second subsection, the background of the LSTM neural network will be presented and detailed. The last subsection will be reserved for explaining the proposed method for solar energy forecasting.

A. Complex Valued Autoencoder

Complex valued autoencoders are the same as autoencoders but with an input, weights, and a mapping function in the complex space. A complex space variable has two parts, one of which is imaginary, and a real part. Assuming a variable x, real part a, and the imaginary b. An example of complex variable can be represented as Eq. (1).

$$x = a + jb \tag{1}$$

Variables in the complex space have more information. A complex-valued autoencoder can be used to process more complex data without raising the computational complexity of the model. Generally, an autoencoder consists of an input layer, a hidden layer, and an output layer. It is used for data reconstruction by regenerating the input data in the output with a minimum error. A complex-valued autoencoder takes as input a real value Re and an imaginary value Im. A combination function is used; C was used to both values to generate the input of the autoencoder. Fig. 1 presented the structure of a complex-valued autoencoder. The autoencoder has two main processes, the encoding process, and the decoding process. The encoding process compresses the data through the hidden layer. The decoding process explodes the data size to reconstruct the input data while presenting more reliable features.

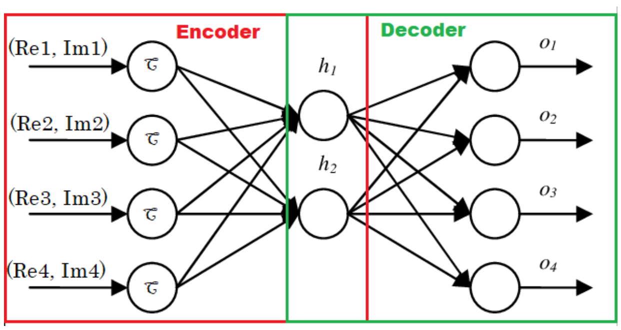

Fig. 1. Complex-valued autoencoder.

Generally speaking, the encoding process is a mapping function that takes the input X and generates an output Y with a size less than the input. The mapping function can be computed as Eq. (2).

$$Y = f\,(X) = E(wX + b_e) \tag{2}$$

Where w is the weights matrix and the bias vector b_e is $\in \mathbb{C}^n$ of the neuron connections. E is a nonlinear activation function. All variables are presented in the complex space. The decoding process is an inverse mapping function that takes Y as input and reconstructs the input data X'. The decode function can be computed as Eq. (3).

$$X' = f'(y) = D(w'Y + b_d) \tag{3}$$

For the encoding process, the radial basis function (RBF) was proposed as a non-linear activation function. The RBF is a very useful function for time-series prediction and approximations. The RBF activation function with complex variables can be computed as Eq. (4).

$$\phi_k(x_i) = \exp(\frac{-j\|x_i - c_h\|^2}{2\sigma_k^2}) \tag{4}$$

Where x_i is the hidden layer's h^{th} neuron's center is designated as c_h and the σ_k^2 is the square of the variance of this neuron. $\|x_i - c_h\|$ define the Euclidian distance between the input data and the center of the hidden layer.

For the output layer, the sigmoid function was proposed as an activation function. The sigmoid function is a bounded function between zero and one. Therefore, it is very useful for probability prediction. Besides, the sigmoid function is differentiable, and the slope can be found between every two points. The sigmoid activation function can be computed as Eq. (5).

$$\phi_k(x_i) = \frac{1}{1+e^{jx_i}} \tag{5}$$

In summary, the proposed complex-valued autoencoder has three layers, an input layer, a hidden layer, and an output layer. For the hidden layer input, the RBF activation function was used. For the output layer, the sigmoid function was used. The input values were concatenated through the C function to provide the complex representation of the input. All weights, activations, and biases were presented in complex space.

B. LSTM Neural Network

The LSTM neural network is a recurrent neural network variant with better temporal data processing. LSTM is very useful for long-term memory which is very useful for time series forecasting. In addition, the LSTM allows avoiding the gradient vanishing problem through processing longer input sequences. It is composed of an input gate, an output gate and a forget gate. As the same as recurrent neural networks, LSTM takes into account the previous time step data value. The input gate controls as to which features are important and should be let through the network. The output gate decides which features that will be pushed to the next layer. The forget gate decides which features to reject. The architecture of an LSTM unit is presented in Fig. 2. An LSTM unit can add and remove features to the current state $S^{(t)}$. Adding features can be performed through the input state and removing features can be performed through the forget gate. The output of the unit is filtered using an activation function (tanh).

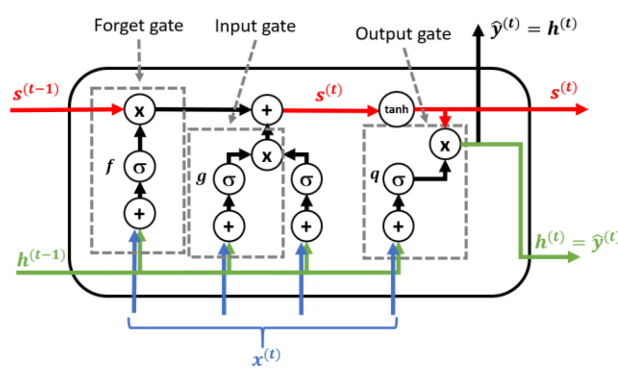

Fig. 2. LSTM neural network unit.

C. Proposed Approach for Solar Energy Forecasting

Solar energy forecasting is based on historical time series processing with consideration to other factors such as weather conditions and the solar panels' condition. Considering that the solar panel produces the maximum possible power, it remains the weather condition to focus on for a trusted prediction on power generation.

The primary goal of the suggested approach was to merge the time-series through the complex-valued autoencoder and use the reconstructed single to train the LSTM neural network for solar energy forecasting. The LSTM neural network learns temporal features according to weather conditions and predicts solar energy production.

The proposed LSTM neural network is composed of three levels of LSTM units. All levels have the same dimension as the input. The proposed LSTM neural network is presented in Fig. 3.

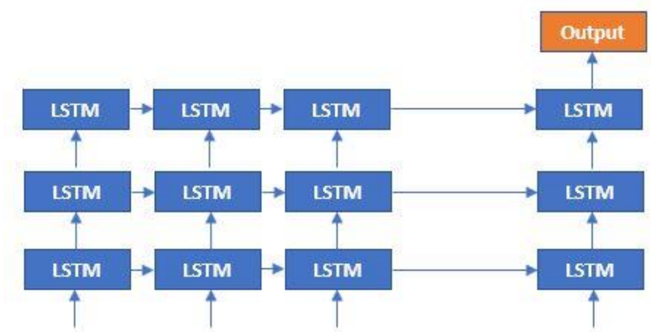

Fig. 3. Proposed LSTM neural network for solar energy forecasting.

In this work, we proposed the combination of a complex-valued autoencoder and an LSTM neural network. The complex-valued autoencoder takes as input the historical time series and the weather conditions. The input data were reconstructed in the output while more features were extracted. The output of the autoencoder was pushed to the LSTM neural network. First, the complex-valued autoencoder was trained separately and then the LSTM neural network. Then, the pretrained complex-valued autoencoder was connected to the LSTM neural network and both networks were trained jointly and considered as a single network. The flowchart of the proposed approach is presented in Fig. 4.

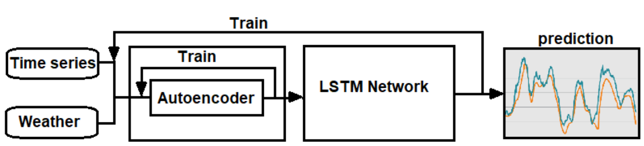

Fig. 4. Proposed approach for solar energy forecasting.

IV. Experiments and Results

All experiments of this work were performed on a desktop with a Linux operating system equipped with an Intel i7 CPU and an Nvidia GTX960 GPU. All models were developed based on the keras deep learning framework. The training data was collected from the Fingrid open data [25]. The collected data was updated hourly. The historical time series and the weather conditions were estimated from a solar power facility installed in Finland. The facility has a total capacity of 1 megawatt per hour. The data was downloaded in the CSV format. The training data was normalized between zero and one based on the min-max normalization technique. Data normalization allows the comparison of the obtained performances without taking into account the capacity of the solar power facility. The data were filtered by eliminating power values at night and on cloudy days. 60% of the data was used for training, 10% for validation, and 30% for testing after dividing it into three sets.

The proposed complex-valued autoencoder was trained using the gradient descent algorithm with a learning rate of 0.002 and a weight decay of 0.002. It was trained and then its layers were frozen and used for the training of the LSTM neural network. The LSTM neural network was trained using gradient descent with momentum with a learning rate of 0.001 and a weight decay of 0.005. There was a 0.9 fixed momentum.

For the evaluation of the proposed approach, three error metrics were proposed. The mean absolute error (MAE) [26], root-mean-square error (RMSE) [26] and mean absolute percentage error (MAPE) [27] were proposed as evaluation metrics. The MAE can be computed as Eq. (6).

$$MAE\ (y,x) = \frac{1}{N}\sum_{n=1}^{N}|y_n - x_n| \qquad (6)$$

Where N is the number of samples of the time series. y is the predicted time series and x is the measured time series. The RMSE can be computed as Eq. (7).

$$RMSE\ (y,x) = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_n - x_n)^2} \qquad (7)$$

The MAPE can be computed as Eq. (8).

$$MAPE\ (y,x) = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{y_n - x_n}{y_n}\right| \qquad (8)$$

The choice of the evaluation metrics was not arbitrary because the comparison between those errors can provide more information on the forecasting system. For example, if the RMSE is higher than the MAE with a big margin then the forecasting system has a big deviation to the measured power. If the RMSE is approximately equal to the MAE then the forecasting system has a small deviation to the measured power. The MAPE is used to measure the robustness of the proposed approach for energy forecasting. A low MAPE means that high performance was achieved.

To avoid an overfitting problem, an early stopping condition was applied. The training stops if the RMSE does not change for 50 consecutive training iterations. The proposed approach was used to predict a day ahead forecast horizon of 24h to 48h. The proposed approach has an alternative training process by pretraining the complex-valued autoencoder then using its pretrained weights in the training of the LSTM neural network. While training the LSTM neural network, the complex-valued autoencoder was used for data reconstruction and its weights are not updated. The LSTM neural network was initialized using samples of two previous time steps.

Calculating the proposed error metrics was done in order to evaluate the proposed approach. Table I presents the obtained error values. The results demonstrated the effectiveness of the suggested strategy. The obtained RMSE is 0.167 which is higher than the MAE with a margin of 0.074; it means that the forecasting approach has a good deviation from the measured power. The achieved MAPE of 0.028 proves that the proposed approach can generate trusted predictions with a low error.

TABLE I. OBTAINED ERRORS FOR THE PROPOSED METHOD

Error metric	Complex valued autoencoder + LSTM neural network
MAE	0.093
RMSE	0.167
MAPE	0.028

The proposed approach has achieved good results based on the obtained error values. A comparison against state-of-the-art models is presented in Table II. Among all methods, the proposed method has a better prediction effect with a better deviation to the measured power. Compared to the state-of-the-art methods, the proposed method has the lowest MAPE which means that it has the best prediction accuracy and can be considered a reliable forecasting system. More accurate prediction means that the integration cost of solar energy in the grid is reduced and fewer problems can be encountered.

TABLE II. COMPARISON AGAINST STATE-OF-THE-ART METHODS FOR SOLAR ENERGY FORECASTING

Method	MAE	RMSE	MAPE
Hybrid neural network [16]	0.17	0.32	0.067
LSTM-CNN [21]	0.124	0.184	-
TCNN [22]	0.221	0.621	0.042
RNN [28]	0.485	0.84	0.03
Proposed	0.093	0.167	0.028

Reliable forecasting values allow the control of solar power injection in the grid safely and that reduces pollution and using fuel power stations. Fig. 5 presents a comparison between state-of-the-art methods and the proposed method in 18 days of January 2023. As shown in Fig. 5, the proposed method (com-Auto-LSTM) has the lowest error compared to the target values. From day 6 to day 13 the energy production is zero and this may be caused by snowfall. Since the proposed method considers weather conditions the predicted power was very close to the target.

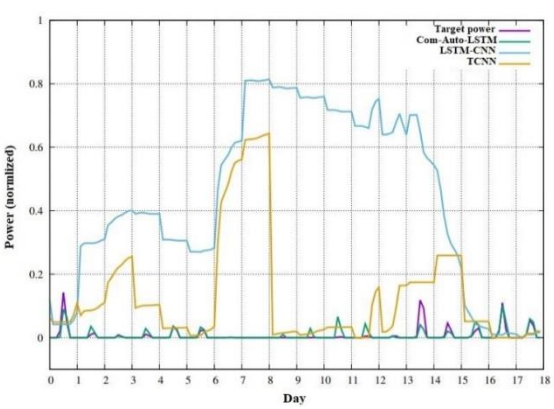

Fig. 5. Comparison against state-of-the-art methods and the proposed method in 18 days of January 2023.

Based on the obtained results, the proposed approach has proved its efficiency. The proposed approach takes advantage of features extraction and combination of the complex-valued autoencoder and the temporal features extraction of the LSTM neural network. The forecasting power of the LSTM neural networks has been improved by combining the historical time series of solar energy production with weather conditions (temperature, humidity, and cloud variation). Through the ability of the proposed complex-valued autoencoder to process complex data with multiple inputs, the input signal of the LSTM neural network was reconstructed by combining the different features. Overall, the proposed method has shown its efficiency for solar power forecasting through the ability to combine historical time series with weather conditions.

V. CONCLUSIONS

Solar power is considered clean energy that can be used to reduce pollution and power costs. However, integrating a solar power generator into the grid is very challenging due to many problems such as high voltage injection and power stability. Energy forecasting is considered as a solution for the safe integration of solar power energy into the grid. In this study, we suggested a neural network-based method for forecasting solar energy that combines two neural network models. First, a complex-valued autoencoder was used to combine the historical time series of power generation with weather conditions. Second, the reconstructed signal was used to train an LSTM neural network. The proposed LSTM neural network was composed of 3 levels of LSTM units with the same size as the input data. The proposed approach was tested and trained using the Fingrid open data. The obtained findings have demonstrated the effectiveness of the suggested strategy, which has a low MAPE when compared to cutting-edge techniques. Besides, the proposed method has a good deviation from the measured power. A comparison against existing models on 18 days of January 2023 has shown that the proposed method has the lowest prediction error. The evaluation has demonstrated the suggested method's high performance, which is attributable to the usage of a combination of an LSTM neural network and a complex-valued autoencoder.

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