HYDROPOWER RESERVOIRS WATER INFLOW FORECASTING BASED ON ADVANCED RECURRENT NEURAL NETWORK MODELS

DỰ BÁO LƯU LƯỢNG NƯỚC VỀ HỒ THỦY ĐIỆN DỰA TRÊN MẠNG NƠ-RON HỒI QUY CẢI TIẾN

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Tóm tắt:

Dự báo dòng chảy nước chính xác cho các hồ chứa thủy điện đã trở thành yếu tố cần thiết để quản lý hiệu quả tài nguyên nước và tối ưu hóa hiệu suất vận hành nhà máy. Điều này giúp giảm thiểu tác động tiêu cực của hạn hán và lũ lụt, đảm bảo sản xuất điện ổn định, đồng thời thúc đẩy sử dụng tài nguyên nước hiệu quả. Nghiên cứu này giới thiệu các mô hình mạng nơ-ron nhân tạo tiên tiến nhằm khắc phục những hạn chế của các phương pháp thống kê truyền thống trong việc dự báo dòng chảy nước ở các hồ chứa thủy điện. Để tối ưu hóa hiệu suất mô hình, các kỹ thuật kiểm định chéo (cross-validation) và tìm kiếm lưới (grid search) được sử dụng để xác định các tham số tối ưu của mô hình. Dữ liệu sử dụng trong nghiên cứu này là dòng chảy nước tại hồ chứa thủy điện Sre Pok 4 từ tháng 1 năm 2013 đến tháng 5 năm 2023. Đánh giá hiệu suất mô hình bao gồm các chỉ số chính như Sai số Tỷ lệ Trung bình Tuyệt đối (MAPE), Sai số Trung bình Tuyệt đối (MAE) và Hiệu suất Nash-Sutcliffe (NSE). Kết quả cho thấy mô hình kết hợp CNN-LSTM có thể dự báo dòng chảy nước với MAPE đạt 6,52%.

Từ khóa: dự báo lưu lượng nước, mạng nơ-ron hồi quy, thủy điện, CNN-LSTM.

Abstract:

Accurate water flow forecasting for hydropower reservoirs has become essential for effective water resource management and optimizing plant performance. It helps to mitigate the negative impacts of droughts and floods, ensures stable electricity production, and promotes the efficient use of water resource. This study introduces advanced artificial neural network models designed to address the limitations of traditional statistical methods for water flow forecasting in hydropower reservoirs. To optimize model performance, cross-validation techniques and grid search are employed to identify the best model's parameter. The data used in this study is the water flow in Sre Pok 4 hydropower reservoir from January 2013 to May 2023. The model performance evaluation includes key metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Nash-Sutcliffe Efficiency (NSE). The results show that the combined CNN-LSTM model can predict the water flow with the MAPE of 6.52%.

Keywords: waterflow forecasting, recurrent neural networks, hydropower, CNN-LSTM.

1. INTRODUCTION

Under Vietnam's Eighth National Power Development Plan, the total power generation capacity for domestic demand is expected to reach 150,489 MW by 2030, with hydropower accounting for 19.5% (29,346 MW) [1]. Hydropower remains a cornerstone of Vietnam's electricity supply. The power shortages in northern area of Vietnam were observed during the early summer months of 2023. This was partly attributed to reduced water inflows to hydropower reservoirs compared to previous years. While hydropower is cost-effective and flexible, its production depends heavily on water flow, rainfall, and environmental conditions. To optimize electricity generation, accurately forecasting water inflow to reservoirs is critical. This enables efficient water resource management and supports informed decision-making for hydropower operations, particularly during dry season.

Hydraulic models for calculating river flow typically demand extensive input data, such as topography, rainfall, and inlet or outlet flow rates. Optimizing these models often requires validation against numerous real-world measurements, which can complicate the selection of suitable parameters. When detailed topographic and geomorphological data are unavailable, machine learning models using artificial neural networks offer an alternative approach for predicting hydrological factors and river flow rate.

Several studies have utilized the application of machine learning models for hydrological forecasting. In [2], the LSTM model is used to predict water levels at hydrological stations in Hải Phòng. Based on hourly historical data, water level was forecasted from 1 to 5 hours at the Quang Phục and Cửa Cấm stations [2]. They also developed a recurrent neural network (RNN) based model to forecast the flood discharge of the Da River in Lai Châu one day ahead [3] and predict the flow of the Hồng River at the Sơn Tây station for 1-day, 2-day, and 3-day ahead [4]. The same method is used to predict the water levels downstream of the Thái Bình River, with forecasting intervals of 6, 12, 18, and 24 hours [5,6]; and in the Cấm River in Hải Phòng City, with prediction intervals of 1, 3, and 6 hours [7].

Notably, these models require only past flow rate data, eliminating the need for topographic or surface cover information. However, most rely solely on LSTM or RNN architectures which subject to short-term forecasting steps only.

In this research, we propose an advance reccurrent neural network model by combining the CNN and LSTM architecture to forecast the water flow in hydropower reservoir for longer steps. The combined CNN-LSTM offers several advantages over using either model alone. The subject of this study is the Sre Pok 4 hydropower reservoir. This is a hydroelectric project built on the Sre Pok River, located in the territories of Dak Lak and Dak Nong provinces, Vietnam. Regulating the flow during the dry season for the downstream in Cambodia and generating electricity for the national grid are the main tasks of the Sre Pok 4 hydropower plant. With a total capacity of 80 MW divided between two units, a total reservoir volume of 31 millions m³, and a lake surface area of approximately 375 hectares, the Sre Pok 4 hydropower plant generates an average of about 336 million kWh per year for the national grid [8]. The water flow data is collected from January 1, 2013 to May 30, 2023.

The paper is organized as follow : Section 1 is the literature review. In section 2, the structure and operating principles of CNN and LSTM networks is presented along with the methods for processing input data and training the model. Section 3 presents the forecast results, and finally section 4 is the conclusion.

2. METHODOLOGY

2.1. Convolutional Neural Network (CNN)

Convolutional neural networks (CNNs) are a class of neural network architecture that is well-suited to processing grid-like data such as images and audio, and is capable of feature detection at multiple levels of abstraction.

CNNs improve performance dealing with big datasets, with a lower number of parameters by having feature filters and the possibility to reuse pre-trained weights. A CNN model architecture generally consists of three types of layers, Convolutional layers, Pooling layers and Fully Connected layers. The model structure is visualized in Figure 1.

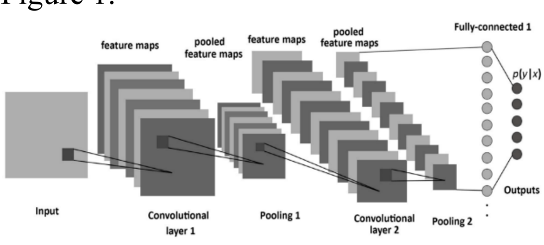

Figure 1. CNN network model structure

2.1.1. Convolutional Layers

The first layers in a convolutional neural network extract features from input data and the most important components are convolutional layers. These layers are compositing filter maps (or convolutional kernels), which are matrices that, via the convolution operation that it executes with the input data, form new feature maps. These feature maps are obtained by weighing components for the input with each of the filter's corresponding coefficients and reducing it. The operation is called convolution.

Filters are applied across various locations of the input data in convolutional layers, which helps reduce the number of weights to train and enhances the model's generalization capability. As the data passes through successive convolutional layers, the network can detect increasingly complex features in the input data. The output becomes multidimensional as it traverses the CNN. To process this data further using other models like LSTMs, it is necessary to convert the multidimensional output into a sequential format before feeding it into the LSTM model.

Additionally, activation functions such as ReLU or tanh are commonly applied after convolutional layers to introduce non-linearity, enabling CNNs to learn more complex patterns and features.

2.1.2. Pooling Layers

Pooling layers are typically placed between convolutional layers and are another component of the CNN architecture. Their primary function is to reduce the spatial dimensions of the data after convolutional layers while retaining essential information. This process decreases computational costs, mitigates overfitting, and enhances the model's generalization.

Common types of pooling layers include Max Pooling and Average Pooling:

- Max Pooling is the most common type of pooling layer. In Max Pooling, the largest value in each small region of the input data is retained. This helps retain important features, while reducing the number of elements to be processed.
- With Average Pooling, the average value of the values in the region is calculated and retained. This reduces the variation between features.

2.1.3. Fully Connected Layers

The fully connected layer acts as a bridge between the extracted features and the desired output. It determines the final conclusions to be drawn from the processed data. In the fully connected layer, each node is connected to all the nodes in the previous layer. This connectivity allows the layer to synthesize information from the entire input data to produce the desired output, usually classification or prediction.

2.2. Long Short-Term Memory (LSTM) Network

The Long Short-Term Memory (LSTM) Network is a specialized variant of the Recurrent Neural Network (RNN), initially proposed in 1997 by Sepp Hochreiter and Jürgen Schmidhuber [9]. Since its inception, it has become a critical tool in the field of machine learning, further refined and widely adopted by numerous researchers.

LSTM networks are specifically designed to address the problem of long-term dependencies, with an inherent ability to retain information over extended time periods. An LSTM network consists of multiple interconnected LSTM cells. The specific structure of each cell is illustrated in Figure 2.

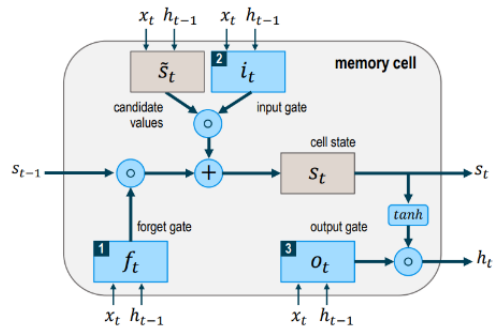

Figure 2. Internal structure of an LSTM cell

The idea behind the LSTM network is to extend the architecture of the Recurrent Neural Network (RNN) by introducing an internal cell state s_t and three gates for information filtering within the cell. These gates are:

1. Forget Gate (f_t): Responsible for discarding unnecessary information from the cell.
2. Input Gate (i_t): Selects the relevant information to be added to the cell.
3. Output Gate (o_t): Determines which information from the cell will be utilized as the network's output.

At each time step *t*, the gates sequentially receive the input value x_t and the value h_{t-1}, which is the output from the hidden state at time step *t-1*. During the propagation process, the cell state s_t and the output h_t are calculated as follows:

In the first step, the LSTM cell decides which information from the previous cell state s_{t-1} should be discarded. The forget gate activation f_t at time step *t* is computed based on the current input x_t, the output h_{t-1} from the LSTM cell at the previous time step, along with corresponding weight matrices W and bias b_t. The *sigmoid* function transforms all values of f_t into the range [0, 1], where an output of

1 indicates retaining all information, and an output of 0 indicates discarding all information.

$$f_t = \sigma\left(W_{f,x}x_t + W_{f,h}h_{t-1} + b_f\right) \quad (1)$$

In the second step, the LSTM cell determines which information should be added to the cell state s_t. The candidate memory cell $\tilde{s}_t$ represents potential information that could be added to the cell state and is computed using a *tanh* activation function with a value range of [-1, 1].

$$\tilde{s}_t = \tanh\left(W_{\tilde{s},x}x_t + W_{\tilde{s},h}h_{t-1} + b_{\tilde{s}}\right) \quad (2)$$

Next, the activation value i_t of the input gate is calculated using equation (3) :

$$i_t = \sigma\left(W_{i,x}x_t + W_{i,h}h_{t-1} + b_i\right) \quad (3)$$

In the third step, the new cell state s_t is updated based on the results from the previous steps through element-wise matrix multiplication:

$$s_t = f_t * s_{t-1} + i_t * \tilde{s}_t \quad (4)$$

In the final step, the output value h_t is further refined. First, a *sigmoid* function determines which part of the cell state should be output:

$$o_t = \sigma\left(W_{o,x}x_t + W_{o,h}h_{t-1} + b_o\right) \quad (5)$$

Then, the cell state is passed through a *tanh* function to scale its values within the range [-1, 1], and it is multiplied by the output of the sigmoid gate to produce the desired output value :

$$h_t = o_t * \tanh(s_t) \quad (6)$$

2.3. Input Data Collection and Processing

2.3.1. Input Data Collection

The input data includes 3,802 daily measurements of the historical water inflow into the Sre Pok 4 hydropower reservoir, with units in m³/s, collected between January 1, 2013, and May 30, 2023. The dataset was collected online from the official website of the Mekong River Commission (MRC) [10] which is freely accessible online.

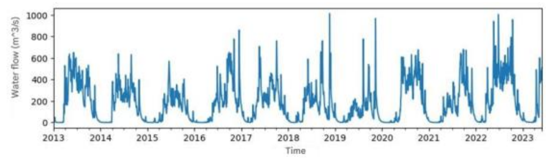

Figure 3. Flow Hydrograph of Water Inflow to the Sre Pok 4 Hydropower Reservoir

2.3.2. Data Preprocessing

The data preprocessing process includes data cleaning and normalization, among which data cleaning involves managing missing data points and outliers. The collected dataset is complete with all 3,802 data points, and there are not any missing data cases.

The original dataset shows notable differences in results for water flow data. Due to the rainy season in the Sre Pok basin, which typically runs from May to September, the data points during this period show substantial increases. Meanwhile, there are certain data points that are extremely low (near zero) in dry months. For this reason, abnormal values are not considered outliers and still be retained to ensure the authenticity of the study's subject.

The input data is normalized by using the Yeo-Johnson transformation, a variation of the Box-Cox transformation from the Power Transform family [11]. The normalization method follows Equation (7):

$$\psi(\lambda, x) = \begin{cases} \dfrac{\{(x+1)^{\lambda} - 1\}}{\lambda} \\ \quad (x \geq 0, \lambda \neq 0), \\ \log(x+1) \\ \quad (x \geq 0, \lambda \neq 0), \\ -\dfrac{\{(1-x)^{2-\lambda} - 1\}}{2-\lambda} \\ \quad (x < 0, \lambda \neq 2), \\ -\log(1-x) \\ \quad (x < 0, \lambda \neq 2). \end{cases} \quad (7)$$

Where x is the input value and λ is the transformation parameter. The value of λ is automatically optimized. After the normalization, the new dataset will have zero mean and unit variance.

Figure 4 displays the water inflow data into the Sre Pok 4 reservoir after normalization.

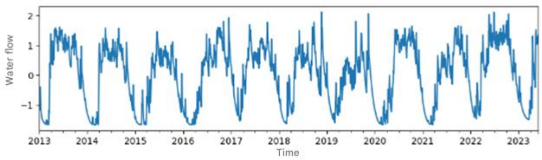

Figure 4. Graph of water flow after normalization

2.4. CNN-LSTM Model for Water Flow Forecasting

The dataset is divided into two separate subsets at an 80/20 ratio. The first subset, which is used to train and fine-tune the model, consists of 3,042 data points recorded between January 1, 2013, and April 30, 2021. Meanwhile, The second subset, consisting of 760 data points measured from May 1, 2021, to May 30, 2023, is used to evaluate the model's performance.

The Cross-fold Validation algorithm is employed to identify the optimal set of parameters for the model. The model is trained and assessed respectively with every possible combination of predetermined parameters. The steps are as follows:

- Determine the parameters that need to be fine-tuned and list potential values for these parameters.
- The training dataset is split into k distinct subsets for every parameter set. Of these, *k-1* subsets are used to train the model, and the remaining subset is used to evaluate the model performance using the *nMAE* error. This process is repeated k times so that all k subsets are evaluated.
- The evaluation error $nMAE$ is the average mean absolute error of the normalized data values. With N data points, , $Q'(i)$ and $Q'_{obs}(i)$are the predicted and observed normalized values at time i, respectively. The $nMAE$ is calculated as in Equation (8):

$$nMAE = \frac{1}{N}\sum_{i=1}^{N}|Q'(i) - Q'_{obs}(i)| \qquad (8)$$

- The final result is the average of the k evaluations. The optimal parameter set is the one corresponding to the smallest *nMAE*/*k*

The CNN-LSTM model is designed to predict water flow in two scenarios: a one-day forecast (one-step model) and a ten-day forecast (ten-step model). The input data is the water flow during last 60 days.

For the CNN network, the parameters fine-tuned include the number of convolutional layers, the number of neurons in each layer, and the of the *kernel_size*. Meantime, for the LSTM network, the fine-tuned parameters include the number of LSTM hidden layers and the number of neurons in each layer. The last Dense layer contains a number of neurons which is equal to the number of desired outputs, in this paper, the number of neurons is 1 (for one-step forecast) and 10 (for ten-step forecast).

In addition to the aforementioned parameters, other technical specifications of the model were experimentally tested and pre-determined to shorten the training time. These include: number of subsets k = 3; optimizer: Adam; learning rate: 0.001; loss function: MAE; Batch_size: 64; and number of Epochs: 50.

Table 1. Optimal parameter set for CNN-LSTM model

Layer	Parameter	One-step forecast	Ten-step forecast
CNN	Conv1D unit	90	90
	kernel_size	3x3	3x3
	Activation function	Leaky ReLU ($\alpha = 0{,}2$)	Leaky ReLU ($\alpha = 0{,}2$)
LSTM	LSTM unit	90	60
	Activation function	ReLU	ReLU
Dense	Dense unit	1	10

This research was proceeded on a personal computer with an Inter® Core™ i5-1135G7 @ 2.40 GHz 2.42 GHz processor and 4.00 GB RAM. Forecasting models are written on the Google Colab platform using the Python 3.10 programming language

2.5. Model Performance Evaluation

Several accuracy metrics are used to evaluate the model's performance, including MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and NSE (Nash-Sutcliffe Efficiency). The formulas for calculating these metrics are given in Equations (9), (10), and (11), respectively:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Q(i) - Q_{obs}(i)}{Q_{obs}(i)}\right| \times 100\% \quad (9)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}|Q(i) - Q_{obs}(i)|^2}{\sum_{i=1}^{N}|Q(i) - \overline{Q_{obs}(i)}|^2} \quad (10)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Q(i) - Q_{obs}(i)| \quad (11)$$

Where N is the number of data points, $Q(i)$ and $Q_{obs}(i)$ are the predicted and observed values at time i, respectively. The closer the error metrics approach their optimal values, the higher the forecasting accuracy of the model.

Table 2. Table of error values

Metrics	Domain	Optimal value
MAE	$[0, +\infty)$	0
MAPE	$[0, +\infty)$	0
NSE	$(-\infty, 1]$	1

3. RESULTS

Using the model structure built as described to re-examine the performance through forecasting for the test set in both cases. In addition to the proposed model, the authors built and trained a number of other forecasting models, including the traditional ARIMA model and some deep learning models such as LSTM, Bi-LSTM and CNN, to evaluate the performance in an intuitive and comprehensive way.

The experimental results of one-step forecasting on the test set of the models are presented in Table 3 and Figure 5.

Table 3. Forecast Error Results on the Test Set for One-Step Forecasting Models

Model	CNN-LSTM	LSTM	Bi-LSTM	CNN	ARIMA
MAPE (%)	6,5225	6,6493	7,1481	7,9081	8,4439
MAE (m^3/s)	13,636	13,9946	15,029	15,460	16,5488
NSE (%)	98,19	98,12	97,86	97,83	97,63

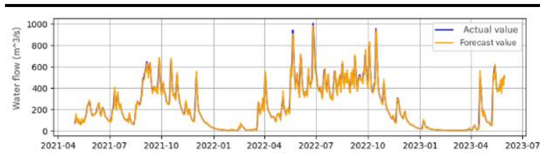

Figure 5. One-Step Forecasting Results on the Test Set Using the CNN-LSTM Model

For the ten-step forecasting model, the experimental results on the test set are presented in Table 4 and Figure 6.

Table 4. Forecast Error Results on the Test Set for Ten-Step Forecasting Models

Model	CNN-LSTM	LSTM	Bi-LSTM	CNN
MAPE (%)	6,8349	6,8934	7,8573	8,1601
MAE (m^3/s)	14,1186	13,9062	14,7340	16,2897
NSE (%)	98,13	98,08	97,99	97,62

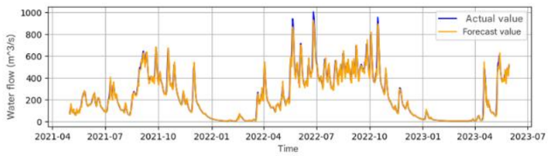

Figure 6. Ten-Step Forecasting Results on the Test Set Using the CNN-LSTM Model

It can be seen that in both cases, the performance of the proposed model is superior to the remaining models. Although the accuracy of the 10-step forecast tends to decrease compared to the 1-step forecast, the MAPE error remains below 10%, and the NSE index is high above 98%. The plot of the forecasted value and the actual value also shows a significant similarity.

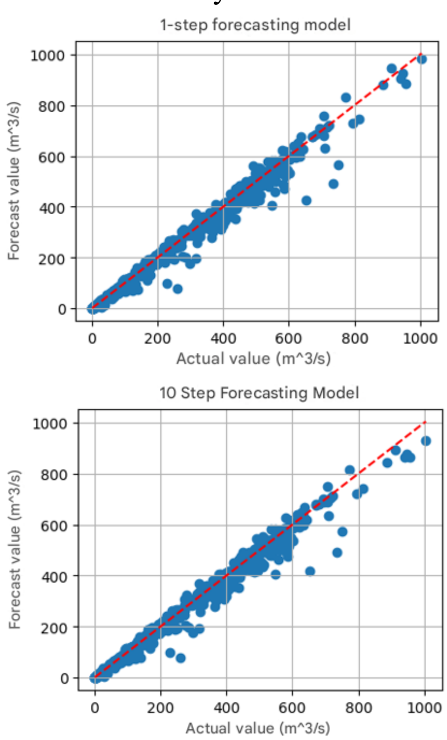

Figure 7. Comparison of Validation Results for One-Step and Ten-Step Forecasting Models

In Figure 7, the scatter plots illustrate a positive correlation between the two variables in both cases. The data points, represented by blue dots, indicate the forecasted values, which are closely aligned with and evenly distributed around the actual values, depicted by the red dashed line. This indicates that the forecasting model achieves high accuracy with minimal errors.

For days with high inflow to the reservoir, the forecasting errors of the proposed model are detailed in Table 5. Overall, the forecasting results for these high-inflow days are quite promising, with MAPE errors remaining below 10% in all cases.

Table 5. Forecast results for some days with high water inflow of two models

Time	Actual Value (m^3/s)	One-Step Forecast		Ten-Step Forecast	
		Forecast Value (m^3/s)	Percentage Error (%)	Forecast Value (m^3/s)	Percentage Error (%)
21/05/2022	940,91	905,0349	3,8128	866,3959	7,9194
22/05/2022	887,02	880,5666	0,7275	845,5861	4,6711
26/06/2022	1004,22	983,1254	2,1006	929,3820	7,4524
27/06/2022	947,33	925,3405	2,3212	877,5455	7,3664
28/06/2022	812,00	747,2673	7,9720	742,4725	8,5625
03/10/2022	793,26	729,9469	7,9814	720,6601	9,1521
04/10/2022	772,56	829,9488	7,4284	816,8373	5,7312
15/10/2022	955,53	886,2628	7,2491	864,5480	9,5216
16/10/2022	912,13	946,4650	3,7643	894,3998	1,9438

The analysis of the results indicates that the error in the case of 10-step forecasting is generally larger than that of 1-step forecasting. This phenomenon can be attributed to the nature of the multi-step forecasting task where multiple sequential predictions have much more complexity than a single value prediction.

The CNN-LSTM architectures combined have an ability to be a powerful tool to capture both short- and long-range dependencies. The experimental evaluation presented on the figures above depicts the implementation model, which can be easily trained with the required parameters given and expounds the performance of the model, in comparison to the conventional and deep learning models. In addition, the selection of the target and forecasting model should be based on the individual problems needed.

4. CONCLUSIONS

Forecasting water inflow to hydropower reservoirs is a critical problem with significant practical implications. Research has demonstrated that advanced machine learning models can provide accurate and reliable forecasts. These advancements not only enhance the prediction of flood and drought risks but also play a vital role in optimizing hydropower plant operations. In this study, the authors applied the deep learning CNN-LSTM model to forecast water inflow into the Sre Pok 4 hydropower reservoir. The input data consisted of historical water flow, with the goal of forecasting 1 day and 10 days ahead. The model was optimized using cross-validation techniques and evaluated for performance with a test set. The validation results indicate that the model achieves high accuracy, and the forecast quality is sufficiently reliable. The proposed model meets the necessary conditions and requirements for effective forecasting.

In future work, we will focus on improving the accuracy of the forecasting model by incorporating relevant weather datasets and combining various deep learning models. Additionally, we aim to expand the application of the CNN-LSTM model to a wider range of hydropower reservoirs, with the goal of improving water resource management on a larger and more diverse scale.

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Giới thiệu tác giả:

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