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An Optimized Seq2Seq Attention Network Considering Multivariate Temporal Correlation for Short-Term Electricity Price Interval Prediction

Hua-Yue Wu

Key Laboratory of Modern Power System Simulation and Control & Renewable Energy Technology
Ministry of Education (Northeast Electric Power University)
169 Changchun Road, Jilin, 132012, Jilin
2202000336@neepu.edu.cn

Tian-Yang Kan

Chengde Power Supply Company
State Grid Jibei Electric Power Co., Ltd.
10 Xinhua Rosd, Chengde, 067000, Hebei
kantianyang@foxmail.com

Hai-Peng Chen*

Key Laboratory of Modern Power System Simulation and Control & Renewable Energy Technology
Ministry of Education (Northeast Electric Power University)
169 Changchun Road, Jilin, 132012, Jilin
chp@neepu.edu.cn

*Corresponding author: Hai-Peng Chen

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Abstract. *In a deregulated electricity market, participants need accurate electricity price forecasting tools in order to maximize their profits and utility. However, accurate electricity price prediction has become a challenging task with increasing renewable energy penetration and the extension of the power system scale. The complexity of electricity market information and insufficient model training limit the prediction accuracy of the existing electricity price forecasting methods. This article proposes a Sequence-to-Sequence Attention algorithm based on the Double Deep Q Network optimization method for short-term electricity price prediction. The article first conducts the maximum information coefficient correlation analysis to select the input sequence from historical electricity price and electrical load. Then, the Sequence-to-Sequence Attention model is proposed for short-term electricity price interval prediction. Finally, the hyperparameters of the model are optimized by the Double Deep Q Network method, which improves the prediction accuracy and the generalization ability of the prediction model. Simulations are carried out on Pennsylvania–New Jersey–Maryland market data and the New South Wales electricity market to validate the proposed method. Numerical results show that the proposed interval prediction method of electricity price has improved the prediction interval coverage probability by up to 10.98% and reduced the prediction interval normalized average width by up to 42.87% compared to four benchmark models. The results suggest that the proposed interval prediction method has good prediction accuracy and generalization ability, providing a powerful decision-making basis for market participants and regulators.*

Keywords: Deep learning; Sequence to Sequence; Attention mechanism; Quantile regression; Probabilistic forecasting

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1. **Introduction.** The introduction of competition and the establishment of a competitive electricity market benefit the rational distribution of energy resources, which has become the tendency of the international electric power industry. In the electricity market environment, accurate electricity price prediction is an essential basis for market participants to adjust bidding strategies and hedge against financial risks [1]. However, large-scale renewable energy integration has increased the uncertainty of the power system and brought significant challenges to adequate supervision and safe operation of the electricity market [2, 3]. An advanced forecasting model can undoubtedly increase electricity price forecasting (EPF) accuracy [4]. Furthermore, the interval prediction results can help market participants to predict the power system operating conditions.

The traditional electricity price forecast studies are mainly based on point forecasting. Chinnathambi et al. [5] presented a Multi-Layered Perceptron deep neural network for the day-ahead EPF and the proposed method is verified in the Iberian market. Chen et al. [6] proposed a bidirectional long short-term memory (LSTM) model for EPF. But point forecast error is difficult to avoid, and it is difficult to realize the quantitative analysis and estimation of forecast error fluctuation range [7]. Therefore, research on probabilistic EPF is propelled [8]. Short-term probabilistic EPF provides a method to assess prediction uncertainty and provide more comprehensive information on future electricity prices. The probabilistic forecasting results of electricity price enable market participants to measure the reliability of the forecast results and prevent possible prediction errors, which plays a vital role in decision-making [9, 10].

Probabilistic forecasting can be divided into the statistical model and the artificial intelligence model [11]. However, most statistical methods are based on linear modeling and have inferior simulation ability for complex nonlinear relations, while artificial intelligence models have attracted attention due to their superior performance in nonlinear prediction [12, 13, 14]. Rafiei et al. [15] proposed a hybrid model for probabilistic EPF, consisting of the clonal selection algorithm and the extreme learning machine combined with the wavelet preprocess. Nowotarski and Weron [16] proposed a Quantile Regression Averaging (QRA) method for constructing prediction intervals. The individual point forecasts are combined in a probabilistic setting using QRA. He et al. [17] proposed a model based on the Nadaraya-Watson estimator, and calculated the predictive densities of electricity price distribution. Brusaferri et al. [18] proposed a novel method for probabilistic EPF based on Bayesian deep learning techniques, and the neural network model is designed to support heteroscedasticity in order to avoid the common homoscedastic assumption.

Despite the existing works in the field, there are still the following research gaps. Firstly, the electricity price is affected by various factors, the multivariate price interval prediction model is worth discussing. However, the increase in the complexity of input data of the probabilistic prediction model brings dimensional disasters, and too much redundant data will also reduce the reliability of interval prediction. Secondly, advanced artificial intelligence technologies such as deep learning and reinforcement learning are developing rapidly, but the application of emerging artificial intelligence technologies in probabilistic EPF remains to be explored. Finally, the prediction accuracy and generalization ability are contradictory to a certain extent. To address the issues mentioned above, a Sequence-to-Sequence (Seq2Seq) Attention network based on the Double Deep Q Network (DDQN) optimization prediction model and the corresponding interval prediction method are proposed for short-term EPF. The main contributions of this article are presented as follows:

(1) The maximum information coefficient is used to evaluate the correlation between future electricity price and the historical electricity price and the electric load. Then, the data with high correlation are selected to form the final input sequence of the prediction network. The input data selection based on maximum information coefficient (MIC) can

effectively offer suitable multivariate input data for the prediction model and effectively improve the performance of the proposed model.

(2) A Sequence-to-Sequence Attention network (Attention-Seq2Seq) is designed to perform short-term EPF. Moreover, the interval prediction of electricity prices is realized by combining the Quantile Regression (QR) method. Interval prediction can offer a range of possible values of future electricity prices and provide a more comprehensive analysis of uncertainty.

(3) The DDQN is adapted as the model optimization method. It can automatically optimize the model's hyperparameters to improve the model's prediction accuracy and model's generalization. The adaptive hyperparameters make the proposed model obtain superior results in different scenarios.

The remainder of this paper is arranged as follows: Section 2 introduces the previous studies of electricity price forecasting. Section 3 describes the proposed DDQN optimized Attention-Seq2Seq (DDQN-Attention-Seq2Seq) electricity price interval prediction method. In Section 4, the experimental results and analysis are given, and the conclusions are provided in Section 5.

2. **Related Work.** To describe the future situation of electricity price, researchers have proposed effective prediction methods, which can be divided into two types depending on the type of prediction result: point prediction and probability prediction. Point prediction can obtain the possible numerical values of electricity prices in the future, while probability prediction can provide the fluctuation range of future electricity prices with a certain confidence level or the probability density distribution of electricity prices, reflecting the potential uncertainty of the prediction results.

At present, machine learning methods have shown excellent performance in the field of electricity price prediction and have been applied to both point prediction and probability prediction. Gao et al. [19] proposed a Elman Neural Network (ENN) combined with enhanced shark smell optimization algorithm for electricity price point forecasting, and the suggested prediction model is evaluated in various approaches. Sencan et al. [20] proposed a deep learning method introducing discrete average true range and wavelet transform. The proposed method analyzed the multiple time scale of input series to extract the electricity price characteristics. The experimental results show that the proposed model has superior prediction accuracy. In previous study [21], an two-stage deep learning method is presented to achieve electricity price forecasting. The integrated spike calibration method efficiently improves the prediction accuracy. Mousa et al. [22] used a deep Gabor Convolutional Network (GCN) for the electricity price probability density function prediction.

Researchers trying to optimize the prediction models to improve the prediction accuracy of electricity price. The existing studied about electricity price prediction model optimization mainly focus on preprocessing the input data and optimizing the parameters of the prediction models. Ghayekhloo et al. [23] processed the input data using game theoretic method and Harmonic analysis approach, combined with the Bayesian recurrent neural network, to achieve electricity price prediction. Qu et al. [24] used the similar day selection approach for input data selection, and a quantile neural network is proposed to obtain the electricity price probabilistic forecasting results. Naz et al. [25] optimized the enhanced extreme learning machine using the gray wolf algorithm and conducted experiments on two datasets, verifying the effectiveness of the proposed model.

3. **Electricity Price Interval Prediction Model.** In this part, the related technologies of the DDQN-Attention-Seq2Seq interval prediction model of electricity prices are

presented. The structure of the proposed model and the interval prediction processes of electricity prices are introduced.

3.1. **Maximum Information Coefficient Correlation Analysis of Electricity Price and Electrical load.** Many factors influence the price of electricity, such as climate, economy, fuel prices, transmission capacity, regulatory structure, and load demand [26, 27, 28]. In addition, the electricity price has a daily and weekly cyclical pattern. Feature selection of electricity price and the electrical load is helpful in eliminating feature redundancy. Since the relationship between these factors and electricity price is nonlinear, MIC is used to analyze the correlation among influence variables. More precisely, MIC is achieved based on Mutual Information (MI), which measures the nonlinear dependence degree between variables. Moreover, the MIC overcomes inconvenience of calculating mutual information among continuous variables. It can better reveal the degree of correlation between characteristics and electricity price [29]. The scatter plot of two variables is partitioned into i columns and j rows, and the maximum MI between partitions is calculated. Then, The maximum value of MI at different partition scales is normalized and taken as the MIC value. The formula is as follows:

$$MIC[X,Y] = \underset{|X||Y|<B(n)}{max}\left(\frac{I[X,Y]}{\log_2 \min(|X|,|Y|)}\right) \tag{1}$$

$$B(n) = 0.6 * n \tag{2}$$

Where $I[X,Y]$ represents the maximum MI, $B(n)$ means the function of the sample size, which represents the constraint of grid X and Y partition, n is the sample size. The MIC value ranges from 0 to 1. Here, a larger value of mutual information means that the two variables have a stronger correlation with electricity price, respectively.

3.2. **Attention-Seq2Seq Forecasting Model of Electricity Price.** The Sequence-to-Sequence (Seq2seq) model is formed by an encoder and a decoder [30, 31]. Seq2Seq model encodes the input sequences into uniform feature vectors and then decodes them. Thus, the feature vector c is required to include the complete information in the original input sequences of electricity price and electrical load. When the input sequence is too long, it is difficult to include all information in a feature vector, which raises information loss inevitably. Therefore, the attention mechanism [32] is introduced to strengthen the critical information and weaken the useless information. Meanwhile, LSTM [33, 34] network has advantages in temporal sequence processing, so this article chooses it as the basic unit of the encoder and decoder. The structure of the Attention-Seq2Seq model is shown in Figure 1. Where $x_0, x_1, ..., x_n$ are the input electricity price and load, $y_0, y_1, ..., y_n$ are the output electricity price, $h_0, h_1, ..., h_n$ are the hidden states of encoder, $d_0, d_1, ..., d_n$ are the hidden states of decoder. Explicit expressions for the Attention-Seq2Seq model are as follows:

$$h_t = LSTM_{enc}(x_t, h_{t-1}) \tag{3}$$

$$d_t = LSTM_{dec}(\hat{y}_t, d_{t-1}) \tag{4}$$

$$a_{ij} = \text{softmax}(e_{ij}) \tag{5}$$

$$e_{ij} = V\tanh(W_A[h_t, d_j]) \tag{6}$$

$$c_j = \sum_{i=1}^{T_X} a_{ij} h_i \tag{7}$$

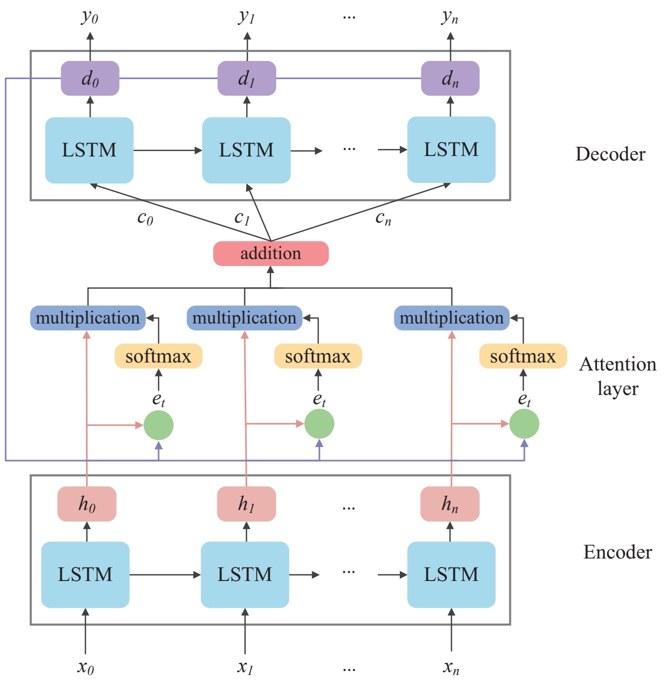

FIGURE 1. Attention-Seq2Seq Model

Where $\hat{y}_i$ means the predicted electricity price, a_{ij} is the attention weight between the ith hidden state and the jth output, e_{ij} is the related parameters of the encoder and decoder's hidden layer state, c_j is the feature vector, V, W_a is the weight matrix.

3.3. **Quantile Regression.** The volatility and uncertainty of electricity prices are inevitable for the existence of power systems' uncertainty (especially with new energy), limitations of model performance, and the unpredictability of market participants' behaviour. Therefore, this article proposed an interval prediction model based on the combination of DDQN-Attention-Sqe2Sqe model and quantile regression. The interval prediction result describes the uncertainties in EPF. Quantile regression studies the linear relationship between the independent variable X and the conditional probability of the dependent variable Y. It establishes the corresponding regression model by the conditional quantile of the dependent variable from the independent variable of electricity price [35]. The relevant formulas are as follows:

$$Q_Y(\tau \mid X) = \alpha_0(\tau) + \alpha_1(\tau)X_1 + ... + \alpha_m(\tau)X_m = X\alpha(\tau) \tag{8}$$

Where τ is quantile, which is between 0 and 1, $Q(\tau \mid X)$ is the estimate of the response variable corresponding to the variable X under the quantile condition.

$\alpha(\tau) = [\alpha_0(\tau), \alpha_1(\tau), ..., \alpha_m(\tau)]^T$ is the quantile regression coefficient defined as:

$$\begin{aligned} \min \sum_{i=1}^{N} \rho_t(Y_i - X_i^T\beta(\tau)) = \min_{\beta} & \sum_{i|Y_i \geq X_i^T\beta(\tau)} \tau|Y_i - X_i^T\beta(\tau)| + \\ \min_{\beta} & \sum_{i|Y_i < X_i^T\beta(\tau)} (1-\tau)|Y_i - X_i^T\beta(\tau)| \end{aligned} \tag{9}$$

Where N is the sample size, ρ denotes the loss function.

When the loss function reaches the minimum value, $\beta(\tau)$ comes to the best estimate. Then, the estimate of the response variable at any quantile can be calculated, and the probability density distribution of the response variable is obtained. The functions for ρ are as follows:

$$\rho_\tau(u) = \begin{cases} \tau u & u \geq 0 \\ (\tau - 1)u & u < 0 \end{cases} \tag{10}$$

3.4. **Double Deep Q Network.** DDQN is developed based on Deep Q Network (DQN). Compared with DQN, DDQN improves the objective function of the algorithm, which reduces the overestimation and makes Q value closer to the true value [36]. The corresponding function of Q value is as follows:

$$Q^\pi(s,a) = E^\pi\left[\sum_{t=0}^{\infty} \gamma^t R_t \mid s_0 = s, a_0 = a\right] \tag{11}$$

Where π is the policy. s is the current status of the agent. a is actions that the agent can take. $\gamma \in [0,1]$ is the discount factor that measures the importance of immediate and later rewards. R_t is the reward at time t. The optimal value under the policy π is $Q^\pi(s,a) = \max_\pi Q^\pi(s,a)$.

DDQN objective function and parameter update formula are as follows:

$$y_t^{DDQN} = R_{t+1} + \gamma Q\left(s_{t+1}, (\mathrm{argmin})\mathrm{Q}(\mathrm{s_{t+1}}, \mathrm{a}, \theta), \theta'\right) \tag{12}$$

$$\theta = \theta + a_l\left(y_t^{DDQN} - Q(s,a,\theta)\right) \bigtriangledown Q(s,a,\theta) \tag{13}$$

Where y_t^{DDQN} denotes the objective function. s_{t+1} represents the next state. θ means the weights of the reinforcement learning network. θ' expresses the parameters of the target network. a_l is the learning rate.

In this paper, the hyperparameters of the Attention-Seq2Seq model are optimized by the DDQN algorithm. The search ranges of hyperparameters are set based on the empirical values of the state space, as shown in Equation (14). The action space contains three actions: increase, decrease, and remain the same.

$$\eta \in [0.001, 0.1] \qquad p \in [0.1, 0.3] \qquad n_h \in [1, 128] \tag{14}$$

Where η is the learning rate. p represents the dropout rate. n_h means the hidden layer neurons number of decoder.

The appropriate reward function has a significant influence on the performance of the model. For the prediction problem studied in this paper, the coefficient of determination R^2 shown in Equation (15) is selected as the reward, and the flowchart of the DDQN optimization process is shown in Figure 2.

$$R^2 = 1 - \left\{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y}_i)^2}\right\} \tag{15}$$

Where y_i denotes the corresponding actual electricity price, $\hat{y}_i$ means the predicted electricity price, $\overline{y}_i$ expresses the mean value of the actual electricity price.

3.5. **DDQN-Attention-Seq2Seq Quantile Regression Model for Electricity Price Interval Prediction.** The quantile regression model is linear. However, the actual electricity price curve is a complex nonlinear form. Deep learning can simulate the nonlinear structure from input to output and effectively solve nonlinear problems. Therefore, this paper combines quantile regression with the DDQN-Attention-Seq2Seq deep learning method for the nonlinear short-term electricity price prediction. According to the selected

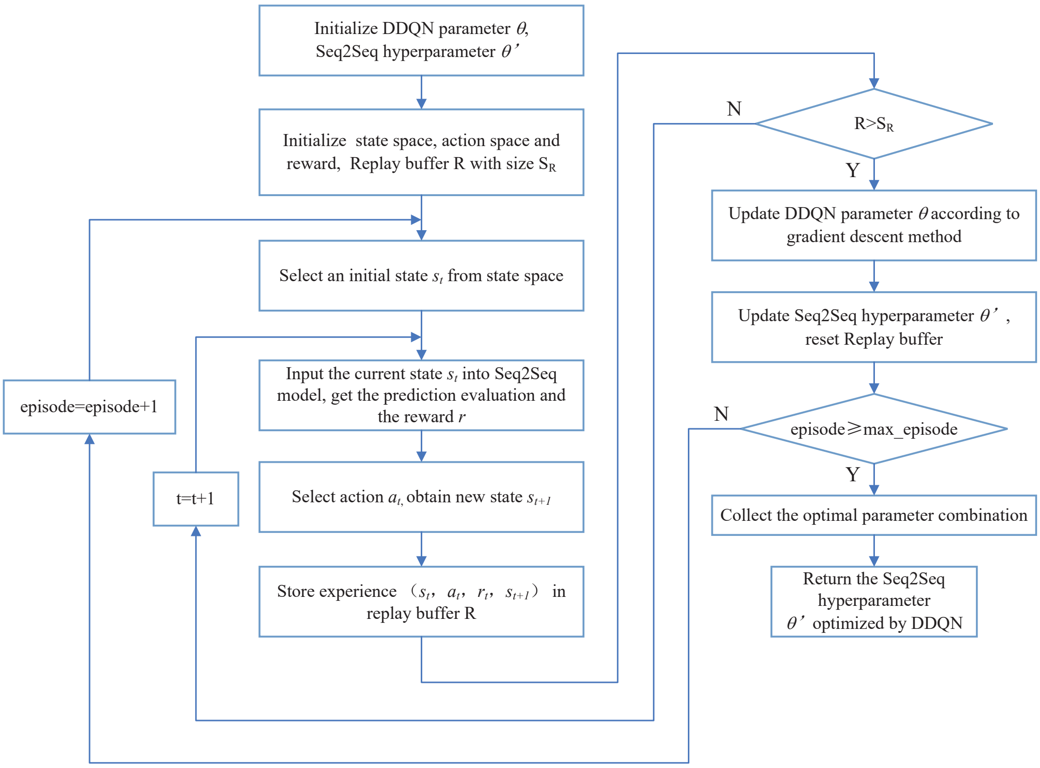

FIGURE 2. Flowchart of hyperparameter optimization by the DDQN algorithm for the short-term electricity price interval forecasting model

quantile, the quantile loss function assigns different penalty values to the overestimated and underestimated predicted values. The quantile loss function is expressed as follows:

$$loss(y, \hat{y}) = \sum_{y_i < \hat{y}_i} (\tau - 1)|y_i - \hat{y}_i| + \sum_{y_i \geq \hat{y}_i} \tau|y_i - \hat{y}_i| \tag{16}$$

Where τ denotes the quantile.

The conditional quantile estimation of Y is as follows:

$$Q_Y(\tau \mid X) = f\left[X, W(\tau), V(\tau)\right] \tag{17}$$

Where $W(\tau), V(\tau)$ are the weight coefficients.

In conclusion, the proposed DDQN optimized Attention-Seq2Seq model for short-term EPF is shown in Figure 3, and the specific procedure is as follows: Step1: Data preprocessing. Calculate the MIC between the candidate input series and the target series of electricity price, extract the series with higher MIC values as the model's input, and then normalize the selected input data. Step2: Constructing and training the DDQN-Attention-Seq2Seq model. Initialize the weight matrices and biases of the Attention-Seq2Seq model. The weight matrices and biases are updated through iterations. And the hyperparameters of the model are optimized by DDQN. Step3: Reach the Electricity price interval prediction result. Specifically, obtain the PIs of electricity price at 40% and 90% confidence levels by combining the proposed model with quantile regression.

4. **Simulation Results and Analysis.** In this part, the proposed model is used for electricity price interval prediction, and the model's interval prediction performance is evaluated as well. Finally, the generalization ability of the proposed model is discussed.

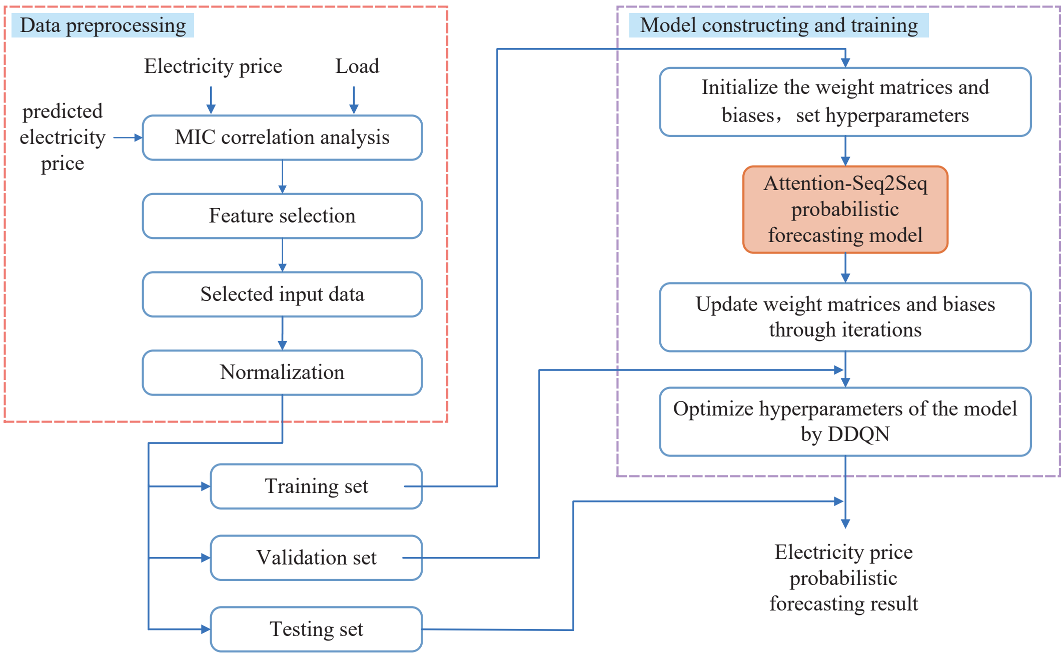

FIGURE 3. Schematic diagram of the proposed short-term electricity price forecasting methodology

4.1. **Experimental Setup.** In this study, the Pennsylvania–New Jersey–Maryland (PJM) data set and New South Wales (NSW) data set are introduced in the forecasting experiments to verify the effectiveness of the proposed algorithm. The first experiment dataset comes from the PJM market data from April 1, 2019 to April 1, 2021, including the electricity price and electric load, and one hour is selected as the time scale. Here,17544 time-period data are sampled to construct the training and testing sample set. 60% of the dataset is taken as the training set, 20% of the dataset is taken as the validation set, and the rest 20% is selected as the test set. The NSW market data from April 1, 2020 to April 1, 2021- nearly 8785 period data is introduced to evaluate the generalization ability of the proposed algorithm. The algorithm simulation environment and computer configuration are shown in Table 1.

TABLE 1. The computer configuration

CPU	Intel Core CPU i3-8100 3.60 GHz
Environment	Python3.6+tensorflow
Internal storage	16G
Training set	10526 time-steps (PJM)/ 5271 time-steps (NSW)
Validation set	3509 time-steps (PJM)/ 1757 time-steps (NSW)
Test set	3509 time-steps (PJM)/ 1757 time-steps (NSW)

4.2. **Evaluation Metrics of Electricity Price Forecasting.** To assess the interval prediction validity of the proposed forecasting method, two metrics, including Prediction Interval Coverage Probability (PICP) and Prediction Interval Normalized Average Width (PINAW), are selected in this paper. PICP reflects the possibility that the actual value falls within the predicted interval, which estimates the model's reliability. The PINAW reflects the sharpness of the PIs for electricity prices. The corresponding formulas are as follows:

$$PICP = \frac{1}{N}\sum_{i=1}^{N}\lambda_i \tag{18}$$

$$PINAW = \frac{1}{NR}\sum_{i=1}^{N}(U_i - L_i) \tag{19}$$

Where N is the number of prediction points, λ is 0 or 1, when the ith electricity price value falls within the prediction interval, $\lambda = 1$, otherwise, $\lambda = 0$. R is the difference between the maximum and minimum predicted values of electricity price, which is the baseline value for normalization. U_i, L_i are the upper and lower bounds of the prediction interval.

4.3. **Input Data Selection for Prediction Model based on MIC.** In this paper, the hourly electricity price and load data of the PJM power market from April 1, 2019 to April 1, 2021 are selected as the input candidate of the proposed network, and the data correlation between the inputs and the output electricity price is analyzed. The MIC analysis results of 288 time periods (hour) are shown in Figure 4. The horizontal axis is the period that the input variable lags behind the target electricity price, and the vertical axis is the MIC values between the input variable and the target electricity price.

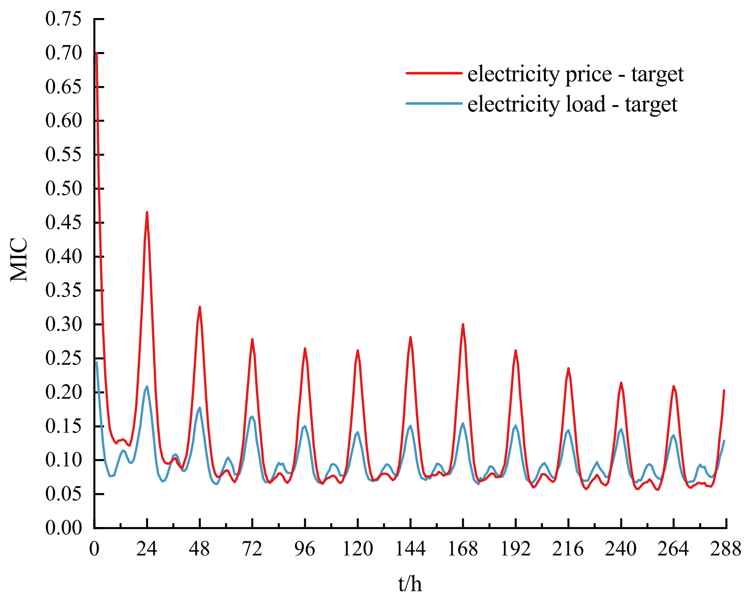

Figure 4. MIC between the target variable of electricity price and the candidate variables of electricity price and electrical load

In general, the MIC between the candidate variables and the target variable decreases with increasing time distance. The closer the period, the higher the correlation of electricity prices. That is to say, adjacent periods of electricity price appear to have a higher correlation through MIC analysis. It is mainly because any period of electricity price contains the correlated fluctuation information of the adjacent period. A similar trend is observed when performing MIC analysis between the electrical load and the target electrical price. The blue curve in Figure 4 indicates that electricity price is tightly linked to the electrical load. Both two MIC curves show a similarly close tendency. In addition, the MIC values between the target electricity price series and the candidate input series show an obvious cyclical pattern. The electricity price in the same period of the day has a higher MIC than the price in other time periods, showing a strong daily periodicity of the electricity price. The MIC values reflect the correlation between the target electricity price and the candidate variables of electricity price and electrical load. Therefore, considering the suitable input size, this article selects the electricity price and electric load data of 8 time periods as the input sequence according to the MIC correlation analysis, including 1-6 hours before the prediction time, 24 hours before the prediction time, and 168 hours before the prediction time.

4.4. **Comparison Results of Interval Prediction for Electricity Price.** Figure 5 shows the interval prediction results of short-term electricity prices under the high confidence level (90%) and low confidence level (40%) in 120 hours. The prediction intervals (PIs) under the two confidence levels and the actual electricity price have similar trend curves. The actual value of electricity price mainly falls within the high confidence level interval of 90% and locates close to the low confidence level interval of 40%. Moreover, the range of prediction intervals is wider at the peak and valley than at the increasing or decreasing period of the actual electricity price curve. This reflects the higher uncertainty of electricity prices during the peak and valley periods. Therefore, the prediction interval of electricity price can track the change of electricity price and well represent the fluctuation of electricity price. In summary, Figure 5 realizes the visualization of the uncertainty of future electricity prices.

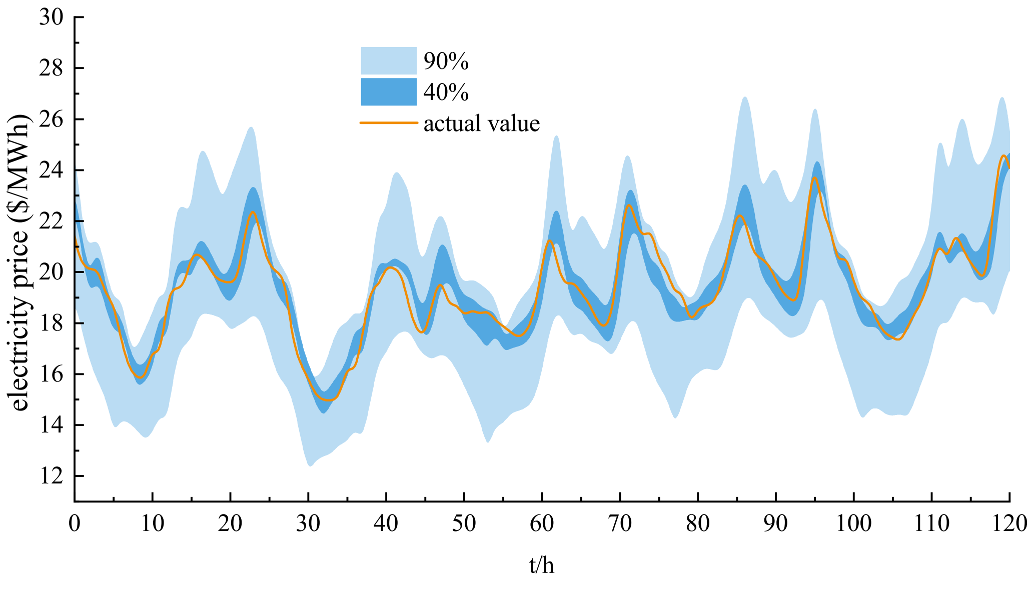

FIGURE 5. Interval prediction results under the high confidence level (90%) and low confidence level (40%)

The interval forecasting results of each model under different confidence levels are given in Table 2 to confirm the performance of the proposed method in interval prediction. The results under 90% confidence level of the LSTM model and our proposed model in a week are shown in Figure 6. As shown in Table 2 and Figure 6, the proposed model achieves a superior performance of interval forecasting. In both cases of high confidence level (90%) and low confidence level (40%), the model presented in this paper has a smaller interval average bandwidth and a higher interval coverage. It is proved that the model presented in this paper has improved the accuracy of short-term electricity price interval prediction. Although the PICP of the DDQN-Attention-Seq2Seq is close to Seq2Seq, it has obvious superiority in PINAW, which means that the proposed method has a smaller interval bandwidth with a similar coverage probability of prediction intervals. Therefore, the validity of the proposed method in interval prediction is verified.

TABLE 2. The interval prediction results of different forecasting models with different confidence levels

Method	confidence level	PICP	PINAW
BPNN	40%	37.43	0.1304
	90%	83.69	0.1436
LSTM	40%	37.17	0.0886
	90%	85.64	0.1268
Attention-LSTM	40%	38.69	0.0986
	90%	88.13	0.1214
Seq2Seq	40%	40.05	0.0967
	90%	89.26	0.1016
DDQN-Attention-Seq2Seq	40%	41.25	0.0745
	90%	91.10	0.0917

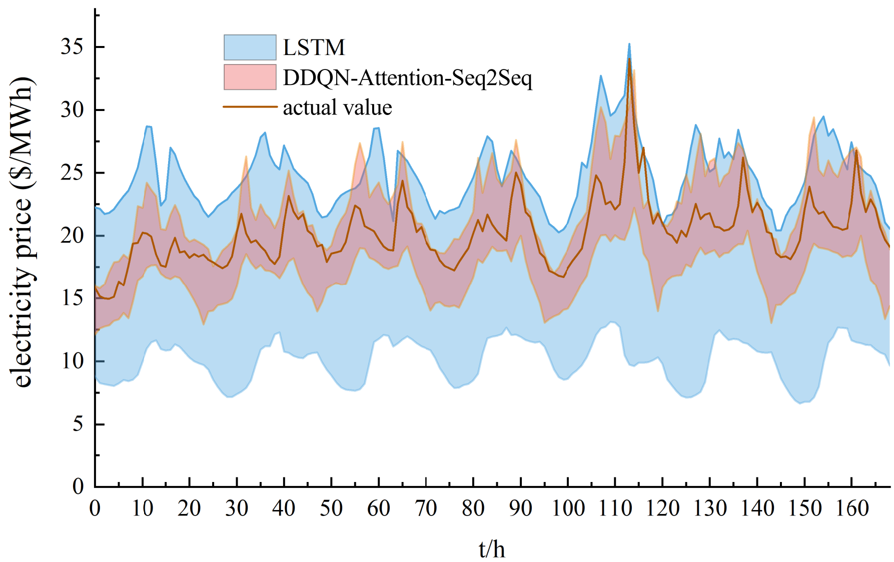

FIGURE 6. Electricity price interval prediction results of different forecasting models with 90% confidence level

4.5. **Comparison Results of Electricity Price Forecasting in NSW Electricity Market.** To verify the proposed model's generalization ability, the proposed model is tested on a different data set. The hourly power price and the regional load of NSW from April 1, 2020 to April 1, 2021 are selected for the experiment. The forecasting results of electricity prices are shown in Table 3. According to Table 3, the DDQN-Attention-Seq2Seq model achieved excellent performance in the NSW data set. Our proposed method has the maximum PICP and the minimum PINAW in the NSW data set compared with other methods. The above results illustrate that the DDQN-Attention-Seq2Seq interval forecasting model has higher prediction accuracy compared with other

TABLE 3. The interval prediction results of different forecasting models in the NSW electricity market

Method	confidence level	PICP	PINAW
BPNN	40%	31.49	0.1501
	90%	79.06	0.2438
LSTM	40%	35.23	0.1387
	90%	83.37	0.2038
Attention-LSTM	40%	37.36	0.1366
	90%	84.19	0.1894
Seq2Seq	40%	37.05	0.1264
	90%	88.26	0.1714
DDQN-Attention-Seq2Seq	40%	39.63	0.1165
	90%	90.20	0.1667

methods in different markets. Accordingly, the effectiveness of model hyperparameter optimization by DDQN is demonstrated.

Furthermore, compared with the PJM market, the overall electricity price prediction error in the NSW market is significantly larger than in PJM with the same model. The NSW market in Australia is highly volatile, and the correlation between the input sequences and the target electricity price is low. However, the PJM market data set has less volatility and a higher correlation between input sequences and the target electricity price. Analysis shows that the prediction error is closely related to the characteristics of the data set.

5. **Conclusions.** This paper presents a short-term electricity price interval prediction model based on the Attention-Seq2Seq network optimized with DDQN. Specifically, this article mainly introduces the input selection technology, a Seq2Seq model combined with the attention mechanism, the hyperparameter optimization algorithm, and the probabilistic forecasting strategy. The results of MIC correlation analysis reflect the daily periodicity of electricity price and provide the basis for model input selection. The proposed prediction model of electricity price is estimated in PJM and NSW electricity market, with two evaluation metrics and four benchmark models. In summary, the proposed DDQN-Attention-Seq2Seq model shows superior forecasting reliability, sharpness, and generalization in interval prediction compared with other electricity price interval prediction methods. In future work, we will study multi-task forecasting or multi-scale forecasting of electricity price. Besides, the impact of micro-grid connection on electricity market is also an interesting topic.

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