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Spatiotemporal Distribution Patterns and Prediction of Construction Material Prices in Sichuan Province

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Abstract

Material prices play a decisive role in construction projects. In order to achieve material price prediction in Sichuan, this study focuses on four types of building materials: first-class sawn timber, shale porous bricks, rebar and white cement. By collecting multi-source data such as economy, climate and geography of cities (and regions) at various levels in 2024, an adaptive neural fuzzy reasoning system (ANFIS) model was built, and the training, verification and testing of the model was completed using MATLAB. The results show that the prediction performance of first-class sawn timber and rebar is relatively good, while the prediction accuracy of shale porous bricks and white cement is low. Research shows that the ANFIS model can be used for preliminary price estimation and trend reference for building materials (such as sawn timber and rebar) affected by macro factors, and provide data support for building materials price regulation and engineering cost management in Sichuan Province.

Keywords

Sichuan Province; Spatiotemporal Distribution; Material Prices; ANFIS Model; Engineering Cost Management.

1. Data Sources and Processing

1.1. Data Sources and Variable Description

This study takes cities (states) in Sichuan Province as the unit, and collects actual price and influencing factor data for four types of building materials: first-class sawned timber, shale porous bricks[1], rebar and white cement. The price data comes from the Sichuan Provincial Engineering Cost Information Network; economic indicators such as regional gross domestic product, fixed asset investment, and total output value of the construction industry are taken from the statistical yearbooks and statistical bulletins of various cities; meteorological data such as average temperature, precipitation and sunshine duration[2] are provided by the Sichuan Meteorological Bureau; geospatial data sources such as height and highway mileage Public information from the Sichuan Provincial Department of Natural Resources and the Department of Transportation. All data is mainly based on the cross-section data in 2024, and the valid samples are 215 first-class sawn timber, 165 shale porous bricks, 220 rebars, and 180 white cement.

Based on literature research and field knowledge, choose 3 independent variables for each building material, with the actual price as the dependent variable. As shown in Table 1.

Table 1. Input and Output Variables for Each Material Model

Building Materials	Independent Variables (Inputs)	Dependent Variables (Output)
First-class Sawn Timber	Gross Regional product, Number Of Construction Enterprises, Average Sunshine Time	Sawn Timber Price
Shale Porous Bricks	Gross Regional Product, Fixed Asset Investment, Average Precipitation,	Brick Price
Rebar	Average Precipitation, Average Height, Highway Mileage	Rebar Price
White Cement	Average Temperature, Fixed Asset Investment, Total Output Value Of The Construction Industry	White Cement Price

The gross domestic product of the region, the number of construction enterprises and the average daylight hours of sawn timber are selected, reflecting the impact of regional construction demand, market competition pattern and natural drying conditions on supply costs respectively; shale porous bricks select the regional gross domestic product, fixed asset investment of the whole society, and the average precipitation, reflecting the indirect effect of economic potential, investment drive and climate on construction and transportation; the average precipitation, average height and highway mileage of rebar are selected to depict the differences in phased demand changes, transportation costs and logistics convenience; white cement selects the average temperature, the investment of fixed assets of the whole society, the total output value of the construction industry, and the impact of hydration response rate, construction heat and industry output scale on demand.

1.2. Data Preprocessing and Partitioning

In order to adapt to the ANFIS model, all variables are linearly normalized to [0,1] intervals to eliminate the difference in the scale. The disrupted data set is divided into 80% and 20% ratios: the former is used as modeling data, which is internally divided into training sets (accounting for 70% of the modeling data) and verification sets (accounting for 30%), which are used for parameter adjustment and over-finding monitoring respectively; the latter is used as an independent test set for the final evaluation of the prediction accuracy of the model. The actual price and the predicted price comparison, absolute error and relative error listed in the result analysis part of the article are all from the test set. The specific sample classification of each building material is shown in Table 2.

Table 2. Dataset Partitioning for Each Construction Material

Building Materials	Total Samples	Training Set (56%)	Validation Set (24%)	Testing Set (20%)
First-class Sawn Timber	215	120	52	43
Shale Porous Bricks	165	92	40	33
Rebar	220	123	53	44
White Cement	180	101	43	36

2. ANFIS Model Construction and Training

2.1. Principles of the ANFIS Model

ANFIS (Adaptive Neuro-Fuzzy Inference System) is an intelligent reasoning model that combines neural networks with fuzzy reasoning systems. It has been widely used to solve

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engineering problems[3]. It has both the interpretability of fuzzy reasoning and the advantages of adaptive learning of neural networks, and uses hybrid optimization strategies to promote parameter optimization[4]. Compared with traditional timing models such as ARIMA, it can effectively handle complex associations of multi-dimensional variables and adapt to multi-factor-driven research scenarios of building materials prices.

2.2. Model Structure Design

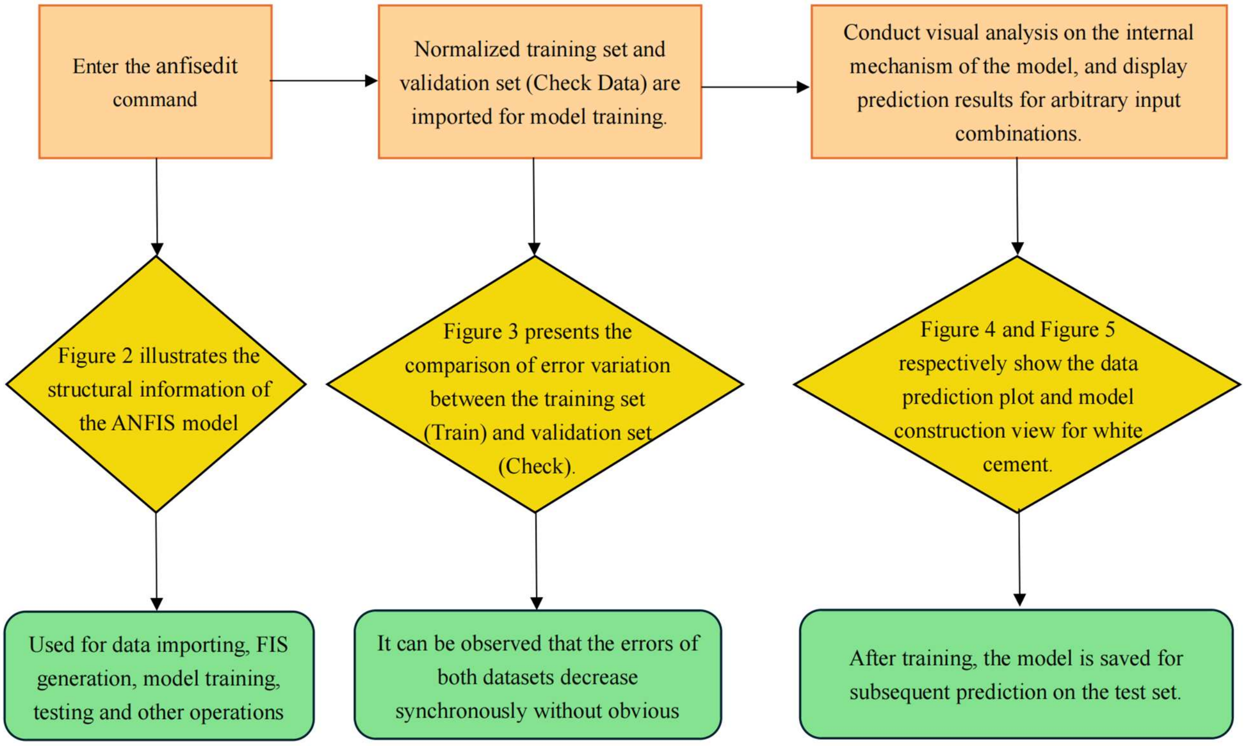

Figure 1. Flowchart of ANFIS Model Structure Design

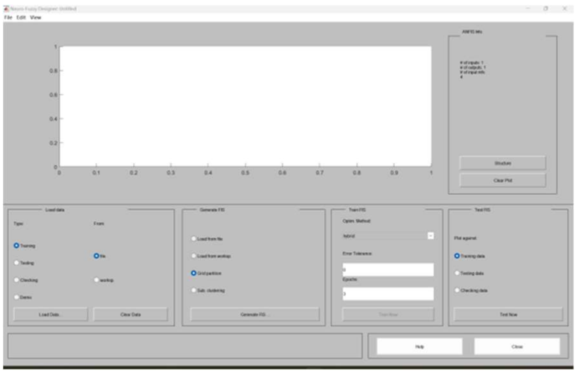

Figure 2. Main Interface of Neuro-Fuzzy Designer

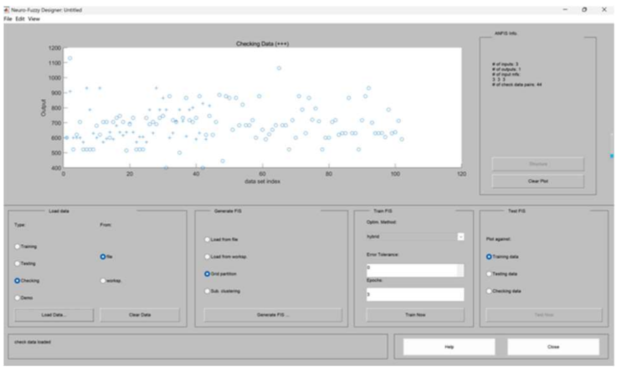

Figure 3. Comparison of Training Set and Validation Set

Figure 4. Prediction View of White Cement Data

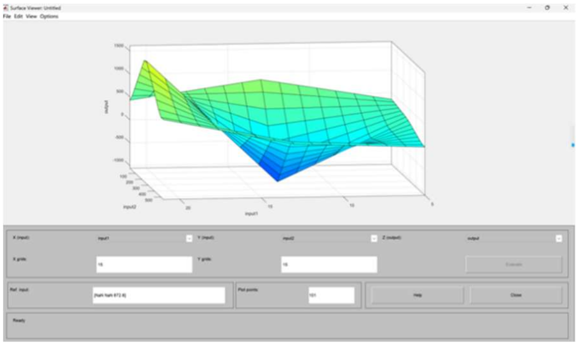

Figure 5. Modeling View of White Cement

3. Prediction Results and Error Analysis Overview

The 20% testing set data was fed into the trained ANFIS model to obtain the predicted prices for the four construction materials. The model prediction accuracy was quantitatively evaluated by calculating two error indicators:

Absolute Error:

$$\text{Absolute Error}=P_r\text{-}P_f \tag{1}$$

Pr: Actual market information price (in Yuan) of the building material in the specific sample.
Pf: Predicted price (in Yuan) of the building material as output by the ANFIS model.

Relative Error:

$$\text{Relative Error}=\frac{P_r\text{-}P_f}{P_r}\times 100\% \tag{2}$$

Pr: actual market information price (Yuan) of the building material for a given sample.
Pf: predicted price (Yuan) of the building material from the ANFIS model.
$|P_r - P_f|$: = absolute difference between the actual and predicted prices (Yuan).

3.1. Prediction Error Analysis for Each Material

3.1.1. First-Class Lumber

Among the 43 samples of the first-class test set of sawn timber, the absolute error positive and negative accounted for 51% and 49% respectively, and the overall error was slightly underestimated; the relative error distribution is shown in Table 3 and Figure 6.

Table 3. Relative Error Distribution for First-class Sawn Timber Predictions

Relative Error Interval	Sample Count	Percentage (%)
≤5%	13	30
5%~10%	4	9
10%~20%	8	19
≥20%	18	42
Total	43	100

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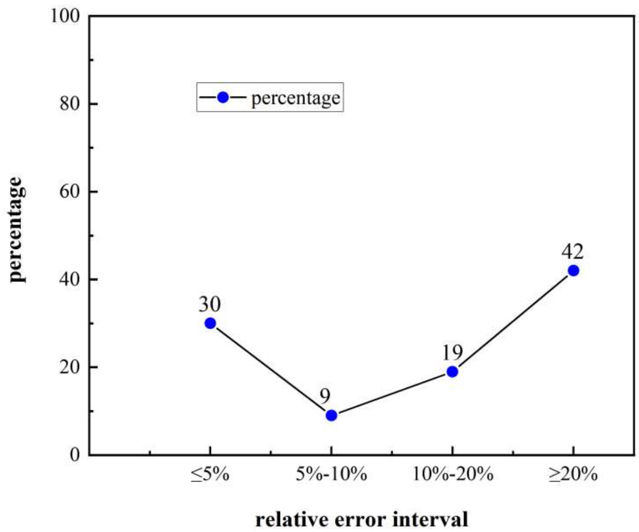

Figure 6. Line Chart of Relative Error for First-class Sawn Timber Predictions

The first-class prediction accuracy of sawn wood is medium. The error within 20% accounts for 58%, and only 37% within 10%. The model can capture the trend but there is still room for improvement. Timber prices are also affected by market supply and demand, origin and transportation distance[5]. The input variables are not fully covered, so the model is suitable for preliminary estimation and has reference value.

3.1.2. Shale Porous Bricks

The error statistics for the 33 samples in the testing set are shown in Table 4 and Figure 7.

Table 4. Relative Error Distribution for Shale Porous Bricks Predictions

Relative Error Interval	Sample Count	Percentage (%)
≤5%	1	3
5%~10%	2	6
10%~20%	2	6
≥20%	28	85
Total	33	100

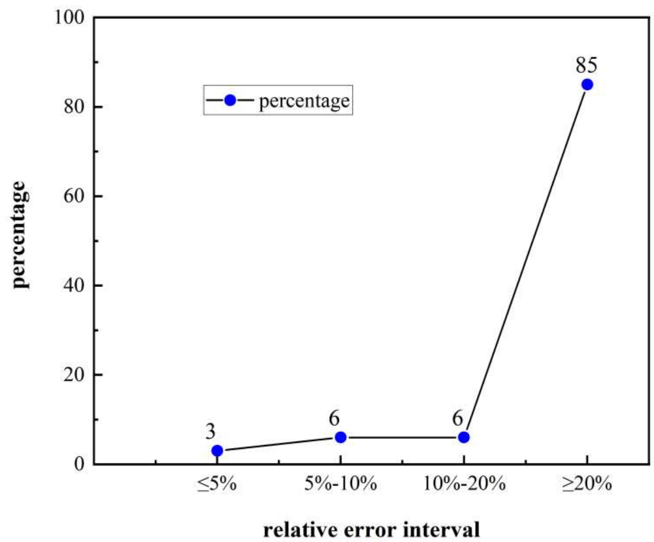

Figure 7. Line Chart of Relative Error for Shale Porous Bricks Predictions

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The prediction accuracy of shale porous bricks is significantly low. Within 10% and 20%, only 9% and 15%, about 85% of the sample error exceeds 20%, and the model effect is not ideal. The reason is that its price is dominated by local factors such as regional resources, environmental protection policies and transportation costs, and the input variables do not capture the core drive; and the sample size is small, price fluctuations show the characteristics of a 3 to 5 year cycle[6], and macro variables are difficult to explain. Therefore, this model is not applicable to the price forecast of shale porous bricks.

3.1.3. Rebar

The error statistics for the 44 samples in the testing set are shown in Table 5 and Figure 8.

Table 5. Relative Error Distribution for Shale Porous Bricks Predictions

Relative Error Interval	Sample Count	Percentage (%)
≤5%	10	23
5%~10%	7	16
10%~20%	8	18
≥20%	19	43
Total	44	100

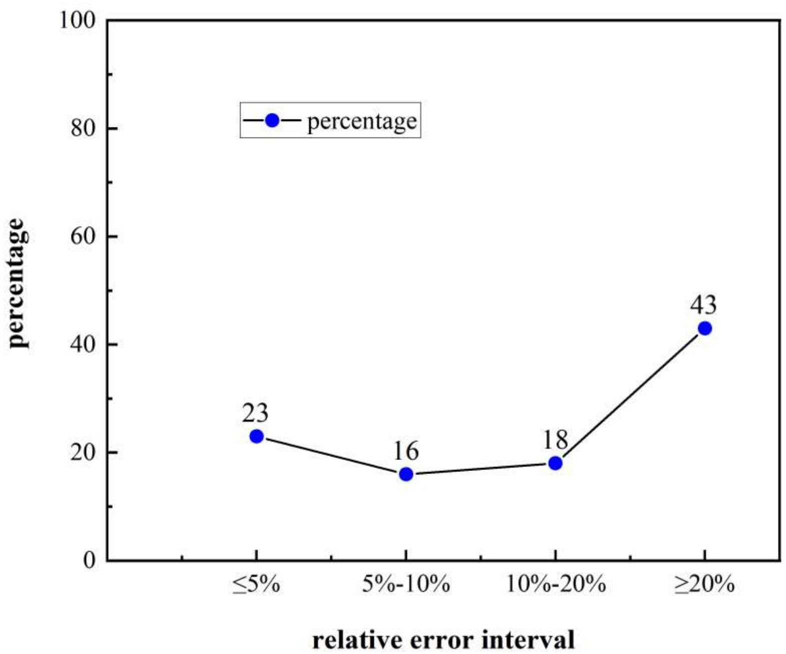

Figure 8. Line Chart of Relative Error for Rebar Predictions

The prediction accuracy of rebar is medium, which is comparable to that of sawn timber. Its price is affected by demand, supply, cost and futures factors[7], and macro variables such as macroeconomics and iron ore prices play a significant role. This model only takes geographical and climatic conditions as the input, and it can still achieve nearly 60% of the sample error of less than 20%, which is not easy. It has trend prediction and regional comparative value, but more macro variables need to be included to accurately predict the absolute price.

3.1.4. White Cement

The error statistics for the 36 samples in the testing set are shown in Table 6 and Figure 9.

Table 6. Relative Error Distribution for White Cement Predictions

Relative Error Interval	Sample Count	Percentage (%)
≤5%	9	25
5%~10%	1	3
10%~20%	8	22
≥20%	18	50
Total	36	100

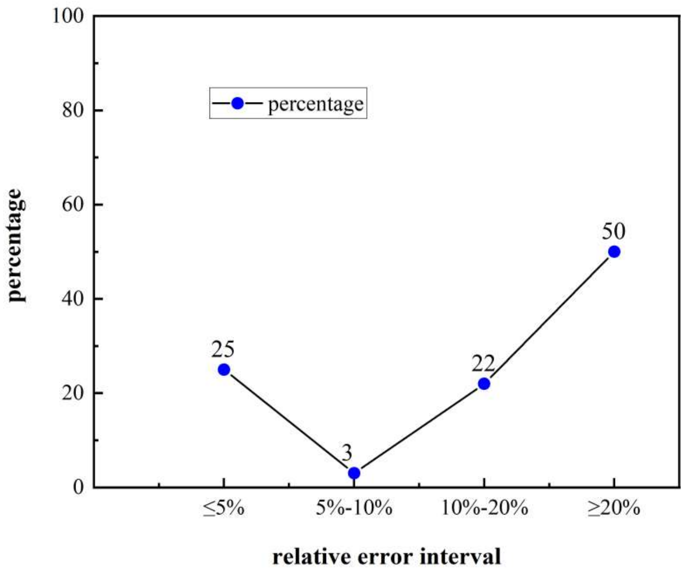

Figure 9. Line Chart of Relative Error for White Cement Predictions

The prediction accuracy of white cement is medium, which is the same as that of sawn timber and rebar. The fixed asset investment and the total output value of the construction industry in the input variables can better reflect the construction demand and have a certain explanatory power. The model performance is suitable for coarse-grained estimation, and it needs to be improved in combination with industry cycle data in the future.

3.2. Comparison of Prediction Accuracy Across the Four Materials

The proportion of the error intervals of the four building materials is summarized in Table 7 for horizontal comparison.

Table 7. Accuracy Comparison Among the Four Materials

Material Type	Test Samples	Error ≤10% Share (%)	Error ≤20% Share (%)
First-class Sawn Timber	43	33	58
Shale Porous Bricks	33	9	15
Rebar	44	39	57
White Cement	36	28	50

It can be seen from Table 7 that the prediction effect of first-class sawn timber and rebar is better, and the prediction accuracy of shale porous bricks is relatively low. The possible reason is that the price of rebar is greatly affected by external factors such as macroeconomic policies and local resources, which are not included in the input variables of this model.

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4. Conclusion

This study takes four types of building materials of first-class sawn timber, shale porous bricks, rebar and white cement in Sichuan Province. Based on the mixed data of two years in 2019 and 2024, economic, climate, geography and other influencing factors are selected as input to establish an ANFIS prediction model. The results show that the prediction effect of sawn timber and rebar is better, and the relative error within 20% is 58% and 57% respectively, which can be used as a preliminary estimate and trend reference; white cement is second, which needs to be used carefully; shale porous bricks are the worst, only 15%, and the model is not applicable. The difference in accuracy is mainly due to the lack of explanation of input variables on specific factors such as local resource endowment and environmental protection policies. In general, the ANFIS model has nonlinear fitting ability for most building materials, but for materials with strong regionality, it is necessary to further optimize the input variables or introduce more localization features to enhance the practicality of the model.

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