 Volume 8 Issue 5, 2022
DOI: 10.6919/ICJE.202205_8(5).0028

Evaluation and Analysis of Boiler Water Wall based on Entropy Weight TOPSIS Method

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Abstract

Aiming at the problem that there are many influencing factors and difficult control of boiler water cooling wall in the past, according to the temperature curve data of different water cooling wall pipelines, a variety of data characteristics are extracted according to the actual engineering environment for standardization, and the dimensional influence between different characteristic variables is eliminated. Combined with the entropy weight method, TOPSIS is improved, the weights of each index are calculated, the positive and negative ideal solution distances are found in combination with the size between the data, and a comprehensive evaluation is carried out. Finally, the boiler water wall temperature is highly optimized, laying the foundation for its accurate regulation.

Keywords

Relay Protection; Neural Network; Smart Grid; Artificial Intelligence.

1. Boiler Water Cold Wall Temperature Influence and Characteristic Variable Extraction

1.1 Boiler Water Cold Wall Operation Mechanism Section Headings

The water-cooled wall is a heating surface that is set up on the inner wall of the boiler furnace and consists of many parallel pipes. It is mainly used to absorb the heat radiated by the high-temperature flame in the furnace chamber, generate steam or hot water in the tube, reduce the furnace wall temperature, protect the furnace wall, and in actual production, the water cooling wall temperature does not exceed 455 ° C. The heat transfer phenomenon of the water-cooled wall on the cross-section is a two-dimensional problem, and its differential equation for heat transfer is:

$$\frac{\partial}{\partial x}\left(k\frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(k\frac{\partial T}{\partial y}\right)=0 \tag{1}$$

where: k is the thermal conductivity, W/ (m·°C); T is the temperature °C.

Empirical formula: (Q_s/Q_p is the ratio of secondary wind to primary wind, U_0 is the wind speed of boiler operation, ρ_b is the average concentration of solid particles in the thin phase area of the bed, T_b is the average temperature of the furnace, and K, α, β are the regression coefficients).

Heat transfer coefficient of the water-cooled wall around the furnace:

$$h_w=K(\rho_b)^{\alpha}(T_b)^{\beta} \tag{2}$$

The average temperature of the furnace chamber:

$$T_b = K(\frac{Q_s}{Q_p})^{\alpha} U_0^{\beta} \tag{3}$$

1.2 The Effect of Temperature on the Water Cooling Wall

In the large-capacity boiler, the flame temperature in the furnace is very high, the intensity of thermal radiation is very large, a large amount of heat in the boiler is absorbed by the water-cooled wall, resulting in serious temperature corrosion of the water-cooled wall pipe, so that the boiler has serious problems in operation, on the one hand, the pipe wall will become thinner, about one to two millimeters per year, which will not only form a hidden danger of safe operation but also increase the cost of boiler maintenance, on the other hand, due to the corrosion problem of the water-cooled wall, it is likely to cause a sudden explosion accident of the water-cooled wall pipe. Cause major safety accidents such as casualties.

1.3 Temper

Ten boiler water wall temperature curves are shown in Figure 1.

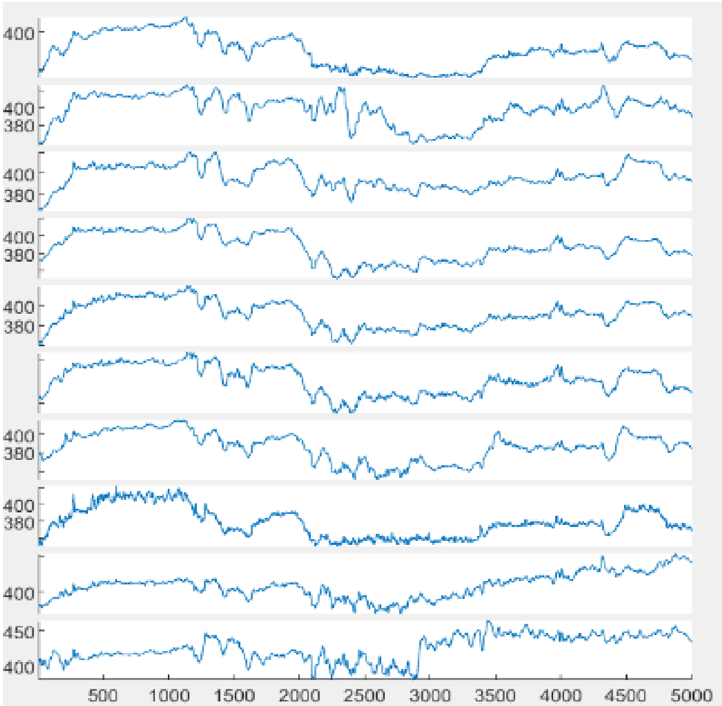

Figure 1. Layer 3 BP network architecture

According to the image, select some feature indicators: maximum, mean, standard deviation, and range, and select peak-to-valley ratio, maximum interval value, and over-temperature ratio as feature indicators in the actual water-cooled wall operation process.

$$\lambda = \frac{S}{D} \tag{4}$$

$$\Delta T = max|T_{n+1} - T_n| \tag{5}$$

$$\gamma = \frac{\sum_{i=1}^{n}(T_i = T \geq 455)}{n} \tag{6}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0028

2. Boiler Water Cooling Wall Operating Temperature Comprehensive Evaluation System

2.1 Feature Data Processing

Comprehensive evaluation first needs to construct the decision matrix A=aij, here, the decision matrix A is composed of j evaluation index (temperature characteristics), and I evaluation objects (water cooling wall), but j different evaluation indicators, often have different dimensions and dimension units, directly calculated, has no practical significance. Therefore, the indicator value must be converted into a dimensionless relative number. This process of removing the index dimension, called the dimensionlessness of the indicator, is the premise of the index synthesis.

First, the data is forward-oriented:

$$\begin{cases} c_{ij} = \frac{Z_{ij}-min(Z_i)}{max(b_i)-min(b_i)} & \text{(positive indicator)} \\ c_{ij} = \frac{max(Z_i)-Z_{ij}}{max(Z_i)-min(Z_i)} & \text{(reverse indicator)} \end{cases} \tag{7}$$

Then normalize the process to remove the dimension:

$$Z_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a^2{}_{ij}}} \tag{8}$$

a_{ij} indicates the jth indicator of the ith evaluation object.

By normalizing the characteristic indicators, as shown in Figure 2:

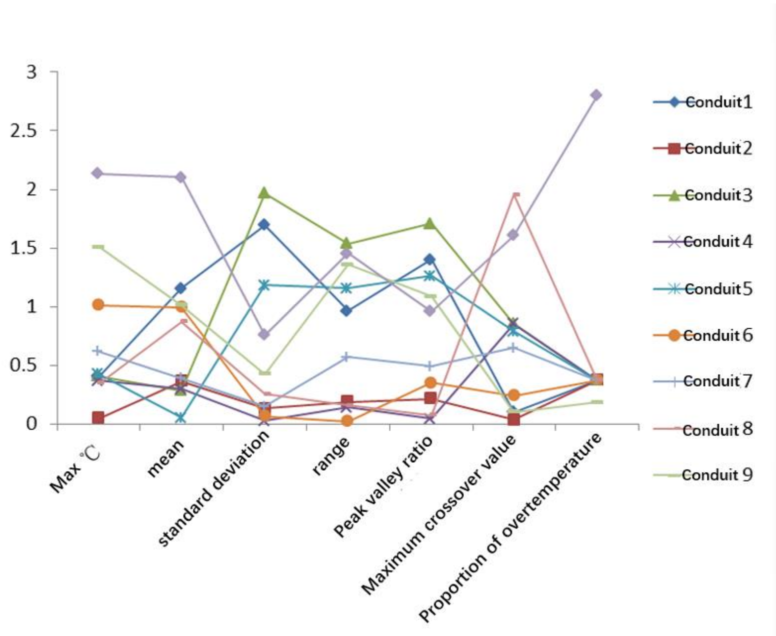

Figure 2. Characteristic metric normalization

2.2 Comprehensive Evaluation of TOPSIS

"Ideal solution" and "negative ideal solution" are two basic concepts in the TOPSIS algorithm. In the assumption of the best solution, its attribute values are the best values for each option, and vice versa is the negative ideal solution. Scenarios are categorized into ideal solutions and ideal negative

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solutions. Choose the best solution for either. Conversely, staying away from the ideal solution is not the best solution.

First of all, n evaluation indicators are regarded as n coordinate axes, from which an n-dimensional space can be constructed, and each object to be evaluated corresponds to a coordinate point in the n-dimensional space according to the data of its various indicators.

Then, the optimal value (ideal solution, corresponding to the optimal coordinate point) and the worst value (negative ideal solution, corresponding to the worst coordinate point) of the index are selected from all the objects to be evaluated.

After obtaining the standardized matrix Z, the distance between the coordinate points of each object to be evaluated to the optimal coordinate point and the worst coordinate point is determined in turn, and the optimal scheme and the worst scheme are determined.

The optimal scheme Z^+ consists of the maximum value in each column in Z:

$$Z^{+} = (max\, Z_{i1}, max\, Z_{i2}, \cdots, max\, Z_{im}) \tag{9}$$

Worst Scheme Z^- Consists of the smallest value in each column in Z:

$$Z^{-} = (min\, Z_{i1}, min\, Z_{i2}, \cdots, min\, Z_{im}) \tag{10}$$

Calculate the distance of each evaluator from Z^+ and Z^- D_i^+ and D_i^-

$$D_i^{+} = \sqrt{\sum_{j=1}^{m} (max\, Z^{+}{}_j - Z_{ij})^2}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{m} (min\, Z^{-}{}_j - Z_{ij})^2} \tag{11}$$

Finally, we can calculate the unorganized score S_i of the ith (i=1,2,⋯,n) evaluation subjects.

$$S_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \tag{12}$$

2.3 Evaluation System under the Improvement of the Entropy Law

For the evaluation indicators used, the evaluation weights they occupy are not considered, and the unified default weights are used for processing, to reduce the impact of the index weights in the TOPSIS model, the entropy weight method can be used to objectively empower the weights of each indicator. The entropy weight method is an objective empowerment method, relying on the data itself to empower the indicator, according to the characteristics of entropy, the smaller the degree of variation of the index data, the less information reflected, the lower the corresponding weight, the greater the degree of dispersion of the indicator, the greater the impact of the index on the comprehensive evaluation (weight).

Calculate the proportion of the ith sample under the jth indicator and think of it as the probability used in the relative entropy calculation:

$$p_{ij} = \frac{\tilde{z}_{ij}}{\sum_{i=1}^{n} \tilde{z}_{ij}} \tag{13}$$

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The information entropy of each indicator is calculated again, and the information utility value is calculated:

$$e = \frac{1}{\ln n}\sum_{i=1}^{n} p\ln(\mathrm{p}) \tag{14}$$

The final normalization obtains the entropy weight of each index, and the temperature evaluation results often water-cooled wall pipes are as follows:

Table 1. The temperature evaluation results

1	2	3	4	5	6	7	8	9	10
0.970	0.097	0.065	0.063	0.061	0.059	0.056	0.053	0.051	0

From the entropy weight analysis, it is concluded that pipeline 1 is the optimal working pipeline and pipeline 10 is the worst working pipeline.

3. Locate the Operating Variable that Causes the Overtemperature Phenomenon

3.1 Positioning is Mainly Overtemperature

The tenth pipe exceeded the overtemperature alarm line after the 3172 sets of data, compared the weights of the pipelines as a unit, used PCA to reduce the overall dimensionality of the influencing factors of the ten water-cooled walls, and obtained the operating variables that have the main impact on the water-cooled wall pipelines

3.2 Comprehensive Evaluation of PCA

Square weighted model construction: [μ is any constant, p is the weight, m is the pipeline-related parameters.

$$p_i = \frac{\mu^2}{m_i^2}(i = 1,2,3.4,5,6,7,8) \tag{15}$$

$$p_1 : p_2 \cdots p_n = \frac{\mu^2}{m_1^2} : \frac{\mu^2}{m_2^2} \cdots \frac{\mu^2}{m_n^2} = \frac{1}{m_1^2} : \frac{1}{m_2^2} \cdots \frac{1}{m_n^2} \tag{16}$$

PCA model:

$$\begin{cases} Z_1 = \alpha_{11}x_1 + \alpha_{12}x_2 + \ldots + \alpha_{1m}x_m \\ Z_2 = \alpha_{21}x_1 + \alpha_{22}x_2 + \ldots + \alpha_{2m}x_m \\ Z_3 = \alpha_{31}x_1 + \alpha_{32}x_2 + \ldots + \alpha_{3m}x_m \\ \ldots\ldots \\ Z_k = \alpha_{k1}x_1 + \alpha_{k2}x_2 + \ldots + \alpha_{km}x_m \end{cases} \tag{17}$$

Where, $\alpha_i = (\alpha_{i1}, \alpha_{i2}, \ \ldots, \alpha_{im})T, i = 1,2, \ldots, k$ is the eigenvector of the eigenvalue λ _I in the covariance matrix C.

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Table 2. The eigenvector of the eigenvalue λ

$\overline{T}$	$\overline{x}_1$	$\overline{x}_2$	$\overline{x}_3$	$\overline{x}_4$	$\overline{x}_5$	$\overline{x}_6$	$\overline{x}_7$
393.04	144.95	753.05	1036.90	3.49	255.79	307.45	315.81
406.65	172.35	941.74	1158.02	2.86	269.34	353.69	336.40
407.07	146.98	761.33	970.78	3.09	258.79	281.75	339.12
403.48	135.35	713.65	935.16	3.23	254.70	271.91	329.74
388.27	106.56	561.91	778.48	4.01	242.91	226.08	327.80
387.15	99.30	527.83	729.46	3.85	239.55	208.34	325.58
386.19	107.60	542.80	752.21	3.78	241.32	213.64	326.42
393.52	130.38	665.37	885.59	3.29	253.01	255.94	329.45
397.32	126.18	647.71	877.82	3.32	252.39	247.24	329.57
404.40	121.61	662.06	873.04	3.28	252.41	247.62	331.22

The covariance matrix C is:

$$C = \begin{cases} cov(x_1,x_1)\ cov(x_1,x_2)\ldots cov(x_1,x_m) \\ cov(x_1,x_1)\ cov(x_1,x_2)\ldots cov(x_1,x_m) \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ cov(x_1,x_1)\ cov(x_1,x_2)\ldots cov(x_1,x_m) \end{cases} \tag{18}$$

Calculate the contribution rate of each principal component, select the eigenvalue λ_1 from high to low, λ_2,...,λ _m corresponding principal component Z_i, the contribution rate formula:

$$\alpha_k = \frac{\lambda_i}{\sum_{k=1}^{p}\lambda_k},\quad i = 1,2,3,\ldots p \tag{19}$$

Table 3. The contribution rate of each principal component

$\Delta_{01}(t)$	$\Delta_{02}(t)$	$\Delta_{03}(t)$	$\Delta_{04}(t)$	$\Delta_{05}(t)$	$\Delta_{06}(t)$	$\Delta_{07}(t)$
0.1318	0.1204	0.1617	0.0297	0.0242	0.1856	0.0312
0.3097	0.3645	0.2620	0.1888	0.0437	0.3282	0.0029
0.1122	0.0972	0.0528	0.1226	0.0007	0.0519	0.0043
0.0311	0.0359	0.0223	0.0726	0.0064	0.0233	0.0152
0.1535	0.1496	0.1135	0.1938	0.0149	0.1137	0.0173
0.2069	0.1971	0.1652	0.1498	0.0254	0.1788	0.0134
0.1402	0.1726	0.1375	0.1318	0.0159	0.1561	0.0183
0.0178	0.0102	0.0077	0.0300	0.0120	0.0127	0.0091
0.0244	0.0459	0.0259	0.0308	0.0001	0.0556	0.0001
0.0776	0.0425	0.0491	0.0603	0.0178	0.0720	0.0130

Cumulative contribution rate formula:

$$\sum_{k=1}^{i}\alpha_k = \frac{\sum_{k=1}^{i}\lambda_k}{\sum_{k=1}^{p}\lambda_k}(i = 1,2,3\ldots p) \tag{20}$$

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Table 4. The Cumulative contribution rate

$\zeta_{01}(t)$	$\zeta_{02}(t)$	$\zeta_{03}(t)$	$\zeta_{04}(t)$	$\zeta_{05}(t)$	$\zeta_{06}(t)$	$\zeta_{07}(t)$
0.2167	0.2325	0.1840	0.5512	0.6012	0.1642	0.5390
0.1053	0.0909	0.1222	0.1619	0.4549	0.1000	0.9266
0.2453	0.2728	0.4085	0.2292	0.9814	0.4127	0.8947
0.5397	0.5039	0.6206	0.3343	0.8509	0.6102	0.7059
0.1919	0.1960	0.2431	0.1583	0.7100	0.2428	0.6783
0.1498	0.1561	0.1808	0.1958	0.5895	0.1694	0.7314
0.2064	0.1744	0.2096	0.2167	0.6965	0.1894	0.6659
0.6721	0.7816	0.8258	0.5487	0.7525	0.7418	0.8004
0.5992	0.4427	0.5848	0.5422	0.9975	0.3961	0.9975
0.3197	0.4618	0.4262	0.3768	0.6721	0.3362	0.7373

3.3 The PCA Model is Used to Derive the Main Operating Stool

Table 5. The main operaing stool

$\gamma_{01}(t)$	$\gamma_{02}(t)$	$\gamma_{03}(t)$	$\gamma_{04}(t)$	$\gamma_{05}(t)$	$\gamma_{06}(t)$	$\gamma_{07}(t)$
0.3246	0.3313	0.3806	0.3315	0.7306	0.3363	0.7677

4. Optimize Processes for Overtemperature Pipes

4.1 Problem Analysis

The 10th water-cooled wall appeared after the 3172 sample, so we established a gray correlation model for the first 3172 and 3172 to 5000 groups respectively and conducted a comparative analysis of the correlation degree, combined with the above main operating variables, based on MATLAB to establish a BP neural network genetic optimization algorithm model, comparative analysis of optimization results, so that the number of optimization operation variables as small as possible, the amount of regulation as small as possible. A regression prediction model combined with optimization is established to make the optimized working curve match the characteristics of curve 1 as much as possible.

4.2 BP Neural Network Construction

We determined that the 10th water-cooled wall temperature in the original table is the reference series T^((t)), which is compared to:

$$x_1^{(t)}, x_2^{(t)}, x_3^{(t)}, \cdots x_{100}^{(t)}, x_{111}^{(t)}$$
$$x_1^{(t)}, x_2^{(t)}, x_3^{(t)}, \cdots x_{100}^{(t)}, x_{111}^{(t)}$$

Let $X_i = (x_i^{(1)}, x_i^{(2)} \cdots, x_i^{(n)})$as the behavioral sequences of the factor Xi.

Initialize:

$$X_i' = \frac{X_i}{x_i^{(1)}} = \left(x_i'^{(1)}, x_i'^{(2)}, \cdots, x_i'^{(n)}\right)$$
$$x_i^{(1)} \neq 0, i = 0,1,2,\cdots m \tag{21}$$

Averaging:

$$X_i' = \frac{x_i^{(k)}}{\bar{X}_1}, \bar{X}_1 = \frac{1}{n}\sum_{k=1}^{n} x_i^{(k)}, k = 1,2,\cdots,n \tag{22}$$

Internalization:

$$X_i' = \frac{x_i^{(k)} - \min_i x_i^{(k)}}{\max_k x_i^{(k)} - \min_k x_i^{(k)}}, k = 1,2,\cdots,n \tag{23}$$

Correlation coefficient calculation.

Set the Reference Number column after processing.

$$X_0' = \{x_0^1(1), x_0^1(2), \cdots, x_0^1(n)\} \tag{24}$$

The Number of Comparisons column.

$$X_i' = \{x_i'(1), x_i'(1), \cdots, x_i'(n)\}, i = 1,2,\cdots,m \tag{25}$$

Two great differences and very small differences.

$$\begin{gathered} \Delta_i(k) = \left|x_0'(k) - x_i'(k)\right| \\ \Delta(min) = \min_i \min_k \Delta_i(k) \end{gathered} \tag{26}$$

Correlation coefficient calculation:

$$\begin{gathered} \gamma_{0i}(k) = \frac{\Delta(min) + \rho\Delta(max)}{\Delta_i(k) + \rho\Delta(max)} \\ \rho \in (0,1), k = 1,2,\cdots,n, i = 1,2,\cdots,m \end{gathered} \tag{27}$$

Find out the maximum and minimum differences:

$$\Delta_{max} \qquad \Delta_{min}$$

Calculate the correlation coefficient, take the resolution ρ, then the calculation formula is:

$$\zeta_{0i} = \frac{\Delta(min) + \rho\Delta(max)}{\Delta_{oi}(t) + \rho\Delta(max)} \tag{28}$$

Calculation and comparison of relational degrees:

$$\gamma_{0i} = \frac{1}{n}\sum_{k=1}^{n} \gamma_{0i}(k), i = 1,2,\cdots,m \tag{29}$$

4.3 Output the Results

The parameters and weights related to each pipeline are shown in Figure 3:

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0028

NUM	λ	ΔT	γ	T	$\bar{T}$	MSE	MAE	RMSE
1	1.240992	2.6	0	0	374.31	460.09	17.70281	21.44976
2	1.195628	2.8	0	0	397.91	283.95	13.45737	16.9507
3	1.153762	1.5	0	0	396.71	113.95	8.932664	10.67488
4	1.200513	1.5	0	0	387.61	268.11	13.89798	16.37418
5	1.166389	1.6	0	0	391.36	168.38	10.82523	12.97639
6	1.211538	2.4	0	0	376.84	277.40	14.28226	16.65520
7	1.187963	1.8	0	0	386.19	256.65	13.16857	16.02019
8	1.199601	5.6	0	0	378.68	296.15	14.09357	17.20896
9	1.232167	2.6	0.0292	152	408.03	313.45	14.18814	17.70464
10	1.228617	5.1	0.1656	624	424.91	349.40	16.17280	18.69221
weight	26.26855	5.016203	99968.37	0.0063	0.000247	0.000488	0.20294	0.139835

Figure 3. Related Parameters and Weights

From the above data, the BP and GASA-BRNN neural networks are constructed to optimize the variables at the same time, and their operation process and results are shown in Figure 4:

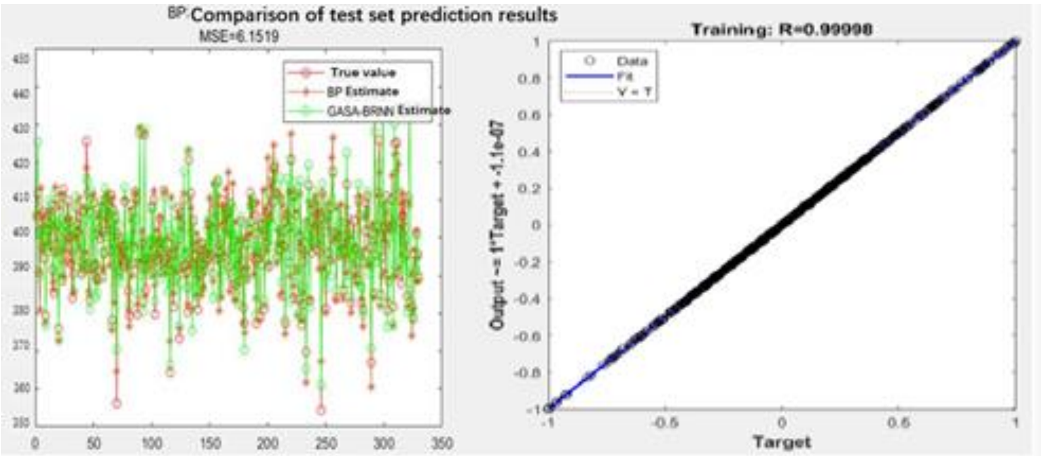

Figure 4. Image of the dual optimization algorithm

As can be seen from the above figure, the data regression after optimization is very high. And the output data is performed for regression calculations:

$$r=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}=0.99998 \tag{30}$$

The minimum error of the regression equation is as follows:

$$Q=l_{yy}-\frac{l_{xy}^2}{l_{xx}}=l_{yy}\left(1-\frac{l_{xy}^2}{l_{yy}l_{xx}}\right)=l_{yy}(1-r^2)\approx 0 \tag{31}$$

It can be seen from the above simulation result image and output result calculation that the prediction optimization simulation system predicts and optimizes the boiler water wall temperature, which is very reliable.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202205_8(5).0028

5. Conclusion

After the curve fitted by the BP neural network, compared with the ideal water-cooled wall pipe curve, the optimization results are verified by analyzing the regression coefficient, and it is concluded that the curve with a large deviation between the initial working environment and temperature structure and the ideal working curve has a significant correction effect, and the correction fit is close to 99%.

This paper provides a complete set of water-cooled wall temperature optimization systems, which reduces the complexity of temperature prediction of water-cooled walls, improves reliability and sensitivity, and provides a quick and convenient solution for engineering applications.

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