Çukurova Üniversitesi Mühendislik Fakültesi Dergisi
Çukurova University Journal of the Faculty of Engineering
ISSN: 2757-9255 CİLT/VOLUME: 39 SAYI/ISSUE: 3 EYLÜL/SEPTEMBER 2024

Time Series Installed Capacity Forecasting with Deep Learning Approach for Türkiye

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Article Info
Received : 25.07.2024
Accepted : 27.09.2024
DOI: 10.21605/cukurovaumfd.1560142

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Keywords
Deep learning
Future prediction
Installed capacity
Time series

How to cite: *ALTIPARMAK, Z., AKSU, İ.Ö., (2024). Time Series Installed Capacity Forecasting with Deep Learning Approach for Türkiye. Cukurova University, Journal of the Faculty of Engineering, 39(3), 709-718.*

ABSTRACT

Deep learning methods have been developed to solve different problems due to the complex nature of real-world problems. Accurate future forecasting of a country's installed capacity is also crucial for developing a good energy sustainability strategy for the country. In this paper, three different time series forecasting methods are used for forward forecasting of installed capacity: Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). Installed power values for the years 1923-2021 were used in the study. Then, future forecasts are made until 2030. The GRU model achieved the best RMSE in the testing phase compared to the LSTM and CNN models. Although CNN is successful during training, it has a higher RMSE during testing compared to GRU. While all models predict a potential increase in electricity capacity by 2030, GRU and LSTM predict a more significant increase up to this point compared to CNN.

Türkiye için Derin Öğrenme Yaklaşımı ile Zaman Serisi Kurulu Kapasite Tahmini

Makale Bilgileri
Geliş : 25.07.2024
Kabul : 27.09.2024
DOI: 10.21605/cukurovaumfd.1560142

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Anahtar Kelimeler
Derin öğrenme
İleri tahmin
Kurulu güç
Zaman serileri

Atıf şekli: *ALTIPARMAK, Z., AKSU, İ.Ö., (2024). Time Series Installed Capacity Forecasting with Deep Learning Approach for Türkiye. Cukurova University, Journal of the Faculty of Engineering, 39(3), 709-718.*

ÖZ

Gerçek dünya problemlerinin karmaşık yapısı nedeniyle farklı problemleri çözmek için derin öğrenme yöntemleri geliştirilmiştir. Ülkelere ait kurulu gücün doğru şekilde ileri tahmini de ülkenin iyi bir enerji sürdürülebilirliği stratejisi geliştirilmesi için büyük önem taşımaktadır. Bu makalede, kurulu gücün ileri tahmini için üç farklı zaman serisi tahmin yöntemi kullanılmıştır: Kapılı Tekrarlayan Birim (GRU), Evrişimli Sinir Ağı (CNN) ve Uzun Kısa Süreli Bellek (LSTM). Çalışmada 1923-2021 yıllarına ait kurulu güç değerleri kullanılmıştır. Daha sonra 2030 yılına kadar gelecek tahminleri yapılmıştır. GRU modeli, test aşamasında LSTM ve CNN modellerine göre, en iyi RMSE'yi elde ederek en doğru model olarak ortaya çıkmıştır. CNN eğitim sırasında başarılı olmasına rağmen, test sırasında GRU'ya kıyasla daha yüksek RMSE sergilemiştir. Tüm modeller 2030 yılına kadar elektrik kapasitesinde potansiyel bir artış öngörürken GRU ve LSTM, CNN'e kıyasla bu noktaya kadar daha belirgin bir artış öngörmüştür.

1. INTRODUCTION

Accurate forecasting of energy production and consumption is crucial for effective energy planning and management. Artificial Neural Networks (ANNs) are preferred for such forecasting problems due to their ability to model complex relationships in data. However, the advent of deep learning techniques has significantly advanced this field. Deep learning methods, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU), have demonstrated superior performance in handling complex and high-dimensional data, leading to more accurate and robust forecasting models. Bilgili et al. [1] focused on forecasting renewable energy generation (REG) using two methods: ANFIS with FCM, and LSTM neural networks. Both models performed well, with LSTM showing particular strength in handling daily fluctuations in energy data. The study highlights the effectiveness of these methods for short-term REG forecasting in Türkiye.

Similarly, Sun et al. [2] used RNN and CNN models for real-time turbine power forecasting with 719 days of DCS data. The RNN model provided the best balance of accuracy and efficiency, outperforming traditional models. Their findings highlight the potential of deep learning for enhancing turbine power prediction and aiding in turbine control and predictive maintenance. Expanding on these approaches, Wan et al. [3] proposed a CNN-LSTM model that combines CNN and LSTM methods for short-term electrical load forecasting. In addition, they improved their work to deal with the information loss in long time series data and added attention mechanisms. As a result, the proposed model has led to improvements in cogeneration systems. When the results are analyzed, it is evident that better prediction results are obtained compared to traditional LSTM models. Meanwhile, Agga et al. [4] introduced a CNN-LSTM model for PV power forecasting in Rabat, Morocco, combining CNN's spatial analysis with LSTM's temporal analysis. This hybrid approach outperformed traditional methods, offering improved accuracy and stability, with potential applications in optimizing power systems and future research in wind power and energy cost forecasting.

Chang et al. [5] introduced the TESDL method for forecasting renewable energy, enhancing the integration of large-scale photovoltaics into the grid. Their deep learning-based model improved accuracy and managed energy volatility effectively, offering better efficiency and robustness, which could reduce costs for photovoltaic farms. Anu Shalini et al. [6] developed a grid-connected hybrid system with solar and wind inputs, using a modified Z source converter and also battery storage. They employed a CNN-BiLSTM deep learning algorithm for power prediction, achieving low harmonic distortion and consistent power supply. The ANN controller and SVPWM method were most effective in reducing harmonic currents and managing energy. Al-Ali et al. [7] developed a solar energy forecasting model using a hybrid CNN-LSTM-Transformer approach. They enhanced accuracy and reduced complexity through clustering and self-organizing maps for feature selection. Their model outperformed existing methods, showing high accuracy in solar power predictions and potential for long-term forecasting and broader energy applications. Additionally, Sözen et al. [8] developed equations for prediction of Türkiye's net energy consumption (NEC) using Artificial Neural Network. They utilized two models. Both models showed high accuracy in training and testing, indicating that ANN can effectively predict future energy consumption. The study highlights the flexibility of the ANN technique and its potential to aid in energy policy planning by providing mathematical equations for future consumption trends. Warkad et al. [9] developed an ANN-based method for predicting day-ahead electricity nodal prices, improving decision-making by managing price volatility. In the IEEE 30-bus system and Indian market simulations, the approach demonstrated accurate predictions using a multilayer feed-forward neural network with back propagation. The Levenberg-Marquardt algorithm provided fast convergence and low errors, making it practical for developing countries to enhance market strategies.

Olcay et al. [10] developed models to predict how environmental factors impact solar power plants (SPPs). Using data from a Turkish solar plant, they applied Random Forest Regression (RFR) and LSTM networks. The LSTM model outperformed RFR in accuracy, showing better capability in handling complex dependencies, thus improving the reliability of energy forecasts in SPPs. Aksu [11] used the LSTM networks method to predict short-term solar irradiance in Türkiye, highlighting its solar potential. The study compared LSTM with ANN and found that LSTM offered more accurate predictions, especially at peak values. Aksu suggested that future research could benefit from combining LSTM with CNN for improved accuracy.

Installed power forecasting in the energy sector plays an important role in strategic planning and operational decisions. Recently, a lot of work has been done on advanced forecasting techniques to improve forecasting accuracy in this area. Luo et al. [12] introduced a new grey prediction model that enhanced the forecasting of wind power installed capacity (WPIC). They combined Particle Swarm Optimization (PSO) with parameter optimization to improve accuracy. Their model outperformed traditional grey models, although they noted some limitations, including the influence of abnormal data points and the need for further parameter refinement. Li et al. [13] compared four forecasting models for coal-fired power installed capacity in China: ARIMA, NMGM, GM-ARIMA and MGM. Their results showed high forecasting accuracy, with a predicted slower growth rate but higher annual added capacity compared to the previous decade. They recommended improving thermal power utilization and increasing renewable energy to balance growth and reduce carbon emissions. Chen et al. [14] introduced a novel grey model with fractional order accumulation, abbreviated as FOGM (1,1), to accurately forecast China's installed generation capacity, which includes wind power, hydroelectric, nuclear, and thermal. After calibrating model using data from 2000 to 2015, they used it to predict the capacity from 2016 to 2020. Their findings suggest that the FOGM (1,1) model is well-suited for this task, showing that wind power capacity in China is expected to rapidly increase in the coming decades, playing an increasingly significant role in the energy mix.

Recently, deep learning methods have been frequently used for solving complex systems. In this study, three different methods popular in the field of deep learning are used to solve a real-time problem. The LSTM method is one of the recurrent method types. The advantage of this method is that it can memorize previous states. This allows it to learn long-term dependencies and model structures. Compared to the LSTM, the GRU method has a faster training time and lower computational effort. The CNN method is successful in capturing similar patterns in consecutive time steps. This study builds on these developments by investigating deep learning techniques to estimate Türkiye's installed capacity. By incorporating and extending methods used in recent studies, we aim to enhance the accuracy and reliability of energy forecasts, thereby contributing to more effective energy planning and management.

2. METHODS

2.1. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks represent a specialized approach within deep learning for handling and modeling sequential data. Unlike standard Recurrent Neural Networks (RNNs), which often struggle with long-term dependencies, LSTMs are designed to address these challenges effectively. The fundamental unit of an LSTM is the memory cell, which preserves a vector of internal state information to retain past data. Each memory cell is controlled by three distinct gates: the forget gate, which determines the portion of the past data to be discarded; the input gate, which controls the extent to which new data is incorporated into the memory cell; and the output gate, which manages how the stored information is used to produce the final output. This structure enables LSTMs to excel in tasks such as time series prediction, language modeling, text classification, and translation. As a result, LSTMs have become integral to both advanced research and practical applications in deep learning. LSTM networks rely on several key components that collaboratively manage and process sequential data. These components include the input gate, forget gate, hidden state, cell state, candidate cell state and output gate. Each component plays a role in maintaining and updating the network's memory, which is a key building block for the method's success.

Forget gate

The forget gate decides how much influence past information has on the cell state. The extent to which this information is removed from the cell state is decided in this gate structure. It outputs a value between 0 and 1, determining how much of the previous memory is retained. The mathematical expression for the forget gate is given by:

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

here, f_t represents the output of the forget gate, W_{xf} , W_{hf} and b_f are the weight and bias parameters, h_{t-1} is the hidden state from the previous time step, and x_t is the current input. σ is a sigmoid function, σ = 1 denotes keeping something, and σ = 0 denotes getting rid of it.

Input gate

The input gate manages the amount of new information that is integrated into the cell state. It outputs a value between 0 and 1, specifying the proportion of new data to be added. The mathematical expression for the input gate is:

$$i_t = \sigma(W_{xi}\, x_t + W_{hi}\, h_{t-1} + b_i) \quad (2)$$

where i_t represents the output of the input gate, and W_{xi}, W_{hi} and b_i are the corresponding weight and bias parameters.

Candidate cell state

This component determines which new information will be incorporated into the cell state. It combines new data with the input gate's output to update the memory. The formula for the candidate cell state is:

$$z_t = \tan h\ (W_{xz}\, x_t + W_{hz}\, h_{t-1} + b_z) \quad (3)$$

here z_t represents the candidate cell state, while W_{xz}, W_{hz} and b_z are the weight and bias parameters involved in the memory update process.

Cell state

The cell state represents the updated memory, which is computed by combining the previous cell state, the input gate's contribution, the candidate cell state and the forget gate's output. The formula for the updated cell state is:

$$c_t = f_t * c_{t-1} + i_t * z_t \quad (4)$$

where c_t denotes the updated cell state and c_{t-1} is the previous cell state.

Output gate

The output gate determines how the cell state information is used to generate the network's output. It produces a value between 0 and 1, which influences the final output. The formula for the output gate is:

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (5)$$

where o_t is the output of the output gate, and W_{x0}, W_{ho} and b_o are the weight and bias parameters.

Hidden state

The hidden state conveys the information from the cell state to the subsequent layers of the network. It is computed using:

$$h_t = o_t * \tan h\,(c_t) \quad (6)$$

where h_t represents the hidden state at the current time step. The structure of the LSTM method is illustrated in Figure 1. LSTM is designed to eliminate the problem of vanishing gradients, which is a major problem for RNNs. To solve this problem, the method uses gates and a special cell structure as shown in the figure. The equations of the gates are given visually in the figure, which increases the comprehensibility of the structure of the method. These gates and the cell state in the structure of the LSTM enable the model to process long-term information efficiently and effectively in the learning process. These features make the LSTM a powerful tool for sequential data and time series analysis.

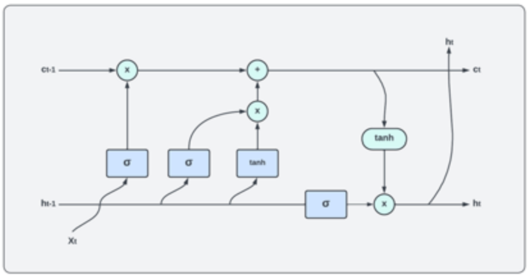

Figure 1. The structure of the Long Short-Term Memory (LSTM) neural network.

2.2. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a specialized class of deep neural networks designed to process and analyze spatial data. They excel in tasks such as image recognition and classification due to their ability to automatically and adaptively learn spatial hierarchies of features. A typical CNN comprises several core components: convolutional layers, which apply learnable filters to extract spatial patterns; activation functions, such as ReLU, which introduce non-linearity to improve learning; pooling layers, which downsample feature maps to reduce dimensionality and enhance computational efficiency; and fully connected layers, which integrate learned features for high-level reasoning and classification. By leveraging these components, CNNs have revolutionized computer vision and are also making significant strides in other fields, such as audio processing and natural language understanding. The basic structure of the CNN is shown in Figure 2. The overall architecture of a CNN structure usually consists of a number of layers, where each layer has the ability to learn and extract different aspects of the data. The basic components of a CNN, as shown in the figure, include: pooling layers, fully connected layers and convolutional layers. Convolutional layers learn local features by applying filters (kernels) on the input data. These processes capture patterns and features in each region of the data. Pooling layers reduce the feature maps from the convolutional layers and summarize the most important information. This reduces the computational cost of the model and helps prevent overlearning (overfitting). Fully connected layers use high-level features for classification or regression tasks. These layers make the final predictions using the network's learned features.

This architecture of CNN is designed to work effectively with high-dimensional inputs such as visual data. In particular, convolutional layers are powerful for capturing local relationships within the data, allowing the network to learn various features of the images. Pooling layers improve computational efficiency, by reducing the data size and strengthening the generalization capacity of the model. Fully connected layers perform final classification or prediction using these learned features. These layer structures of the CNN model enable the network to extract features with high performance, making the method applicable in many different fields.

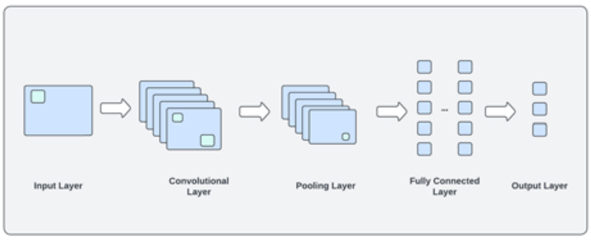

Figure 2. Basic structure of a Convolutional Neural Network (CNN).

2.3. Gated Recurrent Units (GRU)

The Gated Recurrent Unit (GRU) is a simplified variant of the Long Short-Term Memory (LSTM) network, designed to address the vanishing gradient problem and improve the efficiency of RNNs in modeling sequential data. The GRU accomplishes this through its gating mechanisms, specifically the update gate and the reset gate, which manage the flow of information through the network. The following equations describe the functioning of these gates and the overall update of the hidden state in the GRU:

Update Gate

$$f_t = \sigma(W_{xf}\, x_t + W_{hf} h_{t-1} + b_f) \tag{7}$$

The update gate f_t determines the extent to which the previous hidden state h_{t-1} should be preserved and passed to the current hidden state h_t. It combines the current input x_t with the previous hidden state h_{t-1}, applying a sigmoid activation function σ to regulate the update. Where, W_{xf} and W_{hf} are the weight parameters, and b_f is the bias parameter.

Reset Gate

$$r_t = \sigma(W_{xr} x_t + W_{hr} h_{t-1} + b_r) \tag{8}$$

The reset gate r_t controls the degree to which the previous hidden state h_{t-1} contributes to the candidate activation z_t. By modulating the influence of the past state, r_t allows the model to effectively "forget" irrelevant information, making room for more pertinent data. Here W_{xr} and W_{hr} are the weight parameters, and b_r is the bias parameter.

Candidate Activation

$$z_t = \tanh(W_{xz} x_t + W_{hz}(r_t * h_{t-1}) + b_z) \tag{9}$$

The candidate activation z_t represents the proposed update to the hidden state based on the current input x_t and the reset gate's modulation of the previous hidden state. The hyperbolic tangent function tanh is applied to ensure that the candidate activation values remain within a bounded range. Where, W_{xz} and W_{hz} are the weight parameters, and b_z is the bias parameter.

Hidden State Update

$$h_t = f_t * h_{t-1} + (1 - f_t) * z_t \tag{10}$$

Finally, the hidden state h_t is updated by a linear interpolation between the previous hidden state h_{t-1} and the candidate activation z_t , controlled by the update gate f_t. This equation ensures that the network can retain relevant past information while incorporating new information as needed. The architecture of the GRU cell is demonstrated in Figure 3. As shown in the figure, the GRU architecture is similar to the LSTM architecture. GRU's cell architecture, together with the gates that control how information is stored and updated, allows for learning long-term dependencies, as in the LSTM method. However, GRU's structure is designed to provide simpler and faster computations, making it preferable for large data sets and time series problems.

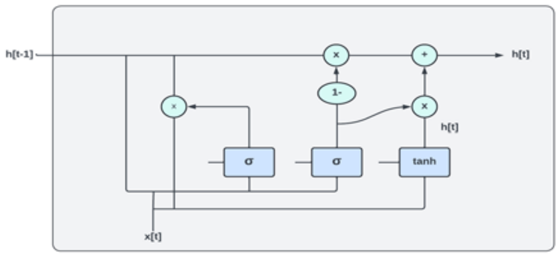

Figure 3. Structure of a GRU cell

3. RESULTS AND DISCUSSIONS

In this study, we analyzed the performance of GRU, CNN, and LSTM models on a dataset [15] of Türkiye's annual installed capacity spanning from 1923 to 2021, consisting of 99 observations. The dataset was preprocessed by applying 0-1 normalization, scaling each value between 0 and 1 using the formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Dataset was divided into 79 data points (approximately 80%) for training and 20 (approximately 20%) for testing, with predictions extended 9 steps ahead to 2030. To effectively capture temporal dependencies, a look-back period of 3 was utilized, meaning that each model predicted future values based on the three preceding data points, resulting in the first three data points being excluded from the predictions. As given in Table 1, the results revealed that the GRU model achieved the lowest RMSE during testing, with a value of 2.51, outperforming both CNN and LSTM. The CNN model had an RMSE of 5.02 during testing and performed better during training with an RMSE of 0.49. The LSTM model had the 2.78 RMSE values during testing and 0.74 during training.

Table 1. Estimation results using different deep learning methods

Model	RMSE (Training phase)	RMSE (Testing phase)
GRU	0.67	2.51
LSTM	0.74	2.78
CNN	0.49	5.02

These results show that the look-back mechanism significantly improves the model's ability to predict future values. The look-back mechanism is a strategy that allows the model to remember patterns and information from past data. Through this mechanism, the model can better understand and predict current and future situations using past data. Especially in time series analysis, effective processing of historical data plays a critical role in improving the accuracy of future forecasts. Therefore, the capacity of the model to learn long-term dependencies by taking into account historical data directly affects the accuracy of forecasts. In particular, the GRU (Gated Recurrent Unit) model shows the highest forecast accuracy among the other models tested, suggesting that the GRU effectively uses this look-back mechanism. The gates in GRU's design are optimized to appropriately store and update historical information. This structural advantage enhances the model's ability to extract meaningful information from historical data and use this information in future predictions. As a result, GRU's high forecast accuracy clearly demonstrates the effectiveness of the look-back mechanism and the model's capacity to learn long-term dependencies. This highlights why the GRU is such a powerful tool in time series data and other sequential data analysis.

Table 2. Forecast results for Türkiye's installed capacity data (GW) between 2022 and 2030

Years	CNN	LSTM	GRU
2022	98.45	105.56	105.95
2023	100.67	110.51	111.05
2024	101.95	115.59	116.52
2025	102.90	121.23	122.43
2026	104.30	126.62	128.21
2027	105.49	132.18	134.23
2028	106.69	137.89	140.38
2029	107.93	143.52	146.58
2030	109.14	149.21	152.89

Following the evaluation of the models' performance, the analysis was extended to forecast future electricity capacity up to the year 2030, with the results being presented in Table 2. Lower values were consistently predicted by the CNN model compared to both LSTM and GRU, with the predicted capacity in 2030 reaching 109.14 GW. In contrast, slightly higher future capacities were forecasted by the LSTM and GRU models, with a peak value of 149.21 GW in 2030 being predicted by LSTM, and 152.89 GW in 2030 being predicted by GRU. These predictions, which examine the future trends of electricity generation capacity, reveal a clear development until 2030. Projections by three different models-GRU, LSTM and CNN-generally signal a potential plateau in electricity generation capacity by 2030. However, each of these models exhibits marked differences in forecasts, reflecting annual growth trends in a different way. In the period up to 2030, the observed gradual increase in electricity generation capacity points to an overall sustained growth. However, the trend and pace of this growth differ depending on the structural features of the model used and the way it processes temporal information.

The prediction results of the CNN model for the training and testing phase are shown in Figure 4. The CNN model closely follows the actual data during both the training and testing phases. Forward prediction results up to 2030 are also given in this figure. In the future prediction segment, there is a slight divergence, with the CNN model predicting a more gradual increase in capacity compared to the actual trend. This suggests that while the CNN model captures the general trend effectively, it may slightly underestimate the rate of growth in the later years.

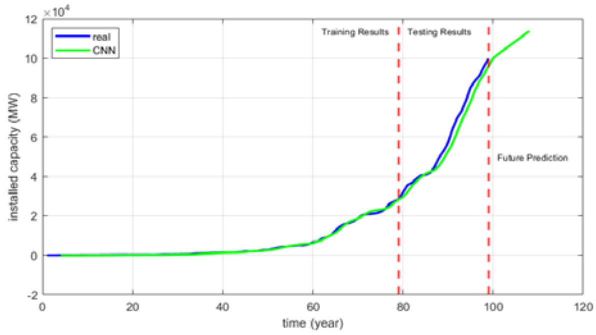

Figure 4. Results for the real and predicted values with CNN model.

Figure 5. illustrates the LSTM model's results. The LSTM model exhibits a strong correlation with the real data throughout the training and testing phases, mirroring the actual trend with high accuracy. In the future prediction period, the LSTM model shows a more pronounced increase in capacity, aligning closely with the observed trend.

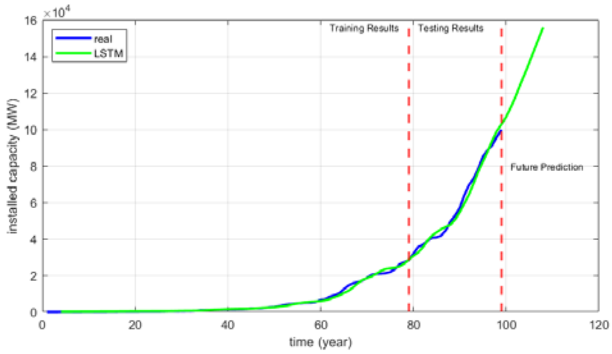

Figure 5. Results for the real and predicted values with LSTM model.

Figure 6. presents the GRU model's performance. The GRU model demonstrates a very close fit to the real data during both training and testing phases, like the LSTM model. In the future prediction section, the GRU model forecasts a continued and consistent increase in capacity, which aligns well with the actual trend. This result suggests that the GRU model not only accurately captures the historical data but also provides reliable future predictions, potentially offering the most stable performance among the three models.

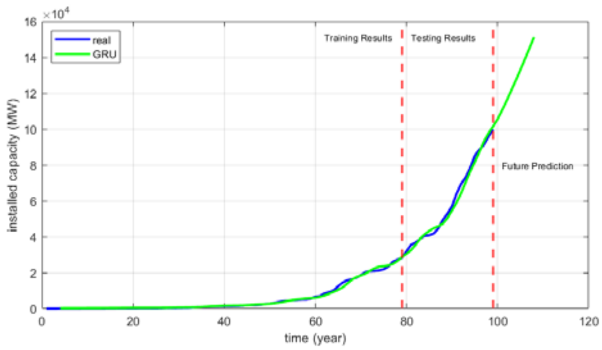

Figure 6. Results for the real and predicted values with GRU model.

The GRU and LSTM models present a steeper growth curve compared to the CNN model, meaning that these models predict a faster capacity growth. This trend is due to the fact that GRU and LSTM process temporal information more intensively and learn long-term dependencies more efficiently. This suggests that these models tend to predict a sharper and faster increase in the future based on past data. The CNN model, on the other hand, processes temporal information differently and tends to better capture local patterns and short-term trends, thus predicting a smoother and more gradual increase. This approach of the CNN allows it to take more explicit account of short-term fluctuations and local characteristics in the time series data, but it is more conservative on long-term trends.

These differences reflect the underlying structures and methodologies of how each model processes temporal information. The GRU and LSTM models predict future growth potential more aggressively, thanks to their capacity to learn long-term dependencies in sequential data, while the CNN model's approach, which prioritizes local characteristics and short-term patterns, leads to a more cautious growth forecast.

While the projections of these three models suggest that a plateau in electricity generation capacity is likely to be reached by 2030, the different trends presented by each model provide important insights for decision makers. Taking these different trends into account can help develop more comprehensive and flexible strategies for energy planning. Models that aggressively predict long-term growth potential may be suitable for scenarios that require faster capacity expansion, while models that predict a smoother ramp-up may be a better guide for risk management and gradual development plans.

4. CONCLUSIONS

This study assessed the forecasting performance of GRU, CNN, and LSTM models on annual electricity capacity data spanning from 1923 to 2021. The GRU model demonstrated the best performance in terms of predictive accuracy, achieving the lowest RMSE during testing. The CNN model, while performing well during training, showed a higher RMSE during testing compared to the other methods.

The results suggest that the look-back mechanism was effective in capturing temporal dependencies, with GRU proving to be the most robust in predicting future values. All models indicated a potential plateau in electricity capacity by 2030, but GRU and LSTM predicted a more pronounced increase leading up to that year, compared to CNN.

This study highlights the importance of selecting appropriate forecasting models based on their performance in capturing both short-term and long-term trends. The GRU model's superior performance underscores its suitability for accurate predictions in long-term capacity forecasting. Future research could build on these findings by incorporating additional data or exploring hybrid models to further enhance forecasting accuracy and address the nuances observed in these predictions.

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