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Neural Network Prediction Model for Sinter Mixture Water Content Based on KPCA-GA Optimization

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Abstract: The design and optimization of a sinter mixture moisture controlling system usually require complex process mechanisms and time-consuming field experimental simulations. Based on BP neural networks, a new KPCA-GA optimization method is proposed to predict the mixture moisture content sequential values with time more accurately so as to derive the optimal water addition to meet industrial requirements. Firstly, the normalized input variables affecting the output were dimensionalized using kernel principal component analysis (KPCA), and the contribution rates of the factors affecting the water content were analyzed. Then, a BP neural network model was established. In order to get rid of the randomness of the initial threshold and weights on the prediction accuracy of the model, a genetic algorithm is proposed to preferentially find the optimal initial threshold and weights for the model. Then, statistical indicators, such as the root mean square error, were used to evaluate the fit and prediction accuracy of the training and test data sets, respectively. The available experimental data show that the KPCA-GA model has high fitting and prediction accuracy, and the method has significant advantages over traditional neural network modeling methods when dealing with data sets with complex nonlinear characteristics, such as those from the sintering process.

Keywords: sintering; moisture content prediction; KPCA; GA-BP hybrid prediction model

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1. Introduction

Since the blast furnace ironmaking industry is nearly saturated, sinter ores are required to possess physical and metallurgical characteristics as well as gas permeability for efficient blast furnace operation. The development trend of the sintering production process has changed to the realization of an intelligent human–machine combination to improve the level of sintering concentrate while reducing the cost of sintered ore. The moisture content of the mixture plays a role in the sintering process, including granulation, heating, and combustion. A moisture content that is too high or too low can have a detrimental effect, leading to poor mixing and granulation and affecting the permeability of the mixture. Ultimately, the sintered ore is under- or over-sintered, reducing product quality and yield [1]. To be able to govern and control the production process in real time and with consistency, the relevant parameters and control indicators need to be predicted so that the moisture content of the mixture is kept within a certain range during the sintering process. The moisture content of the mix depends on the moisture content of the raw materials and the amount of water added. In addition, other factors, such as temperature and evaporation rate, may have a slight effect on the moisture content, so moisture prediction and control under complex working conditions are demanding and significant. Current plants mainly rely on workers to add water manually based on manual estimates, and the moisture content often varies widely. Therefore, considering the limitations of empirical models, it is critical to developing a superior moisture prediction model.

The optimal design of a moisture control system for a sintering platform using conventional predictive control techniques is very complex. The literature [2] uses fuzzy logic inference to rectify the controller parameters, which need to be adjusted in real time according to the structural characteristics of the sintering furnace and the control performance requirements to stabilize the sinter mix moisture. With the application of moisture meters developed based on infrared, microwave, and neutron principles in sintering plants, more refined data have led to the study of various optimization methods for sintering processes. For example, Wu et al. added many independent variables, such as material layer thickness and combustion rate, in the process of modeling the temperature field and subsequently advanced a three-step optimization strategy to optimize the coke ratio [3]. Meanwhile, Liu et al. emphasized the porous media heat transfer model in the process of building the sintering temperature field model and used a particle swarm optimization algorithm to solve the problem of parameter matching [4–6].

Artificial neural networks have also been applied in the field of sintered moisture prediction due to their advantages such as classification recognition, optimal computation, and nonlinear mapping. In the literature [7], an exogenous nonlinear autoregressive (NARX)-based model was proposed to predict the target time series considering external past and present values to keep the moisture values at an acceptable accuracy, which can be further validated. There is also still room for improvement in reducing the model complexity and improving its accuracy. The limitation of the neural network model is the overfitting problem, which may lead to poor prediction accuracy [8,9], so an attempt was made to combine various algorithms with neural networks. The genetic-based BP algorithm optimization method is less prone to falling into local minima, and the trained network performs well in terms of stability and has greater generalization ability [10]. Kernel principal component analysis (KPCA) is an effective nonlinear application technique to obtain rich information on the working conditions in the sintering process [11,12]. In recent years, in data-driven process monitoring applications, Jingxin Zhang et al. proposed a hybrid probabilistic principal component analysis algorithm based on clustering [13], which replaces the traditional dimensionality reduction of principal component analysis with singular value decomposition and reduces the computational complexity, making the experimental data more intensive. The combination of the KPCA algorithm and neural networks has been successfully applied in many fields, such as brain MR image classification [14], autonomous driving pattern feature extraction [15,16], and complex industrial variable prediction and fault identification [17–19].

For the modeling and prediction of complex processes similar to sintering, many researchers have combined meta-heuristic optimizers with ML models, such as the Gray Wolf Optimizer [20,21], Political Optimizer, and Moth Flame Optimizer [22–24]. In terms of performance, the optimized ML model has higher prediction accuracy, while the black-box model avoids solving various link parameters in the process and reduces the difficulty of the calculation. This indicates that artificial intelligence provides novel solutions for heavy industries such as material processing and steel manufacturing.

The main contributions of this paper are summarized as follows:

1. A new hybrid intelligence algorithm was developed to predict the moisture content of the mix in real time during the sintering process.
2. Analysis and modeling of the dynamic, non-linear, and other characteristics of the predicted object were performed for the two-stage mixing and water addition method commonly used in sintering plants.
3. The GA optimization algorithm was used to reduce the shortcomings of BP neural networks, such as slow convergence, a long training time, and the tendency to fall into local minima, comparing the effect before and after optimization to illustrate its necessity.

The results obtained from this method can be used as a prerequisite for the next step of mixture moisture control, which is of practical importance in the sintering industry.

2. Sintering Mixing and Water Addition Process Mechanism

2.1. Material Conservation Moisture Content Model

The sintering plant mostly adopts the two-stage mixing arrangement, and the arrangement diagram is shown in Figure 1. Raw material preparation, ignition, and cooling are the three main stages of iron ore sintering. A sinter mixture made of iron ore fines, fluxes, solid fuels such as coke breeze, and return fines from the sinter plant is prepared before the sintering process starts. Then, different amounts of water are added to the primary and secondary mixers to achieve efficient mixing and granulation (18–22 t; 2–3 t). After laying out the mixture on the sinter machine, several burners are used to ignite the coke particles at the surface of the sinter bed. A series of oxidative exothermic reactions occur between different raw materials at different temperature stages.

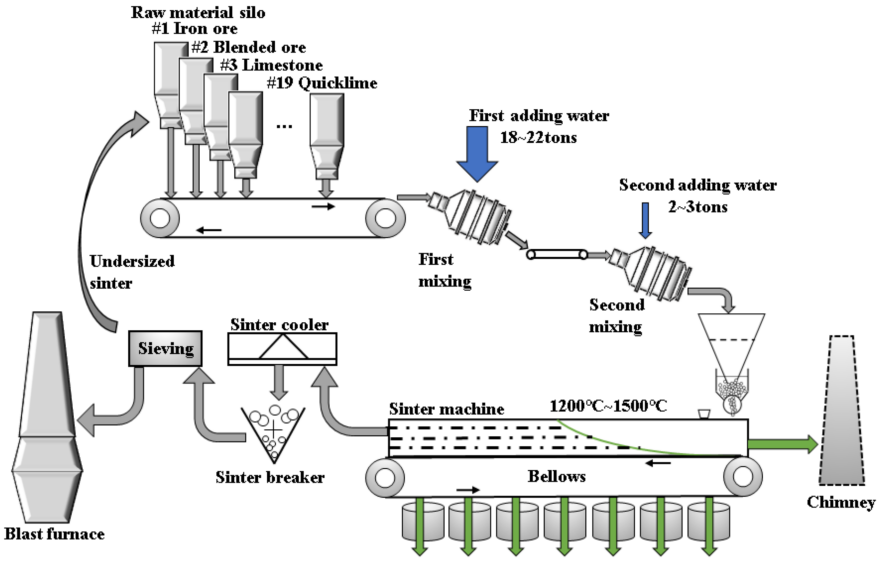

Figure 1. Sintering process layout diagram.

The principle of material conservation is used to obtain the formula for calculating the moisture content of the mixture, as shown in Equation (1):

$$M = \frac{\sum_{i=1}^{n} K_i K_i + U_1 + U_2}{\sum_{i=1}^{n} W_i + U_1 + U_2} \tag{1}$$

where M is the moisture content of the mix, K_i and W_i are the moisture content and mass, respectively, of Sinter Mixture Component I, while n is the total number of sinter mixture components. U_1 and U_2 denote the mass of water added to the primary and secondary mixers, respectively. The expected value of the total water addition U is:

$$U = U_1 + U_2 = \frac{1}{1 - M} \sum_{i=1}^{n} (M - K_i) W_i \tag{2}$$

A neural network model was chosen since the moisture content K_i of the raw material in the mechanism model equation was difficult to determine directly and K_i will fluctuate with different batches of material.

2.2. Prediction Problem Description

The mixing process of sintered mixes is divided into two stages: primary mixing and secondary mixing. The traditional manual water addition operation or feed-forward moisture control is difficult to meet changes in the water content due to fluctuations in raw materials and other factors, resulting in an uncertain time-varying and lagging minute system.

There is an interval of about 8 min between the addition of water to the primary mixing and the moisture meter measurement; therefore, a single-point mix water content prediction is defined as a kind of step-ahead time series prediction problem. Assuming that $X_{1:k} = \{x_1, x_2, \ldots, x_k\}$ denotes the amount of material in the k bins, in a multivariate prediction problem, the variables at time t in the future denote the mixture water content using the known variable matrix X in the past $t - \alpha_i$ moments:

$$y^t = f\left(X_1^{t-\alpha_1}, X_2^{t-\alpha_2}, \ldots, X_M^{t-\alpha_M} \mid \theta\right) \tag{3}$$

where y^t denotes the observed value at the prediction point at time t, f is a function of the prediction model, θ is a matrix of model parameters, and α_i denotes the delay time of the ith bin arriving at the observation point. Since the bins are arranged in different positions and the time difference between the spare bins is neglected, the time difference between the total amount of water added U to the moisture meter for the two mixing processes is considered to be β. Then, the predicted value Y at the moisture meter detection can be simplified as:

$$Y^t = F\left(X^{t-\alpha}, U^{t-\beta} \mid \theta\right) \tag{4}$$

2.3. Factors Influencing the Moisture Content of the Mixture

The sintered mix moisture content is mainly affected by two factors. The system factors include water addition fluctuation, mixing efficiency of the mixing machine, system drum coefficient, ambient temperature and humidity, etc. The raw material factors include material proportioning, material volume fluctuation, and the fluctuating moisture content of raw materials. In this paper, we focus on the analysis of the relationship between the fluctuation of water addition and raw material factors under the condition of certain environmental temperature and humidity and mixing efficiency. Figure 2 shows the correlation fraction between the mass of each mix and the total amount of water added. The value of each intersection indicates the Pearson coefficient between the two different factors named at the bottom left of the graph.

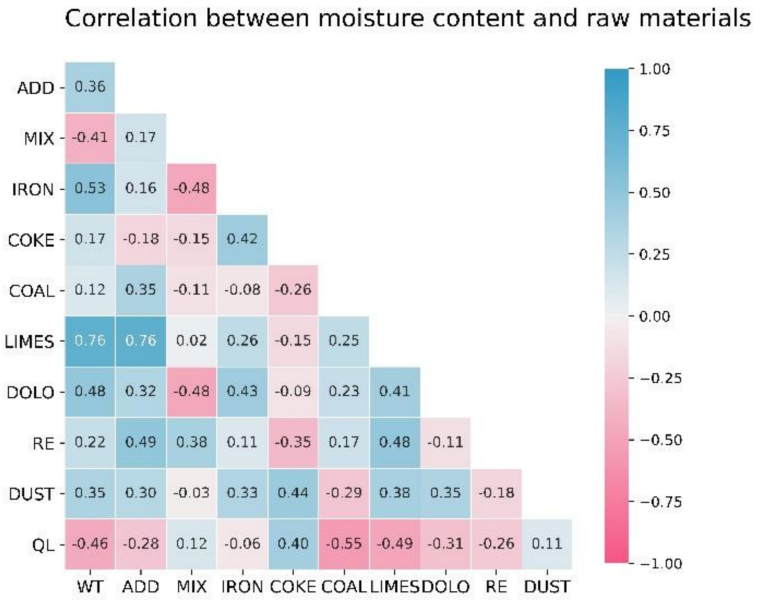

Figure 2. Correlations between moisture contents of raw materials.

According to the correlation coefficients between the water content of the mixture and each raw material, it can be seen that the water content has the highest correlation with limestone at 0.76, and quicklime has a weak negative correlation with water content WT

−0.46. The correlation between raw materials varies from −0.55 to 0.76, which indicates the redundant correlation information between different raw materials, while we selected the four variables with the highest correlation with the water content of the mixture as the main influencing factors, which were limestone, iron ore concentrate, total water addition, and dolomite.

3. Moisture Prediction Model

3.1. KPCA

KPCA is a nonlinear extension algorithm of PCA, and its basic principle is that the input data are projected into a high-dimensional feature space, and then principal element analysis is performed on the mapped data in the high-dimensional feature space [25]. The projection of the data on the nonlinear principal elements is then computed in the high-dimensional feature space so as to extract the data features. $X = \{x_i \mid x_i \in \mathbf{R}^m\}$, $i = 1, 2, \ldots, n$, is the sample set of data affecting the moisture content, n denotes the number of samples, m denotes the number of sample dimensions, and the data were first mapped from the original input space to the high-dimensional feature space F by the nonlinear mapping $\phi(x)$: $R^N \rightarrow F$. The sintering data in the high-dimensional feature space F satisfied the equation after normalization:

$$\sum_{i=1}^{M} \phi(x_i) = 0 \tag{5}$$

Thus, the covariance matrix C for the M-sample estimation is calculated in F as follows:

$$C^F = \frac{1}{M} \sum_{i=1}^{M} \phi(x_i)\phi(x_i)^T \tag{6}$$

The characteristic decomposition of covariance matrix C:

$$\lambda v = C^F v \tag{7}$$

where λ is the eigenvalue of the covariance matrix $\lambda \geq 0$, and v is the covariance of the eigenvectors corresponding to the covariance matrix. Multiplying Equation (7) simultaneously by $\phi(x_i)$ obtains the following:

$$\lambda\phi(x_i)v = \phi(x_i)C^F v \tag{8}$$

The eigenvector v corresponding to the non-zero eigenvalues can be obtained from Equation (8):

$$v = \sum_{i=1}^{n} \alpha_i \phi(x_i) \tag{9}$$

By introducing the kernel matrix K, we can consider the equivalence in Equation (9):

$$M\lambda K\alpha = K^2\alpha \tag{10}$$

where the kernel matrix $K = \phi(x_i) \cdot \phi(x_i)^T$, and α denotes the column vector in v.

The obtained eigenvalues are arranged in descending order, the corresponding eigenvector units are orthogonalized, and the first t principal elements are extracted based on the contribution rate of the principal elements. Finally, the projection of the kernel matrix on the partial eigenvectors is obtained. The above conclusion is based on the $\sum_{i=1}^{n} \phi(x_i) = 0$ case, which does not necessarily hold in the real case and requires a correction to the kernel matrix K_{ij} in Equation (11):

$$K'_{ij} = K_{ij} - IK_{ij} - K_{ij}I + IK_{ij}I \tag{11}$$

where I is an n × n matrix with 1/n elements. Following the KPCA procedure, the duplicate data in the initial sintering data are removed, resulting in a solid database for the creation of data-driven models.

3.2. Improved Genetic Algorithm for Multilayer Neural Networks

A BP neural network is a "universal model and error correction function" that can accurately express a nonlinear ingredient mixing system by establishing a BP neural network, effectively solving the problems of a mathematical model of mixture moisture content. Depending on the training results and expected results, error analysis is carried out, and then the weights and thresholds are changed to produce a model that is compatible with the anticipated outcomes. In forward propagation, the input samples are passed from the input layer and processed by each implicit layer to the output layer [25]. If the desired output is not obtained in the output layer, it is transferred to the back-propagation stage of the error. The back-propagation of the error is done by back-propagating the output error in some form through the hidden layer to the input layer and spreading the error to all units in each layer so as to obtain the error increment of each unit, thus correcting the weights and thresholds of each unit. The learning and training process of the network is repeated, and this process is carried out until the output error of the network is reduced to an acceptable degree or until the predetermined learning times are reached. In the actual problem of sintering, the selection of the nodes of the hidden layer is determined on the basis of an empirical formula. The network topology of the sinter mixture moisture content prediction system proposed in this paper is shown in Figure 3. The three-layer BP neural network was selected, the sigmoid function was chosen as the activation function, and the learning rule of the fastest descent method was used. The BP neural network input was chosen as the principal element after kernel principal component analysis, and the output was the moisture content of the controlled object.

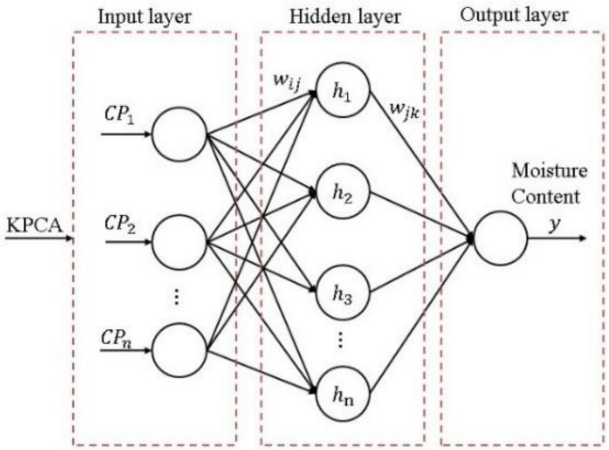

Figure 3. Basic structure of BPNN.

In Figure 3, w_{ij}, w_{jk} denote the weights between the input and implicit layers and the implicit and output layers, respectively, and x_n and y_m denote the input and output, respectively. After iterative training and adjustment, the optimal weights and thresholds were found later to fit the functional relationship between the sintered data. However, the straightforward BP network topology is also susceptible to local minima due to the random selection of weights and thresholds.

Genetic algorithms are a class of stochastic search algorithms that are inspired by the principles of evolutionary theory and genetics and are applicable to adaptive probabilistic optimization algorithms for complex system optimization [26]. The basic idea of a genetic algorithm is to eliminate the poorly adaptive individuals in an initial population through selection, crossover, mutation, and other operations, and retain the highly adaptive individ-

uals to finally filter to get the optimal solution. The main steps of the algorithm include (1) selection, which is achieved by random computer generation or the roulette wheel method; (2) crossover, which is an important means to generate new individuals; (3) mutation, which changes the genes of individuals with a certain probability. The above three steps can realize the search for the optimal solution in the global range, thus compensating for the defect that BP neural networks easily fall into local minima. The design of the parameters of the sintered water content GABP network considers the following three aspects, which are the coding length of chromosomes; the population size and the maximum genetic number; and the fitness function. In this study, the reciprocal of the BP neural network objective function was chosen as the fitness function. In summary, the water content prediction process based on the KPCA-GABP algorithm is shown in Figure 4.

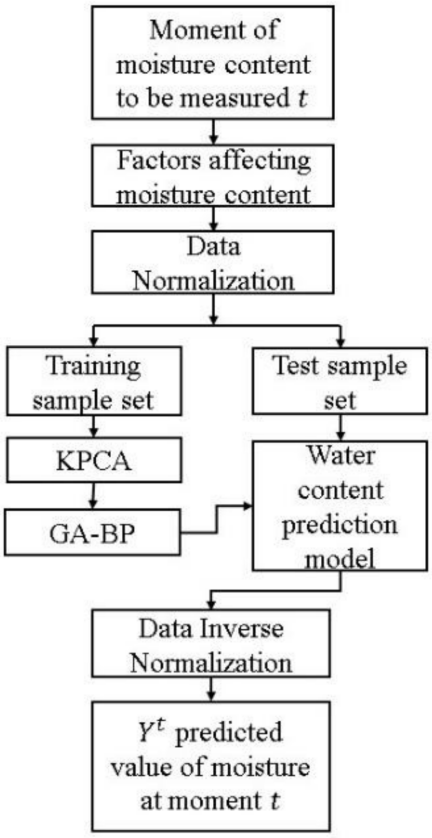

Figure 4. Moisture prediction strategy steps.

4. Simulation Results and Analysis

4.1. KPCA Data Pre-Processing

The data in this paper were obtained from the online production data of a metal materials sintering plant company from 10 to 19 October 2020, with microwave conductivity moisture meter sensors collected every 20 s and a total of 38,809 sets of samples in the data set, some of which are shown in Table 1. Eleven parameters were selected as the input variables, as described in Section 2.3 above, namely blended ore (MIX), iron ore concentrate (IRON), coke (Coke), pulverized coal (COAL), limestone (LIMES), dolomite (DOLO), return sinter fines (RE), dust (DUST), quicklime (QL), and first-mix water addition and second-mix water addition (ADD). We organized the new data set obtained by merging the bin data between the stored identical materials into a new matrix X, and matrix X was used to generate the KPCA standard principal components, where X has 38,809 measurements and 11 variables. Figure 5 illustrates the sintering data input for KPCA-GABP.

Table 1. Sample data overview.

No.	First Moisture Content (%)	Second Moisture Content (%)	Total Water Added (t)	Blended Ore (t)	Iron Ore Concentrate (t)	Dust (t)	Quicklime (t)	Date and Time
3529	7.62	7.34	15.89	390.96	110.85	10.89	29.58	18 October 2020 13:44
3530	7.56	7.34	16.04	390.31	109.68	10.78	29.84	18 October 2020 13:44
3531	7.62	7.21	15.92	380.49	108.22	9.99	29.06	18 October 2020 13:43
3532	7.62	7.34	16	399.17	108.34	9.24	29.14	18 October 2020 13:43
3533	7.69	7.47	15.97	378.95	105.96	9.11	28.75	18 October 2020 13:43
3534	7.49	7.22	16.03	399.05	112.44	9.54	28.82	18 October 2020 13:42
3535	7.62	7.41	15.9	375.54	108.33	9.66	28.87	18 October 2020 13:42
3536	7.56	7.02	15.99	389.96	112.8	10.59	28.43	18 October 2020 13:42

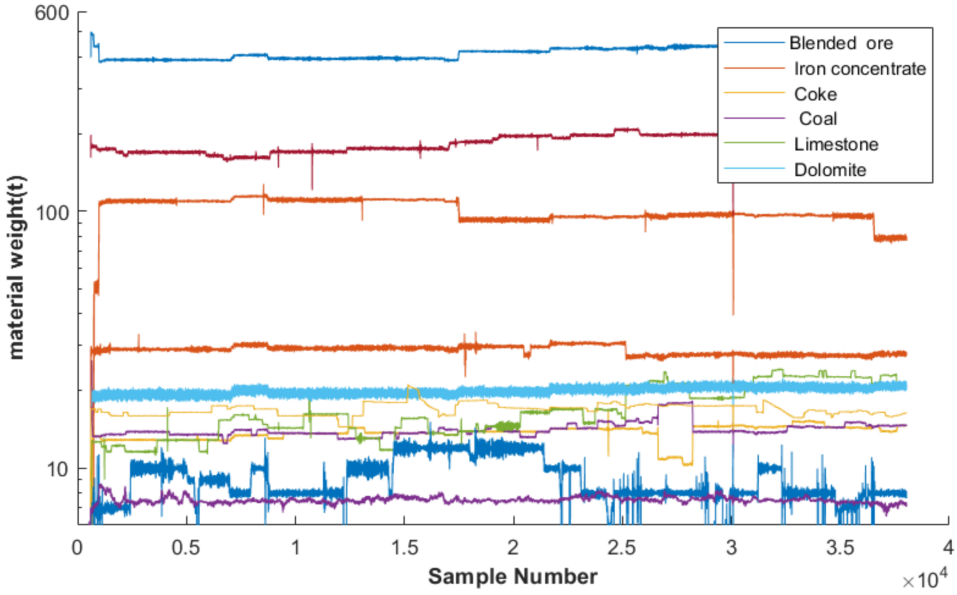

Figure 5. Sintering data input for KPCA-GABP.

In this study, a highly applicable Gaussian radial basis kernel function was used, defined by Equation (12).

$$k(x, x_i) = \exp\left(-\frac{|x - x_i|^2}{2\sigma^2}\right) \tag{12}$$

where x is the sample data and x_i is the centroid of the data. Before the data downscaling procedure, the kernel parameter, which is a single variable in KPCA, needed to be defined. The parameters in the KPCA method have a strong influence on the prediction effect, and the KPCA parameters in this study were x = 7.5. Meanwhile, the parameter gamma in the KernelPCA function is related to the number of features, which was set to 1/10 in this study. Thus, the eight principal components were obtained in the order of their corresponding variance contribution rates, as shown in Table 2. The first principal component is a linear combination of all the variables with the largest variance, so it accounts for as many variables as possible in the data. After this, the variance of each latter component is the largest in turn, subject to the constraint of being orthogonal to the previous component. The first seven principal components accounted for 93% of the cumulative variance. This shows that to fully explain the variance, only the top eight major components need to be retained.

Table 2. KPCA.

Principal Components	Variance Contribution Rate (%)	Cumulative Contribution Rate (%)
CP1	22.30	22.30
CP2	19.17	41.47
CP3	17.10	58.57
CP4	10.03	68.60
CP5	9.21	77.81
CP6	8.05	85.86
CP7	7.14	93
CP8	7.0	100

4.2. GA-BP Prediction Results

After performing the KPCA dimensionality reduction on the above experimental data, the original inputs affecting the moisture content of the sinter mixture were replaced by CP1 to CP8, from which the number of input layers of the network structure could be determined as eight layers. In the training process of the neural network, 28,500 samples from the plant data set were used as the training data set, 5700 samples as the validation data set, and 5700 samples as the test set, according to the principle of randomness. The initial number of nodes in the hidden layer was determined to be 10 according to the empirical formula. Therefore, the network structure of the BPNN was determined to be 8-10-1, the weight value was 90, the threshold value was 11, and the coding length of the genetic algorithm was 101. Through extensive experimental verification, the operating parameters were set, the maximum number of iterations was 200, the learning rate was 0.3, and the test error range was ±2%. The absolute value of the sum of the prediction errors of the training data was taken as the individual fitness value, and the smaller the individual fitness value, the better the individual is. Figure 6 shows a schematic diagram of the BP neural network model training validation and the test sample data regression.

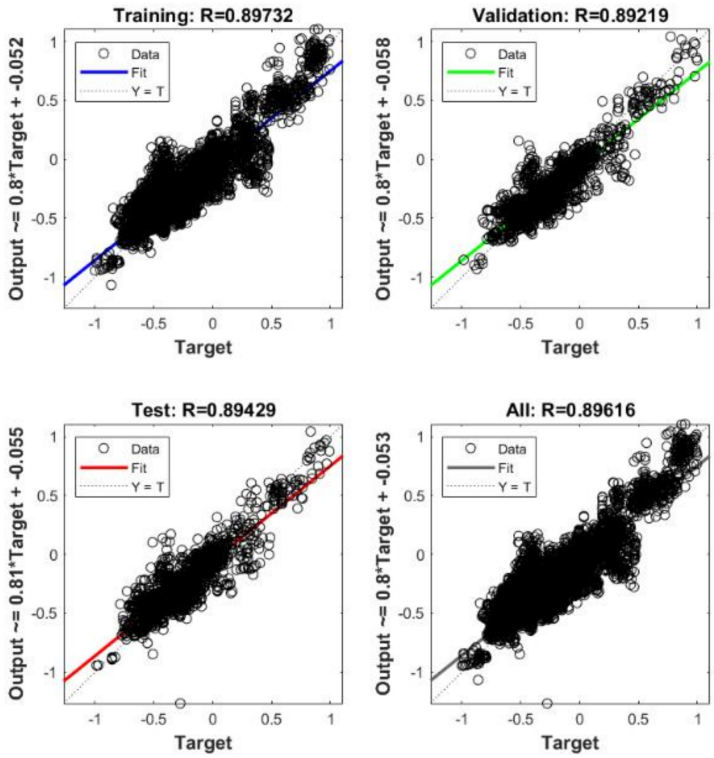

Figure 6. Training validation test sample regression schematic.

In Figure 6, it can be seen that there is a gap between the predicted and target values of the sample data, where the R value of the test set is 0.832, and the results show that the error is about 10%, which is a poor fit. The accuracy of the prediction results did not significantly improve as the computation time increased by adding more hidden layer neurons. To further improve the model performance, the initial thresholds and weights of the optimized object-BP neural network were used as the initial populations, and they were computationally optimized using the GA toolbox that comes with MATLAB. The parameter settings of the optimal genetic algorithm optimization model were selected through repeated experiments, as shown in Table 3.

Table 3. Genetic algorithm optimization parameter settings.

Parameters	KPCA-GABP Model
Initial generation	10
Population size	100
Crossover rate	0.3
Variation rate	0.15
Number of genes	random 1–3
Gene value boundary	−15~15

The improved BP neural prediction model for sintered water content using genetic algorithm optimization and the comparison of the training and regression curves for both sets of predictions are shown in Figures 6 and 7.

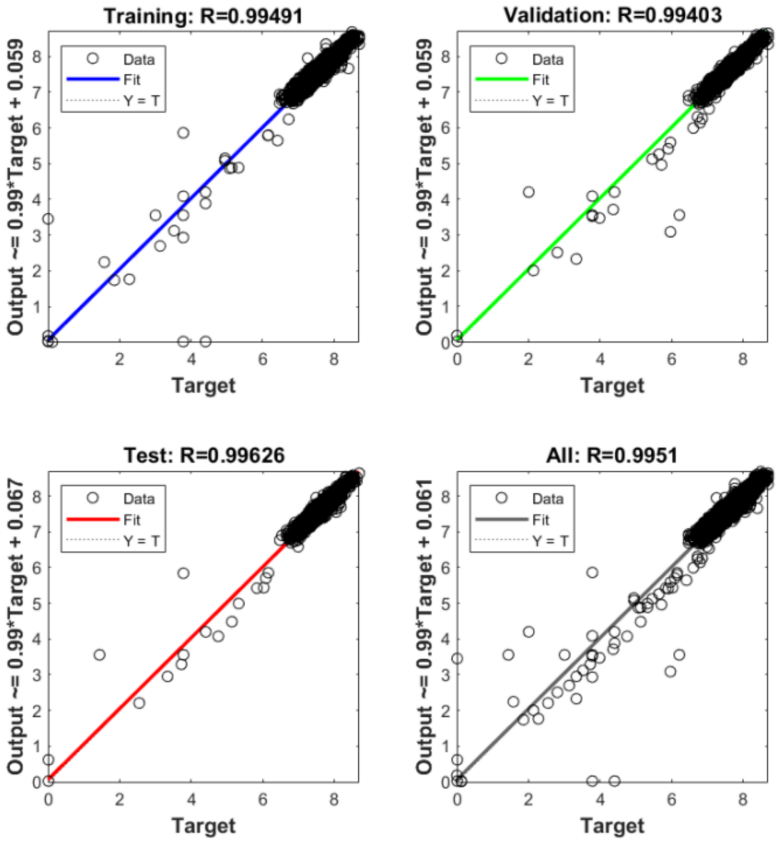

Figure 7. Regression diagram of training validation test samples after optimization.

The prediction results are close to the test data of the training sample. The correlation coefficient of the training data is 0.99491. The results show that the fit is good. In addition, the R-values of the validation and test data are 0.99403 and 0.99626, respectively. To obtain

a clearer view of the model performance, we plotted the mean square error (MSE) iterative effect of the data set, as shown in Figure 8. The blue, green, and red lines represent the MSEs of the training, validation, and test sets, respectively. The validation data modified the parameters of the model based on the training data. From Figure 8, it can be seen that the model has the best performance at the ninth iteration. The GABP training terminated at the 15th generation without overfitting. Therefore, the model can be considered reliable.

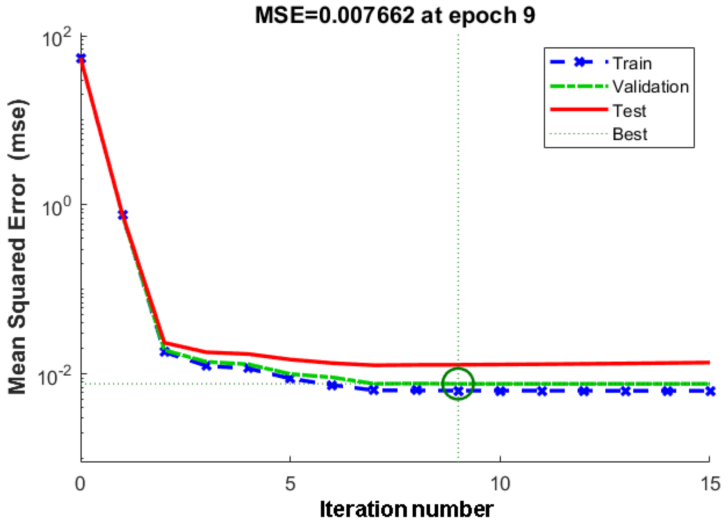

Figure 8. Optimized neural network training performance.

In this study, the mean absolute error (MAE), root mean square error (RMSE), and efficiency coefficient (EC) were used as evaluation indexes, where the MAE and RMSE were used to measure the predictive ability and the model error of the model, respectively. The obtained model prediction errors are shown in Table 4.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(y_k - \overline{y}_k)^2}{n}} \tag{13}$$

$$MAE = \sqrt{\frac{\sum_{k=1}^{n}|y_k - x_k|}{n}} \tag{14}$$

$$R = \frac{\sum_{k=1}^{n}(x_k - \overline{x})(y_k - \overline{y})}{\sqrt{\sum_{k=1}^{n}(x_k - \overline{x})^2 \sum_{k=1}^{n}(y_k - \overline{y})^2}} \tag{15}$$

$$EC = 1 - \frac{\sum_{k=1}^{n}(x_k - y_k)^2}{\sum_{k=1}^{n(x_k - \overline{x})^2}} \tag{16}$$

where x_k and y_k are the measured data, $\overline{x}$ and $\overline{y}$ are the average of the data, and n denotes the number of samples.

Table 4. Performance evaluation of the investigated ML models.

Evaluation Indicators	MSE	RMSE	MAE	R^2	EC
KPCA-BPNN	0.131	0.362	0.276	0.720	0.735
KPCA-GABP	0.046	0.067	0.053	0.992	0.975

Figure 9 shows the predicted results of the moisture content of the mix for October 2020 using the two prediction models. The red solid line in the figure indicates the actual values, the green dashed line indicates the predicted results of KPCA-BPNN, and the blue dashed

line indicates the GA-optimized fitted values, where more than 90% of the predictions lie in the range of 6.5–8.6. Among them, the real value of the mixture water content fluctuated widely between samples 1400 and 1600, The maximum difference was less than 0.2%, and the KPCA-GABP model captured the fluctuation of the mixture water content during this time to avoid serious deviations generated by local minima, which shows the consistency of the optimized model. Meanwhile, in terms of accuracy optimization, when the number of iterations was about 30, the evolution of the GA process reached the lowest average adaptation value.

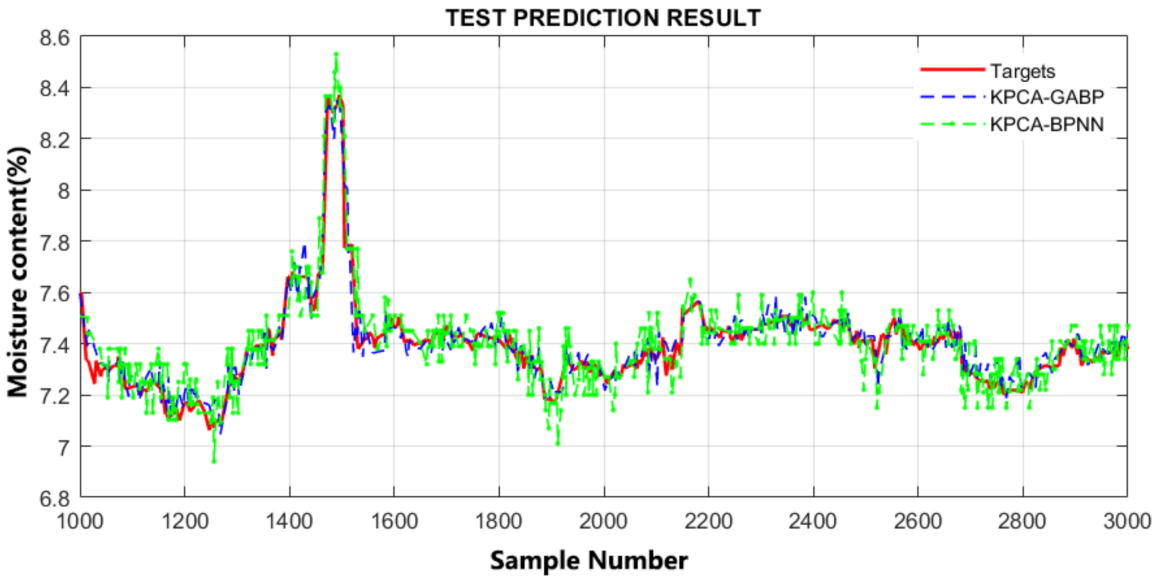

Figure 9. Prediction results of optimized water content model.

Figure 10 shows the prediction errors of the two methods. It can be seen that the average absolute error of the prediction of the optimized neural network using the genetic algorithm was reduced from 0.276 to 0.053, the root mean square error was reduced from 0.362 to 0.067, and the R-squared value increased from 0.720 to 0.992. This was due to the advantage of KPCA for complex sintering process data processing, combined with GA optimization to obtain the optimal network structure parameters to maximize its prediction accuracy at the expense of an acceptable runtime.

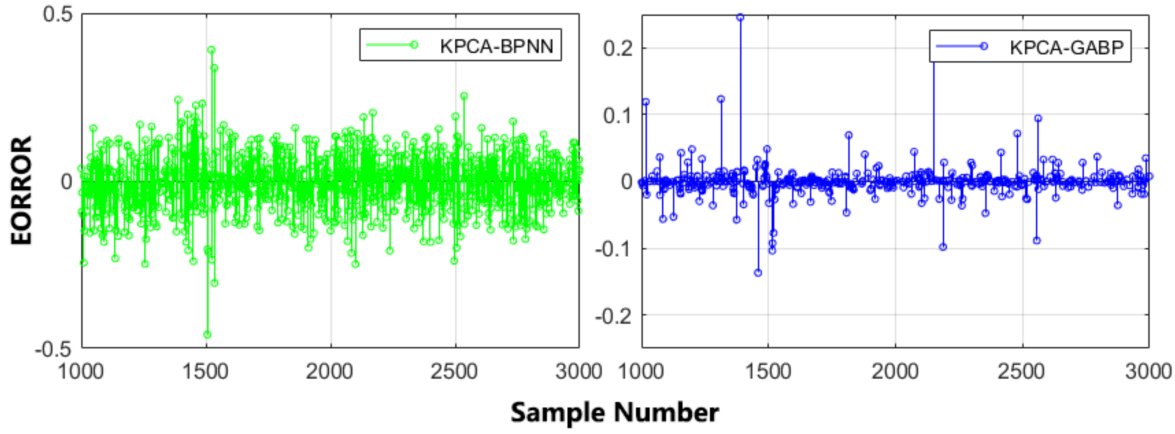

Figure 10. Error of moisture content prediction result.

5. Conclusions

In this paper, we analyzed and discussed the mixed water addition mechanism model of a sintering plant and obtained the main factors affecting water content through correlation analysis. We determined the input of the neural network by combining KPCA and the BP neural network and then optimized the neural network by using a GA. Finally, we established the KPCA-GABP prediction model, which can reduce the influence of multiple variables caused by the sintering water addition process. The prediction model can reduce the impact of multivariate coupling and time-varying delay between variables on the prediction model due to the sintering and water addition process and effectively improve the prediction accuracy of the mixture water content under complex working conditions. The prediction model can reduce the influence of multivariate coupling and time delay between variables on the prediction model and effectively improve the prediction accuracy of mixture moisture content under complex working conditions.

In future research, probabilistic confidence prediction can be used to further estimate the integrated physicochemical properties of the sinter mixture and to evaluate the quality of the sinter mixture. By modeling the spatial 3D distributed parametric system of the sintering process, it is possible to predict the indices of the moving material layers on the sintering machine. Nevertheless, there are still some issues to be solved in further research, such as the selection of the model parameters and the calibration of the measurement sensors; the solutions to these problems will be the priority of our future work.

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Abbreviations

BPNN	Back-propagation neural network
GA	Genetic algorithm
GRBK	Gaussian radial basis kernel
KPCA	Kernel principal component analysis
PCA	Principal component analysis
MFO	Moth flame optimizer
ML	Machine learning
NARX	Nonlinear autoregressive with exogenous inputs neural network

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