ISSN: 3007-9632 DOI: https://doi.org/10.70114/aimedr.2026.3.1.P12

Research on Distribution Network Material Price Forecasting Based on Machine Learning

Cheng Ge [1,a], Yanlong Li [1,b], Liang Yang [1,c], Xian Zhang [1,d], Long Qian [1,e],Shushu Ma [2,f],Chen Zhao [3,g], Xiangyu Cao [4,h] *

[1] Economic Research Institute of State Grid Anhui Electric Power Company, Hefei 230022, China;

[2] State Grid Huainan Electric Power Supply Company, Huainan 232008, China;

[3] Anhui Electric Power Design Institute Company, Hefei 230061, China;

[4] North China Electric Power University, Baoding 071003, China

[a] gec5013@ah.sgcc.com.cn, [b] 2563891625@qq.com, [c] yxyl_jessie@163.com,

[d] zhangx0614@ah.sgcc.com.cn, [e] qianl1209@ah.sgcc.com.cn, [f] 240626594@qq.com,

[g] zcncepu2017@163.com, [h] caoxiangyu010228@163.com

Abstract. To tackle price volatility in distribution network material procurement and improve precision in setting reference prices, this study introduces two hybrid machine learning methods for price forecasting. Materials are first classified using the ABC method. CNN-SVM and TCN-GRU hybrid models are then developed, incorporating historical procurement data and market factors. Prediction is optimized through error analysis and a model selection mechanism. Results show that the models effectively capture nonlinear and temporal patterns, with a mean absolute deviation consistently below 3.5% across material categories. The proposed "classification and optimized selection" framework supports cost-effective procurement and digital transformation.

Keywords: Distribution Network Materials, Price Forecasting, ABC Classification, Machine Learning

1. Introduction

Accurate and economical procurement of distribution network materials is crucial for new power systems, yet current methods suffer from unscientific classification leading to inefficient strategies, and over-reliance on historical data and expert judgment failing to address market-driven price volatility, resulting in frequent cost overruns and tender failures.

Machine learning has demonstrated strong potential in forecasting tasks. It is widely used in power load forecasting [1] and fault diagnosis [2-5]. Specific applications include wind power forecasting using VMD-GRU [2] and hybrid models for photovoltaic prediction [3]. In price forecasting, machine learning has been applied to bond futures [6] Airbnb pricing [7] and transformer cost estimation [8]. Zhang et al. [9] further proposed a CEEMDAN-GRU model for the prices of materials used in power grids. However, research on distribution network materials, particularly studies integrating material categorization with price forecasting, remains insufficient.

This study fills these gaps via a data-driven approach: classifying materials by ABC analysis, identifying price factors, and applying CNN-SVM and TCN-GRU models for category-specific prediction. Key contributions include an ABC-ML framework, hybrid models for nonlinear prices, and a selection mechanism with under 3.5% deviation, supporting reliable procurement decisions.

2. Network Material Classification Based on the ABC Classification Method

The ABC method classifies materials into A, B, and C categories by importance—primarily based on annual procurement amount in this study—to enable differentiated management and optimize resource allocation. Classification criteria and key examples are shown in Table 1.

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Table 1 ABC Classification Criteria for Distribution Network Materials and Typical Material Examples

Classification	Classification Criteria	Typical Materials
Class A	High value, low quantity; critical to grid safety and reliability; high supply risk	Composite insulators, large cement poles, high-current metering boxes
Class B	Moderate value and quantity; affect operational efficiency and local stability	AC insulators, mid-sized cement poles, cable protection pipes, standard metering boxes
Class C	Low value, high quantity; standardized consumables with strong substitutability	Hardware fittings, strain insulators, aluminum tapes, basic metering boxes

3. Material Price Forecasting Model Based on Hybrid Intelligent Algorithms

3.1 CNN-SVM Model

The CNN-SVM model utilizes a 1D convolutional network to automatically extract local temporal features from price sequences, which are then regressed by a support vector machine with an RBF kernel to achieve robust prediction with limited data. Assuming the input data is denoted as x, the calculation can be expressed using the following formula:

$$h = f(x \otimes W + b) \tag{1}$$

In the formula: $\otimes$: the convolution operation; W: the weight of the convolution kernel; b: the bias term; $f()$: the activation function of the Rectified Linear Unit (ReLU). ReLU can introduce nonlinear factors into the network, enabling it to better address complex problems. The expression of ReLU is as follows:

$$f(x) = max\,(0, x) \tag{2}$$

Suppose there is a set of training samples $(x_i, y_i) \in R^n \times R$, where x_i denotes the input variable y_i represents the output variable, and $i = 1,2,3 \ldots\ldots I$ is the number of samples. The feature function of SVM is defined as follows:

$$f(x) = \omega^T \cdot \varphi(x) + b \tag{3}$$

$\varphi(x): R^n \rightarrow R^{n_h}$: a linear function mapping from a low-dimensional space to a high-dimensional space; ω: the weight; b: the bias. To achieve linear separability in the high-dimensional space, SVM introduces an insensitive parameter ε and slack variables (ξ_i, ξ_i^*). The constraint conditions are as follows:

$$min\, {}^1/_2\, \|\omega\|^2 + c \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{4}$$

$$s.t. \begin{cases} y_i - \omega^T x_i - b \leq \varepsilon + \xi_i \\ \omega^T x_i + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{5}$$

The penalty parameter c balances fitting accuracy and model complexity. For nonlinear regression, a kernel function transforms inputs into a higher-dimensional space, with the decision function and specific kernel formulation given in Equations (6) and (7), respectively.

$$f(x) = \sum_{i=1}^{1} (a_i - \widehat{a_i}) k(x_i, x) + b \tag{6}$$

$$k(x_i, x) = exp\{\frac{-\|x_i - x\|^2}{2\sigma^2}\} \tag{7}$$

3.2 TCN-GRU Model

$$F(s) = (x * d) f(s) = \sum_{i=0}^{k-1} f(i) X_{s-d\cdot i} \tag{8}$$

X: the time series; $*$: the convolution operation; k: the size of the convolution kernel; d: the dilation factor, with $d = [1, \ldots, 2]$. The activation function is as follows:

$$\hat{R}_t^{(i,1)} = f(W^{(1)} R_{t-s}^{(i,i-1)} + W^{(2)} S_t^{(i,i-1)} + b) \tag{9}$$

$$R_t^{(i,1)} = R_t^{(i,1-1)} + V \hat{R}_t^{(i,1)} + e \tag{10}$$

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Where $W^{(1)}$ and $W^{(2)}$ are weight matrices, b is the bias term, $S_t^{(i,1)}$ denotes the activation function of the $i-th$ block in the 1st layer, $\widehat{R}_t^{(i,1)}$ represents the result of dilated convolution at time t, and $R_t^{(i,1)}$ indicates the result of dilated convolution with the residual value added at time t.

The calculation method of the update gate is shown in Formula (11), and the calculation formula of the reset gate is shown in Formula (12).

$$Q_t = \sigma(W_{(x,Q)} \cdot [u_{t-1}, x_t] + b_Q) \tag{11}$$

$$R_t = \sigma(W_{(x,R)} \cdot [u_{t-1}, x_t] + b_R) \tag{12}$$

W: the weight, u_{t-1}: the state at the previous time step, x_t: the input at the current time step, b: the bias vector.

The output of the GRU is then computed by integrating the update and reset gate values through a series of transformations involving activation functions such as Sigmoid or Tanh, ultimately generating the current hidden state. Its calculation formula is:

$$H_t = tanh(\omega_H \cdot [R_t \cdot H_{t-1}, x_t] + b_H) \tag{13}$$

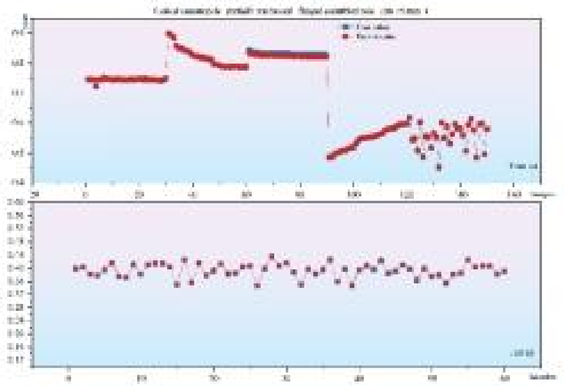
$$\widetilde{H}_t = (1 - Q)H_{t-1} + Q_t \cdot H_t \tag{14}$$

ω: the weight, tanh is the activation function, x_t: the input at the current time step, b: the bias vector.

4. Empirical Analysis of the Model

To validate the proposed hybrid forecasting model, procurement data (2020-2025) from a provincial grid company were utilized, including cable protection pipes and representative A/B/C-class materials. The dataset was divided into training (2020-2024) and testing (2025) sets. Following data preprocessing involving outlier removal and feature encoding, key predictive variables were identified via Pearson correlation analysis. Selected features were subsequently processed through MATLAB for model forecasting.

This section evaluates the three forecasting models by comparing predicted values with actual procurement prices. The figures present selected samples of representative materials (excluding the underperforming multiple regression model) to illustrate overall trends. As shown in Figures 1-2, both CNN-SVM and TCN-GRU achieve high accuracy with minimal errors, effectively capturing nonlinear and temporal patterns in bidding prices to deliver reliable trend forecasts.



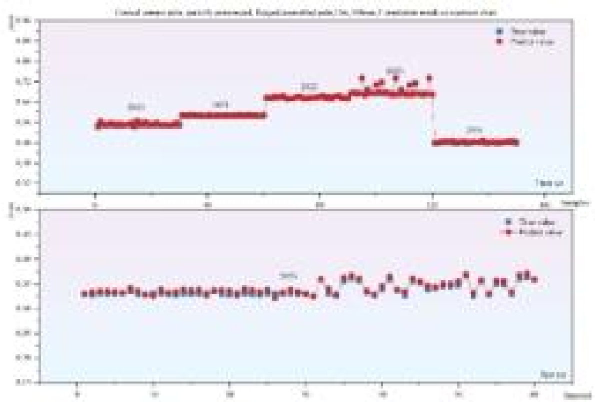


Figure 1,Figure 2 Predict conical cement poles - partially prestressed - flanged assembled poles -12m-350mm -t using CNN-SVM, TCN-GRU

To enhance reference price reliability, error analysis of cable protection pipes demonstrates both models maintain high accuracy with low errors across all specifications. TCN-GRU shows higher R^2 values while CNN-SVM achieves smaller absolute errors for certain cases. Optimal model selection by specification can further enhance prediction accuracy.

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This study further compares the predicted prices of the two algorithms with the actual procurement prices using the 2025 bidding data test set, and the results are presented in Table 2.

It can be seen from the table above that the predicted reference prices of cable protection pipes are generally lower than the actual average winning bid prices. Specifically, the TCN-GRU model yields result with small deviations and high accuracy for cable protection pipes in underground installation mode, while the CNN-SVM model performs well for those in trenchless installation mode; both models also achieve small deviations and high accuracy in predicting tapered cement poles, protective hardware fittings, and electric energy metering boxes. The average deviation between the predicted prices of all material types and the actual average procurement prices in 2025 is maintained within ±3.5%.

Table 2 Comparison Between Forecasting Results and Average Procurement Prices

Material Name	2025 Average Procurement Price	CNN-SVM	Deviation Rate	TCN-GRU	Deviation Rate
100 (Underground Installation)	0.0047586	0.0044945	-5.55%	0.0046288	-2.73%
100 (Above-Ground Installation)	0.0030750	0.00297769	-3.16%	0.0029117	-5.00%
175 (Underground Installation)	0.0138270	0.01328830	-3.90%	0.0137149	-0.81%
175 (Above-Ground Installation)	0.0094318	0.00918266	-2.64%	0.0089659	-4.94%
200 (Underground Installation)	0.021654	0.02063215	-4.72%	0.01967067	-1.70%
200 (Above-Ground Installation)	0.0123	0.01212927	-1.39%	0.01185843	-2.63%

5. Conclusions

This study constructs a framework for forecasting material prices in the distribution network by integrating ABC classification and machine learning. The CNN-SVM and TCN-GRU hybrid models significantly improve forecasting accuracy, and an innovative "classification-based optimal selection" mechanism is proposed to select the optimal algorithm adaptively according to material characteristics. This research provides accurate and reliable data support for the procurement strategies of power grid enterprises, effectively enhancing procurement efficiency and cost control capabilities.

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