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Prediction of enterprise human resource demand based on internet of things and data mining technology

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Abstract In the enterprise's human resource management, the enterprise's human resource demand forecast is used by the enterprise as one of the bases of its strategic planning, and the human resource demand forecast indicates the direction for the enterprise's human resource strategy development, and ensures the scientificity and effectiveness in its implementation. This paper combines the grey correlation model and BP neural network, and optimizes the two models to form a human resource demand forecasting model based on grey BP neural network. The test enterprise is selected, and after the screening of indicators, the model is used to predict its human resource demand. The four indicators that have a great influence on the analysis of human resources demand of the test enterprise are the length of transmission network, the number of substations under the jurisdiction of the company, the total number of users, and the amount of electricity sold on the Internet, and the values of these four indicators in 2023 are 4905.987 kilometers, 193 seats, 690.348 million people, and 55,569.614 million kWh, respectively. Considering the influence of various types of characteristics on the results of the model predictions, the data on the impact of different elements on the demand for human resources were sorted out. It can be seen in the size of the number of recruits of different enterprises in the past few years, the number of recruits is mainly concentrated in the range of 50~200 people, among which the frequency of enterprises recruiting 60-80 people is the highest, with a total of 158 times, and the size of the number of recruits is relatively balanced.

Index Terms gray correlation model, BP neural network, human resource demand forecast, recruitment number scale

I. Introduction

With the rapid development of modern enterprise management, it is an indisputable fact that talent has become one of the core competitiveness of the enterprise, and the traditional personnel management has been unable to meet the needs of contemporary enterprises for human resource development and application, and human resource management has received more and more attention [1], [2]. Enterprise human resource planning as the first step of human resource management is very important for enterprises to obtain excellent, suitable and effective human resources [3]. Only on the basis of clear personnel demand required for future development according to their own reality, enterprises can make a planned forecast of enterprise human resource supply and carry out reasonable human resource planning on the basis of the balance between supply and demand [4]-[6]. Too much personnel demand forecast will bring burden and burden to the enterprise, while too little personnel demand forecast will cause the enterprise talent shortage, hindering the further development and growth of the enterprise [7], [8]. It can be seen that scientific enterprise human resource demand forecasting can provide important data support for the introduction of relevant human resource policies and the realization of enterprise strategic objectives [9], [10].

At present, domestic and foreign human resources demand forecasting methods can be generally divided into two categories: qualitative macro forecasting and quantitative micro forecasting. Commonly used macro forecasting methods package Delphi method, empirical forecasting method, manager judgment method, etc [11]. This type of method is generally based on human experience judgment, very flexible, can adapt to the changing internal and external environment, but at the same time by the human subjective factors have a greater impact, so it is commonly used in the judgment of the trend [12], [13]. Commonly used micro-forecasting methods mainly include trend analysis, ratio analysis, etc [14]. This type of method uses the concept of data analysis, established under the objective indicators of the enterprise, which can give a clear prediction result, easy to interpret and understand, and more operational in practical application [15], [16]. However, at present, when the micro forecasting method is applied in practice, the selection of the forecasting model can only be based on the experience of the forecaster, and often needs to simplify the influencing factors and the historical situation in order to ensure acceptable computational complexity, and it is very easy to exclude the key factors incorrectly, which leads to the failure of forecasting [17]-[19]. Therefore, the problem of enterprise human resource demand forecasting is categorized as a data mining problem, and the process of exploring the intrinsic laws between enterprise human resource demand and influencing factors from IoT data makes enterprise human resource demand forecasting a good reference value [20]-[23].

In this paper, based on the modeling mechanism of the gray correlation model, the Lagrangian function is used for interpolation, which overcomes the problem that the background value of the model is prone to errors, and the simulation prediction is realized with the fitting function corresponding to the optimized background value. An improvement scheme is proposed for the learning rate adaptive method in BP neural networks. Associate the gray correlation degree and BP neural network to establish the human resource demand prediction model based on gray BP neural network. Enterprise A is selected as the experimental object, and the model is applied to predict the human resource demand of Enterprise A. Combined with the actual situation of Enterprise A, the analysis index system of the enterprise is established and all the indexes are screened based on the gray correlation method, and the key analysis indexes of human resource demand are determined. The model is trained and tested on the network to predict the future recruitment demand of the enterprise.

II. Enterprise human resources demand forecasting model construction

II. A. Principle of GM(1,1) model construction and error analysis

II. A. 1) Modeling mechanism of the GM(1,1) model

Definition 1 Let the original data $x^{(0)}(k)=\left\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\right\}$, $x^{(0)}(k)>0\left(k=1,2,\ldots,n\right)$, then its one-time cumulative generating sequence is $x^{(1)}(k)=\left\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\right\}$.

where:

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),k=1,2,\ldots,n \tag{1}$$

Theorem 1 Let $x^{(0)}(k)$ be a nonnegative quasi-smooth sequence, then a one-time cumulative generating sequence $x^{(1)}(k)$ of $x^{(0)}(k)$ has a quasi-exponential law, where the quasi-smooth test and the quasi-exponential law are defined as follows:

Quasi-smooth test:

$$\rho(k)=\frac{x^{(0)}(k)}{\sum_{i=1}^{k-1}x^{(0)}(i)}<0.5,\frac{\rho(k+1)}{\rho(k)}<1 \tag{2}$$

Quasi-exponential laws:

$$\sigma(k)=\frac{x^{(1)}(k)}{x^{(1)}(k-1)}\in\left[1,1.5\right) \tag{3}$$

This theorem is the theoretical basis for the modeling of gray systems, which is satisfied by claiming that the sequence obtained after performing one accumulation satisfies the first-order linear differential equation as follows:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b \tag{4}$$

Eq. (4) is the whitening equation of $GM\left(1,1\right)$ model [24]. Where a is the development coefficient, which reflects the development trend of the simulated values of the primary cumulative generated series and the simulated values of the original data series, and b is the gray role quantity, which originates from the behavioral sequence of the system and reflects the change rule of the system data.

Since the analyzed data are discrete, in order to solve the parameters a, b, the first-order linear differential equation is discretized in the form of definite integral:

That is, $\int_{k-1}^{k}\frac{dx^{(1)}}{dt}dt+\int_{k-1}^{k}ax^{(1)}dt=\int_{k-1}^{k}bdt$ is obtained after discretization:

$$x^{(1)}(k)-x^{(1)}(k-1)+\int_{k-1}^{k}x^{(1)}dt=b \tag{5}$$

By the definition of one-time cumulative generation it follows that $x^{(1)}(k)-x^{(1)}(k-1)=x^{(0)}(k)$, and hence by its discrete form, the process of solving for the background value of the $GM(1,1)$ model from the geometric point of view of integration is the process of solving for the definite integral of $x^{(1)}(t)$ over the interval $[k-1,k]$.

Definition 2 Let $x^{(0)}(k)$, $x^{(1)}(k)$ be as shown in Definition 1, then its one-time immediate neighborhood mean generation becomes:

$$Z^{(1)}(k)=\left\{z^{(1)}(2),z^{(1)}(3),\cdots,z^{(1)}(n)\right\},k=2,3,\ldots,n \tag{6}$$

which is the background value of Tradition $GM(1,1)$, where:

$$z^{(1)}(k)=\frac{1}{2}\left(x^{(1)}(k)+x^{(1)}(k-1)\right) \tag{7}$$

This formula is the background value construction formula for the traditional $GM(1,1)$ model, and from its construction it can be seen that the trapezoidal formula is used as an approximate substitute for the definite integral $\int_{k-1}^{k}x^{(1)}dt$ over the definite interval $[k-1,k]$.

The background value construction formula is obtained by substituting it into the discretized equation:

$$x^{(0)}(k)+az^{(1)}(k)=b \tag{8}$$

Eq. (8) is called the gray differential equation and is the core foundation of the $GM(1,1)$ model.

The following analyzes the process of solving parameters a, b. The traditional $GM(1,1)$ model solves the parameters according to the least squares method with the following theorem:

Theorem 2 Let $x^{(0)}$, $x^{(1)}$, $z^{(1)}$ be as shown in Definitions 1, 2, if we make $\hat{a}=[a,b]^T$

$$Y=\begin{bmatrix}x^{(0)}(2)\\x^{(0)}(3)\\\vdots\\x^{(0)}(n)\end{bmatrix} B=\begin{bmatrix}-z^{(1)}(2) & 1\\-z^{(1)}(3) & 1\\\vdots & \vdots\\-z^{(1)}(n) & 1\end{bmatrix} \tag{9}$$

Then the least squares estimated parameter of the $GM(1,1)$ model is listed as $\hat{a}=\left(B^TB\right)^{-1}B^TY$, the proof of which is omitted here.

After obtaining the parameters, the form of the analog solution of the primary cumulative generating series is solved according to the form of the first order linear differential equation solution, and this solution is defined as the time response series of the $GM(1,1)$-model with the following equation:

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak}+\frac{b}{a},k=1,2,\ldots,n \tag{10}$$

Once again, the one-time cumulative generation sequence simulation solution is reduced according to the definition of cumulative generation to obtain its one-time cumulative reduction value as:

$$\hat{x}^{(0)}(k+1)=\left(1-e^{a}\right)\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak},k=1,2,\ldots,n \tag{11}$$

From the above solution process of the whole $GM(1,1)$ model, it can be seen that parameters a and b are the direct factors affecting the simulation accuracy of the $GM(1,1)$ model, while the way of the composition of the background values $z^{(1)}(k)$ determines the values of a and b. Therefore, creating scientific background values is the key to the whole calculation process, which will effectively improve the prediction accuracy of the model.

II. A. 2) Errors due to model background values

From the discrete form of the whitening equation $\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b$, it can be seen that the background value is the area value enclosed by the $x^{(1)}(t)$ and x axes, i.e., the constant integral value.

And the traditional $GM(1,1)$ model order $z^{(1)}(k)=\frac{1}{2}\left(x^{(1)}(k)+x^{(1)}(k-1)\right)$, using the trapezoidal area formula directly instead of the integral value, in the original data present some special laws, making the model prediction accuracy of a large deviation of the situation. Specific analysis is as follows: Since $x^{(1)}(t)$ is a fitting curve, according to the principle of least squares, not all points of a cumulative generation sequence are on the curve.

II. B.Optimization of GM(1,1) model based on human resources demand forecasting

II. B. 1) GM(1,1) model background value optimization process

According to the source of error of the GM(1,1) model, from the integral geometric meaning of the background value formation, appropriate points are inserted in the integration interval $[k-1,k]$, and here the Lagrangian function is used for interpolation to approximate the value of the $x^{(1)}(t)$ function at the interpolation point. And combined with the variable step trapezoidal algorithm, by selecting the appropriate step length, that is, in each integral interval of m equal parts, select the appropriate m value, the sum of m small trapezoidal area to approximate instead of the curved trapezoidal area. This is illustrated by the downward concavity of the minor intervals, as shown in Fig. 1.

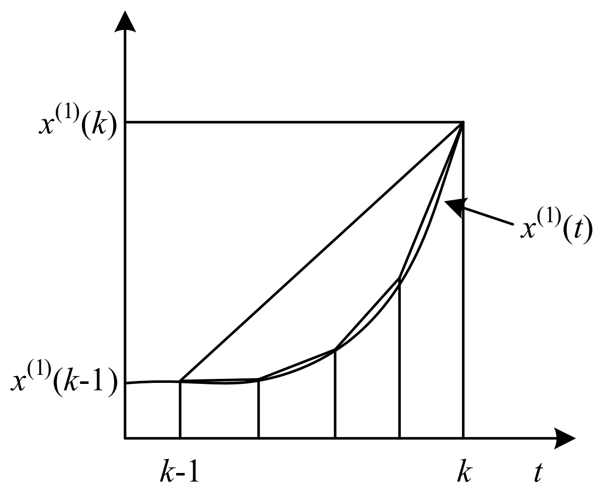


Figure 1: Ares approaching Schematic diagram

With the above geometrical description of the error sources, this paper chooses the Lagrangian interpolation formula and the variable step-size trapezoidal algorithm to optimize the background values, defined as follows:

If the function $y=f(x)$ is defined on $[a,b]$ and the value at $m+1$ nodes $a=x_0<\cdots<x_m=b$ is known, then $L_m\left(x_j\right)=y_j(j=0,1,\cdots,m)$.

Definition 3 is defined when the m th degree polynomials $l_i(x)$, $\left(j=0,1,\cdots,m\right)$ are available at $m+1$ nodes:

$$l_c(x)=\frac{\left(x-x_0\right)\cdots\left(x-x_{c-1}\right)\left(x-x_{c+1}\right)\cdots\left(x-x_m\right)}{\left(x_c-x_o\right)\cdots\left(x_c-x_{c-1}\right)\left(x_c-x_{c+1}\right)\cdots\left(x_c-x_m\right)} \tag{12}$$

Then this $m+1$ polynomial $l_0(x),l_1(x),\cdots,l_m(x)$ is said to be the m th interpolating basis of node $x_0<\cdots<x_m$.

At this point, the m times interpolated basis function can be expressed as:

$$l_j(x_c)=\begin{cases}1 & c=j\\ 0 & c\neq j\end{cases}(j,c=0,1,\cdots,m) \tag{13}$$

Thus the interpolating polynomial $L_m(x)$ satisfying Eq. (13) can be expressed as:

$$L_m(x)=\sum_{c=0}^{m} y_c l_c(x) \tag{14}$$

Equation (14) is called the Lagrange interpolation function, or L_m for short.

Definition 4 Let $[a,b]$ be divided into m equal parts with a total of $m+1$ nodes, and then bisect it so that the number of points increases to $2m+1$, while each subinterval $[x_d,x_{d+1}]$ undergoes bisection with only one additional point, i.e., $x_{d+\frac{1}{2}}=\frac{1}{2}(x_d+x_{d+1})$, where $x_d=a+ih$, $i=0,1,\cdots,m$, and $h=\frac{a-b}{m}$, is obtained by solving for the area within the subintervals by the complex trapezoidal formula:

$$\int_{x_d}^{x_{d+1}} f(x)dx\approx\frac{h}{4}\left[f(x_d)+2f\left(x_{d+\frac{1}{2}}\right)+f(x_{d+1})\right] \tag{15}$$

$$T_{2m}=\frac{h}{4}\sum_{d=0}^{m-1}\left[f(x_d)+f(x_{d+1})\right]+\frac{h}{2}\sum_{d=0}^{m-1} f\left(x_{d+\frac{1}{2}}\right) \tag{16}$$

Because:

$$T_m=\frac{h}{2}\left[f(a)+2\sum_{d=1}^{m-1} f(x_d)+f(b)\right] \tag{17}$$

So:

$$T_{2m}=\frac{1}{2}T_m+\frac{h}{2}\sum_{d=0}^{m-1} f\left(x_{d+\frac{1}{2}}\right) \tag{18}$$

Equation (18) gives the recursive relationship between T_m and T_{2m}, reducing the amount of computation, which shows that the variable-step trapezoidal algorithm for the complexification of the trapezoidal formula of the step-by-step fractional-half algorithm, the following discussion of how to determine the number of equivalent fractions m.

In this paper, the background value $z^{(1)}(k)$ is calculated by m, and the fitting function $\hat{x}^{(0)}(k)$ is obtained by $z^{(1)}(k)$ determining a and b, and the relative error $\varepsilon(k)$ and the average relative error $\bar{\varepsilon}$ are calculated by $\hat{x}^{(0)}(k)$ and $x^{(0)}(k)$. m In the process of change, $z^{(1)}(k)$, $\varepsilon(k)$ and $\bar{\varepsilon}$ are made to change sequentially, and finally $\bar{\varepsilon}$ is minimized in the process of change, and the value of m at this time will be used as the number of equal parts.

Figure 2 shows the curve fitting, first of all, the use of gray modeling software to calculate the original model average relative error $\bar{\varepsilon}_0$. Secondly, according to the 1-AGO exponential law to select the appropriate initial value, if you make the initial value of $m=m_1$, dichotomous $m=m_2$, $m_2=2m_1$, $m_1=1,2,\cdots,n$. Two m corresponding to the background value, the relative error, the average relative error are $z_1^{(1)}(k)$, $\varepsilon_1(k)$, $\bar{\varepsilon}_1$, $z_2^{(1)}(k)$, $\varepsilon_2(k)$, $\bar{\varepsilon}_2$, respectively.

(1) If $\bar{\varepsilon}_0<\bar{\varepsilon}_1$, use the original model.

(2) If $\bar{\varepsilon}_0>\bar{\varepsilon}_1$ and $\bar{\varepsilon}_1<\bar{\varepsilon}_2$ choose $m=m_1$ when calculating the background value.

(3) If $\bar{\varepsilon}_0 > \bar{\varepsilon}_1 > \bar{\varepsilon}_2$ then continue to increase m until some m value, set to m_*, if continue to increase m, then $\bar{\varepsilon}$ increase. Calculate the background value as m_*.

(4) In the process of $\bar{\varepsilon}$ decreasing, as m increases, the difference between the sum of the areas of two adjacent m calculated small trapezoids is decreasing, and the corresponding $\bar{\varepsilon}$ difference $\Delta\bar{\varepsilon}$ also decreases, and it may be provided that when $\Delta\bar{\varepsilon}$ is less than a particular value $\Delta\bar{\varepsilon}^*$, the calculation is stopped, and the one which minimizes the $\bar{\varepsilon}$ is chosen to m calculate the background value.

When the original data is a volatile data series, especially $1-AGO$ the more obvious the exponential pattern, then L_m the overall downward concave or upward convex, can make L_m and $x^{(1)}(t)$ the trend of change closer, then $\bar{\varepsilon}$ the more space can be reduced.

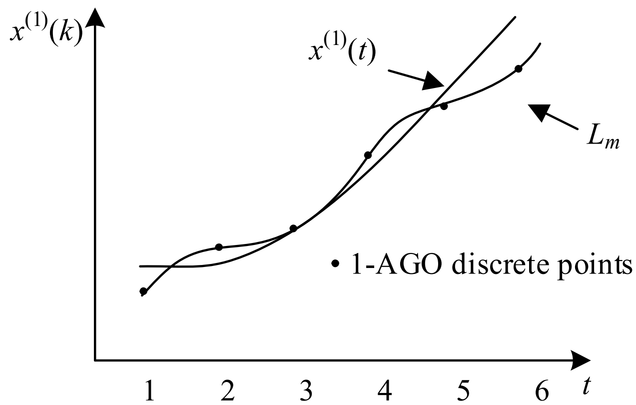


Figure 2: Curve Fitting Figure

II. B. 2) Optimization of GM(1,1) model construction

First, the software is used to calculate the average relative error of the original model $\bar{\varepsilon}_0$. Calculation $\sigma(k)$ analyzes the quasi-exponential law, sets the initial value m_1, and calculates the function value at the m_1 equidistant point on the interval $[k,k+1]$ from the L_m function.

Second, calculate the background value from the m_1 value and the function value at the interpolation point according to the trapezoidal algorithm with variable step size.

Third, the values of parameters a and b are calculated according to Theorem 2, and the simulated values of the original data are obtained according to Eq. (18).

Fourth, calculate the relative error $\varepsilon_1(k)$ and the overall average relative error $\bar{\varepsilon}_1$ of the simulated values.

Fifth, if $\bar{\varepsilon}_0 < \bar{\varepsilon}_1$, use the original model. Otherwise m continue to take the value, repeat the first to the fourth until the calculation stops when $\bar{\varepsilon}_e < \bar{\varepsilon}_f (e < f; e, f = 1, 2, \cdots, n)$ or $\bar{\varepsilon}_e - \bar{\varepsilon}_f = \Delta\bar{\varepsilon} \le \Delta\bar{\varepsilon}^*$, choose the value of m that minimizes $\bar{\varepsilon}$, recorded as m_*, and calculate $Z^{(1)}(k)$ that is:

$$z^{(1)}(k) = \frac{h}{2}\left[x^{(1)}(k-1) + 2\sum_{i=1}^{m_*-1} x^{(1)}(k-1+ih) + x^{(1)}(k)\right] \tag{19}$$

And simulated predictions were made with the fitting function $\hat{x}^{(0)}(k)$ corresponding to the optimized background values.

II. C.BP neural network model design based on human resources demand forecasting

II. C. 1) BP Neural Networks

Figure 3 shows the learning process of BP neural network, which has the following characteristics [25].

(1) The network consists of multiple layers, the nodes between the layers are fully connected, and the neuron nodes within the same layer are not connected.

(2) The transfer function is microscopic. The Sigmoid function is generally used, as shown in Equation (20), where $x \in R$, $f(x) \in (0,1)$. In the specific application process, it is also possible to increase the parameters to achieve the purpose of controlling the position and shape of the curve in order to improve the adaptability:

$$f(x) = \frac{1}{1+e^{-x}} \tag{20}$$

(3) Learning using error back propagation algorithm. The data starts from the input layer and is processed layer by layer in the hidden layer and then propagated backward layer by layer until it reaches the output layer. And when training the network, the weights of the network connections need to be corrected according to the error, starting from the output layer and going through the layers in the hidden layer layer by layer forward.

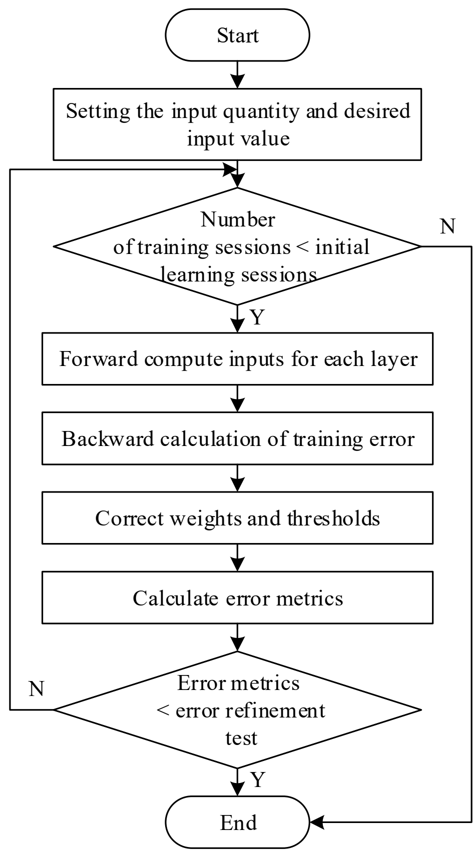


Figure 3: BP neural network learning process

II. C. 2) Steps of the BP neural network algorithm

(1) Preprocessing of data

Before neural network training, data preprocessing is required. The main purpose is to ensure the learning speed and prediction accuracy of the neural network by reducing the randomness of the data.

Data preprocessing is an important part of training neural networks, and the performance of neural networks is to some extent affected by the results of data processing. The most common practice of data processing is to normalize the original data, i.e., to completely restrict the input data to a certain interval through certain transformations, so that the values of the data become some kind of relative value relationship. The normalization of data can use the method of linear function transformation, the indicator sample value minus the minimum sample value and then divided by the maximum difference of the indicator sample, see formula (21):

$$y_i = \frac{x_i - \min x_i}{\max x_i - \min x_i} (i = 1, 2, \cdots, n) \tag{21}$$

(2) Determination of BP neural network structure

1) The design of the number of layers of the network. From the definition and characteristics of neural network, it can be seen that three-layer neural network is the most superior, if the network design structure is reasonable, and the weights of the neural nodes are taken appropriately, it can approximate any continuous function.

2) Input layer node design. The number of nodes in the input layer is the number of input features, and these input features have a great influence on the prediction results.

3) Implicit layer node design. The number of nodes in the implicit layer is related to the accuracy and learning efficiency of the whole BP network, so the number of nodes must be determined by minimizing the total sample error according to the actual running results.

4) Output layer node design. The design of the number of nodes in the output layer is determined according to the actual needs, and the nodes are set to several if several outputs are needed.

II. D.Improvement of BP algorithm

II. D. 1) Learning Rate Adaptive Approach

The goal of improving the BP algorithm is mainly to improve the prediction level, to speed up the training or to avoid falling into local minima, which are the three main objectives. In the standard BP neural network, the default optimization method of gradient descent is used to update the weights, but because this method has a fixed and constant search learning rate, the search efficiency is relatively low. If the original gradient descent method remains unchanged, the idea of improving the learning rate adaptive algorithm is as follows.

Let the error objective function $\min E(w)$ of the BP neural network has a first-order partial derivative, and the minimum value of the function can be obtained at the w^* point. Only from the initial state, step by step iterations can slowly approach the point w^* where the error is minimized, Eq. (22) illustrates the iterative calculation of the error of the objective function, i.e., at the point $w(n)$, a η-length migration is performed in the direction of $d(n)$:

$$w(n+1) = w(n) + \eta d(n) \tag{22}$$

where $w(n)$ is the point of error value for the n rd search for the minimum error w^*, η is the search step, and $d(n)$ indicates the search direction.

Expanding the error function $E(w)$ at $w(n+1)$ as a Taylor's formula, we have Eq. (23):

$$\begin{aligned} E[w(n+1)] &= E[w(n)+\eta d(n)] \\ &= E[w(n)] + \eta \nabla E[w(n)]^T d(n) + O(\eta) \end{aligned} \tag{23}$$

where $\nabla E[w(n)]$ is the gradient of $E(w)$ at $w(n)$ and $O(\eta)$ is the higher order infinitesimal of η if η is small enough.

Assuming that the gradient of $E(w)$ at $w(n)$ is not equal to 0, $O(\eta)$ is the higher order infinitesimal of η if the search step η is small enough. Equation (25) is obtained by adding equation (23) to equation (24). Only if the smallest $d(n)$ is found, it is guaranteed that Eq. (24) and Eq. (25) hold. Since the function value decreases the fastest in the negative gradient direction, searching along this direction leads to the fastest point of the function's minima:

$$\nabla E[w(n)]^T d(n) < 0 \tag{24}$$

$$E[w(n+1)] < E[w(n)] \tag{25}$$

In the adaptive learning rate algorithm, the step size η can be adjusted to a certain extent by measurement, and its adjustment rule is: if the error value decreases, the learning rate increases, if the error value increases, the learning rate then decreases, and if the error value does not change much, the learning rate is allowed to remain unchanged. The step size adjustment function is expressed by equation (26):

$$\eta(n) = \begin{cases} a \times \eta(n-1) & \text{Which } E(n) < E(n-1) \\ b \times \eta(n-1) & \text{Which } E(n) > cE(n-1) \\ \eta(n-1) & \text{Other situations} \end{cases} \tag{26}$$

where a, b and c are constants with the following ranges of values: $a \in (1,2)$, $b \in (0,1)$, $c \in [1,1.1]$, $E(n)$ and $E(n-1)$ represent the error values of the two times, respectively.

II. D. 2) Learning rate adaptive method improvement

The learning rate adaptive algorithm has been improved so that in the initial stage of searching for the minimum value of the error function $\min E(w)$, a relatively small η can be selected as the initial learning rate. If formula (25) is satisfied, it means that the error is decreasing, then keep the original search direction unchanged, expand the step size and continue learning. If the formula (27) is satisfied, it means that the error starts to increase, indicating that it is getting farther and farther away from the minimum value point, and it is necessary to reduce the step size, and to change the search direction to the opposite direction of the original search direction to continue learning, in order to continue to reduce the error.

$$E\left[w(n+1)\right] > E\left[w(n)\right] \tag{27}$$

II. D. 3) Improved BP neural network algorithm process

Let X be the input vector as shown in Eq. (28):

$$X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1I} \\ 1 & x_{21} & x_{22} & \cdots & x_{2I} \\ 1 & x_{31} & x_{32} & \cdots & x_{3I} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{M1} & x_{M2} & \cdots & x_{MI} \end{bmatrix} = \left(X_{mi}\right)_{M\times(I+1)} \tag{28}$$

U is the matrix of coefficients from the input layer to the implicit layer as shown in Eq. (29):

$$U = \begin{bmatrix} u_{01} & u_{02} & \cdots & u_{0J} \\ u_{11} & u_{12} & \cdots & u_{1J} \\ u_{21} & u_{22} & \cdots & u_{2J} \\ \vdots & \vdots & \vdots & \vdots \\ u_{I1} & u_{I2} & \cdots & u_{IJ} \end{bmatrix} = \left(u_{ij}\right)_{(I+1)\times J} \tag{29}$$

V is the coefficient matrix from the implicit layer to the output layer as shown in Eq. (30):

$$V = \begin{bmatrix} v_{01} & v_{02} & \cdots & v_{0P} \\ v_{11} & v_{12} & \cdots & v_{1P} \\ v_{21} & v_{22} & \cdots & v_{2P} \\ \vdots & \vdots & \vdots & \vdots \\ v_{J1} & v_{J2} & \cdots & v_{JP} \end{bmatrix} = \left(v_{jp}\right)_{(J+1)\times P} \tag{30}$$

Network during forward propagation, f is the excitation function as shown in Eq. (31):

$$f(x) = \left(1+e^{-ax}\right)^{-1}, a \text{ is a constant} \tag{31}$$

Y is the output vector, Y_j denotes the output of the input layer to the implicit layer as shown in equation (32), and Y_p denotes the output of the implicit layer to the output layer as shown in equation (33):

$$Y_j = f\left(\sum_{i=1}^{I+1} x_{mi} u_{ij}\right) \tag{32}$$

$$Y_p = f\left(\sum_{j=1}^{J+1} Y_j v_{jp}\right) \tag{33}$$

E is the error function as shown in equation (34), where d_y is the desired output value:

$$E(n)=\frac{1}{2}\sum_{p=1}^{p}\left(d_y-Y_p\right)^2 \tag{34}$$

Gray model (GM) is used to construct a gray differential equation prediction model by using known data, so as to achieve the purpose of describing the long-term law of the development of things, especially when the amount of known data is relatively small, the use of GM model is more advantageous. A n nd order differential equation model consisting of m variable is called $GM\left(n,m\right)$.

II. E. Construction of human resources demand forecasting model based on gray BP neural network

Let $x^{(0)}=\left\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\right\}$ be the original data sequence and the data is accumulated once to generate a new data sequence $x^{(1)}$, i.e.:

$$x^{(1)}=\left\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\right\} \tag{35}$$

In the formula:

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),k=1,2,\cdots,n \tag{36}$$

A tight neighborhood averaging of $x^{(1)}$ produces the sequence $z^{(1)}$, i.e:

$$z^{(1)}=\left\{z^{(1)}(2),z^{(1)}(3),\cdots,z^{(1)}(n)\right\} \tag{37}$$

In the formula:

$$z^{(1)}(k)=\frac{1}{2}\left(x^{(1)}(k)+x^{(1)}(k-1)\right),k=2,3,\cdots,n \tag{38}$$

Construct a first-order univariate differential equation $GM\left(1,1\right)$ with respect to variable t from gray theory for $x^{(1)}$, i.e:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b \tag{39}$$

where a is the development coefficient and b is the gray role quantity.

Coefficient a is used to measure the development trend of the predicted reduction values, coefficient b to measure the intrinsic changes in the original data, and least squares is used to solve for the values of coefficient a and coefficient b. The data prediction model is [26]:

$$\hat{x}^{(1)}(k)=\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-a(k-1)}+\frac{b}{a},k=1,2,\cdots,n \tag{40}$$

Sequence data prediction results are:

$$\hat{x}^{(0)}(k)=\left(1-e^{a}\right)\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-a(k-1)} \tag{41}$$

where $\hat{x}^{(0)}(k)$ is the sequence of original data reduction values.

When $k\le n$, $\hat{x}^{(0)}(k)$ is the fitted value of the $GM\left(1,1\right)$ model and when $k>n$, $\hat{x}^{(0)}(k)$ is the predicted value of the $GM\left(1,1\right)$ model.

Let the input data be $X_t^{(0)}=\left(x_t^{(0)}(1),x_t^{(0)}(2),\cdots,x_t^{(0)}(n)\right)$, where $t=1,2,\cdots,N$. One accumulation of data $X_t^{(0)}$ produces a new data sequence $X_t^{(1)}$, i.e.:

$$X_t^{(1)}=\left(x_t^{(1)}(1),x_t^{(1)}(2),\cdots,x_t^{(1)}(n)\right),t=1,2,\cdots,N \tag{42}$$

In the formula:

$$x_t^{(1)}(k)=\sum_{i=1}^{k}x_t^{(0)}(i),k=1,2,\cdots,n \tag{43}$$

For ease of expression, $X^{(1)}(t)$ is used in place of $X_t^{(1)}$. The differential equation is constructed from equation (43), viz:

$$\frac{dX_1^{(1)}(t)}{dt}+aX_1^{(1)}(t)=b_1X_2^{(1)}(t)+b_2X_3^{(1)}(t)+\cdots+b_{N-1}X_n^{(1)}(t) \tag{44}$$

Where, $X_2^{(1)}(t)$, $X_3^{(1)}(t)$, ..., $X_n^{(1)}(t)$ are the input parameters of the neural network, $X_1^{(1)}(t)$ is the output parameters of the neural network, a, b_1, ..., b_{N-1} are the differential equation coefficients.

Solving the differential equation to obtain the time response equation, i.e:

$$\begin{aligned}X_1^{*(1)}(t)=&\left(X_1^{(1)}(1)-\frac{b_1}{a}X_2^{(1)}(t)-\frac{b_2}{a}X_3^{(1)}(t)\right.\\&\left.-\cdots-\frac{b_{n-1}}{a}X_n^{(1)}(t)\right)e^{-at}+\frac{b_1}{a}X_2^{(1)}(t)\\&+\frac{b_2}{a}X_3^{(1)}(t)+\cdots+\frac{b_{n-1}}{a}X_n^{(1)}(t)\end{aligned} \tag{45}$$

where $X_1^{*(1)}(t)$ is the predicted value.

Transformational deformation of Eq. (45) yields the mathematical model of BP neural network, i.e.:

$$\begin{aligned}X_1^{*(1)}(t)=&\left(\left(X_1^{(1)}(1)-D\right)-X_1^{(1)}(1)\frac{1}{1+e^{-at}}\right.\\&\left.+2D\frac{1}{1+e^{-at}}\right)\left(1+e^{-at}\right)\end{aligned} \tag{46}$$

In the formula:

$$D=\frac{b_1}{a}X_2^{(1)}(t)+\frac{b_2}{a}X_3^{(1)}(t)+\cdots+\frac{b_{n-1}}{a}X_n^{(1)}(t) \tag{47}$$

This results in a gray neural network with $n-1$ inputs and 1 output.

III. Gray BP neural network-based enterprise human resources demand forecast analysis

III. A. Business profile

The object of analysis selected for this paper is a large-scale power supply enterprise A in a certain region, and the details of the company are described as follows: Company A is the main power supply and management unit in the region, covering 29 townships and 2 forest farms under the jurisdiction of the region, with a total of 31 secondary power supply companies. The Company has been established for more than 30 years, and over the long term, the Company's staffing structure and the scope of its business (service area) and volume (mainly electricity sales and equipment) have changed dramatically. By 2023, unmanned substation types have accounted for more than 97% of the Company's existing point stations, and the service has formed a power supply network based on eight 500 kV substations. With the deepening of the market-oriented reform of the State Grid, the development of the enterprise is facing new challenges, management methods need to be improved, personnel structure needs to be optimized, power supply equipment and facilities need to be further upgraded. Against this background, Company A has put forward the human resources slogan of “Positive Change, Talent Priority”, striving to build a human resources management system that adapts to the new situation, and striving to become a first-rate power supply company in China and a leader in the industry. The information on human resources and company performance of

Company A is mainly obtained through the organization and summarization of the company's information dissemination.

Figure 4 shows the trend of the number of employees and electricity sales of Company A from 2013 to 2023. It can be seen that the number of employees of Company A has been maintaining an increasing trend with a relatively slow growth rate. While the electricity sales of Company A slipped by 2,240 kWh in the year 2019, in addition to this, the overall growth has been maintained at a good rate and remained good despite the total growth in the last year, for the decline in demand for electricity during the year 2019 may be caused by factors such as the weakness of the domestic economy.

Although the number of employees of the Company has maintained growth, with the adjustment of relevant national policies and changes in the Company's internal human resource structure, it has led to certain problems in the Company's personnel structure, which is specifically manifested in the higher demand for power dispatching and transmission and transformation personnel in the main power transmission network. In this regard, it is necessary for the Company to plan its human resources department in advance, complete the forecast of human resources demand as early as possible, adjust and optimize the personnel structure, clean up the surplus personnel, and introduce the insufficient number of professionals to serve the Company's long-term development goals.

Through the above basic situation, it can be seen that the information related to the development history of Company A is relatively detailed, rich in data, and the collected data show a certain degree of volatility, which is suitable for analyzing and forecasting its human resource demand by using gray BP neural network.

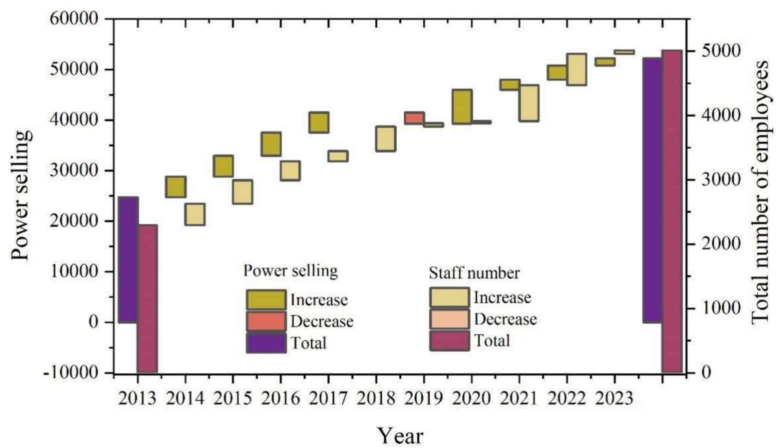


Figure 4: The number of employees and the changing trend of the sales of a company in 2023

III. B. Model Analysis Indicators and Screening

This paper combines the actual situation of enterprise A, establishes the analysis index system of the enterprise and screens all the indexes based on the gray correlation method, and determines the final key analysis indexes of human resource demand. The establishment of human resources demand analysis indicators should be consistent with the size of the enterprise, enterprise production and operation, internal and external human resources environment and other factors, based on the above principles, this paper selects the following analysis indicators as the initial analysis system of human resources demand forecast of Company A, the specific sinks are shown in Table 1.

Table 1: A company human resources demand forecast analysis system

1 category of analysis indicators	2 types of analysis indicators	Specific analysis index
Company development resources	The core resources owned by the company	Length of transmission network (a_1)
		Number of substations under the jurisdiction (a_2)
Market development of the company	Company market size	Total number of users (a_3)
		Total serving population (a_4)
Market development of the company	Company size	Annual revenue of the company (a_5)
	Company operating condition	Online electricity sales (a_6)

III. C. Network Training and Testing

III. C. 1) Network training

After the construction of the original system of demand forecast analysis is completed, it is necessary to screen the indicators that affect the human resources demand of Company A, that is, the key indicators. The screening method used is to calculate the comprehensive correlation degree in the gray correlation analysis method, and the analysis results are shown in Table 2. The correlation between each indicator and human resources is calculated by the gray system modeling software, and the specific results are:

$$\begin{gathered}\rho_{a_1}=0.7866\rho_{a_2}=0.6352\rho_{a_3}=0.6798\\ \rho_{a_4}=0.5975\rho_{a_5}=0.5436\rho_{a_6}=0.6056\end{gathered}\tag{48}$$

The higher the correlation value, the greater the impact on human resource requirements. Sorting the above correlation degree values, we can get: The values of the four variables of a_1, a_2, a_3 and a_6 are relatively large, that is, the length of the transmission network, the number of substations under its jurisdiction, the total number of users, and the four indicators of online electricity sales have a greater impact on the analysis of human resource demand, so the above four analysis indicators are selected as the key indicators, and the values of these four indicators in 2023 are 4905.987 kilometers, 193 buildings, 690348 people and 55569.614 million kWh respectively.

Table 2: A Summary of analysis results of key indicators of enterprise human resource demand"

Year	Total number of users (10,000)	Network length (km)	Annual income of the company (million yuan)	Total number of employees (number)	The total population of the service (10000)	Internet sales (millions)	Number of substations (stations)
2013	645.395	2032.548	8560.725	2297	145.631	28169.615	92
2014	644.287	2143.645	9734.045	2628	157.899	32187.988	98
2015	656.198	2502.348	10456.699	2993	162.596	36185.658	109
2016	668.136	2718.365	11648.698	3288	171.698	40236.965	120
2017	684.935	2853.368	13425.398	3445	176.896	44236.931	124
2018	687.135	3187.985	14365.985	3826	185.658	44316.963	138
2019	681.468	3325.856	15789.658	3879	190.985	42798.664	146
2020	685.348	3612.348	17269.648	3913	202.699	4769.662	153
2021	690.726	3921.487	20036.495	4469	205.685	51896.315	155
2022	690.548	4209.648	22165.635	4957	210.988	53198.636	168
2023	690.348	4905.987	25915.365	63485	228.948	55569.614	193

The network training uses the data from 2013-2023 as the training samples. In order to improve the efficiency of the network and ensure the consistency of the research data, it is necessary to apply the mapminmax function in MATLAB to normalize the training samples before training. After the sample data processing is completed, the technical skills talent demand prediction model is created by calling the newff function in MATLAB, inputting the data and using the train function for network training. The specific training process is:

TRAIN, Epoch 2/1000, MSE 0.000405/0.001

Gradient 0.0463/1e-07TRAIN, Performance goal met.

When the number of hidden layer units is 12, the network training results are shown in Fig. 5, and the best validation performance is 0.00099852.

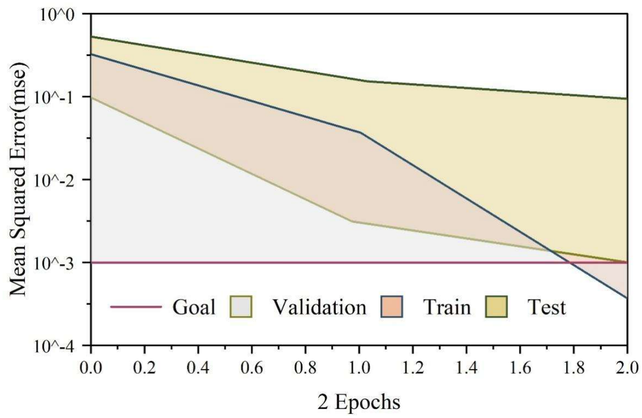


Figure 5: Network training results

III. C. 2) Network test results

(1) Network validation

In order to test whether the network is overfitting, the 2015-2017 data is used as the test set, i.e., the 2015-2017 data is put into the trained neural network. Figure 6 shows the results of the test set, none of the 2015-2017 prediction error percentages exceeded 6.5%, the neural network is more accurate, there is no overfitting problem, and the number of future employee demand can be predicted.

Firstly, using the gray prediction model, the data of the length of the transmission network, the number of substations under the jurisdiction, the total number of users, the total number of population served, the amount of annual revenue of the company, and the amount of electricity sold on the Internet are predicted respectively for the period of 2024-2026, and then the data of the period of 2024-2026 are brought into the trained network. The network predicts that the total number of employees in 2024-2026 will be 7581, 7798, and 7633, respectively.

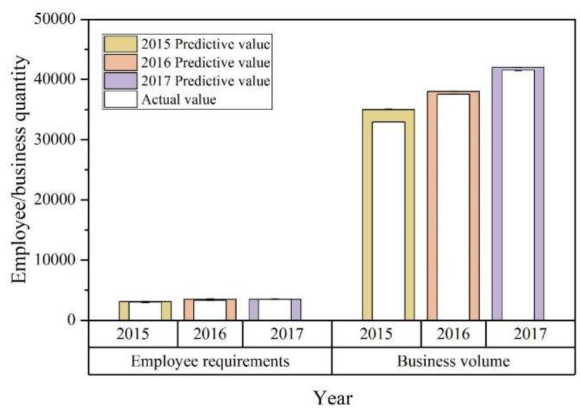


Figure 6: Test masking

(2) Analysis of test results

After the model training, it is tested to verify the accuracy of the model prediction. Taking the data from 2013-2023 as the test sample, the test sample is input into the trained neural network model using the above method, and the network simulation is carried out, out=sim(net, test sample). Compare the error between the output value and the real value to test whether the network performance is good, and the test results are shown in Table 3. The average value of the error between the gray BP neural network and the real value is -12.343, which is lower than the gray predicted value of -84. Therefore, no matter the size of the value or the overall trend, the BP neural network model is closer to the real value.

The possible reasons for this are (1) The gray prediction uses a cumulative generating sequence, and the predicted values show an upward trend, while the number of employees fluctuates. (2) For the gray prediction model, the more sample data, the greater the simulation error. (3) The neural network has instability, and there is no guarantee that the predicted value at each point is equal to the actual value.

Table 3: Comparison of grey BP neural network and grey predicted value

Year	Actual value/number	Grey BP neural network value/ number	Gray predicted value/ number
2013	2297	2349	1534
2014	2628	2610	2530
2015	2993	2804	2665
2016	3288	3332	2743
2017	3445	3430	3619
2018	3826	3849	3877
2019	3879	3892	3496
2020	3913	3923	4703
2021	4469	4428	4194
2022	4957	4829	4683
2023	5008	5121	5740
2024	-	7581	8045
2025	-	7798	8164
2026	-	7633	8246

III. D. Performance testing

III. D. 1) Forecast accuracy analysis

A comparison of their forecasts and true values is shown in Figure 7. The number of employees in most enterprises is between 0 and 200, and is mainly concentrated between 50 and 100, reflecting that the number of recruited employees of this size can meet the daily operational needs of most enterprises and allow for expansion or contraction accordingly. Meanwhile, the data fit between the true value and the predicted value $R^2 = 0.93624$, indicating a good fit. Such results also suggest that the model related to human resource demand forecasting can pay more attention to the development needs of enterprises of this size, thus having universal application value for the operation and development of small and medium-sized enterprises.

The overall predictive power of the model performs well with a small error size. This suggests that the model has a significant advantage in capturing and utilizing trends and cyclicality in historical data. Its forecast errors typically tend to underestimate the number of firms in demand. This may imply that the model has a conservative preference for future demand growth or changing trends to forecast more cautiously.

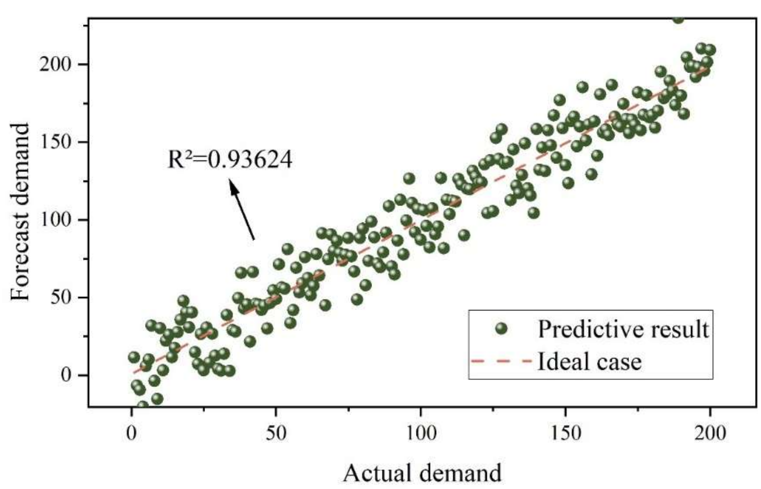


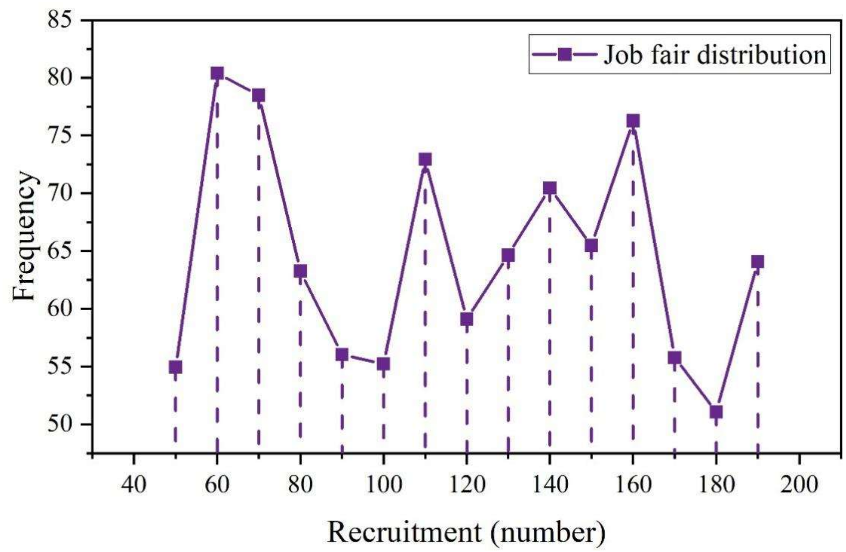
Figure 7: The projected scale of human resource needs

III. D. 2) Forecast results and characterization

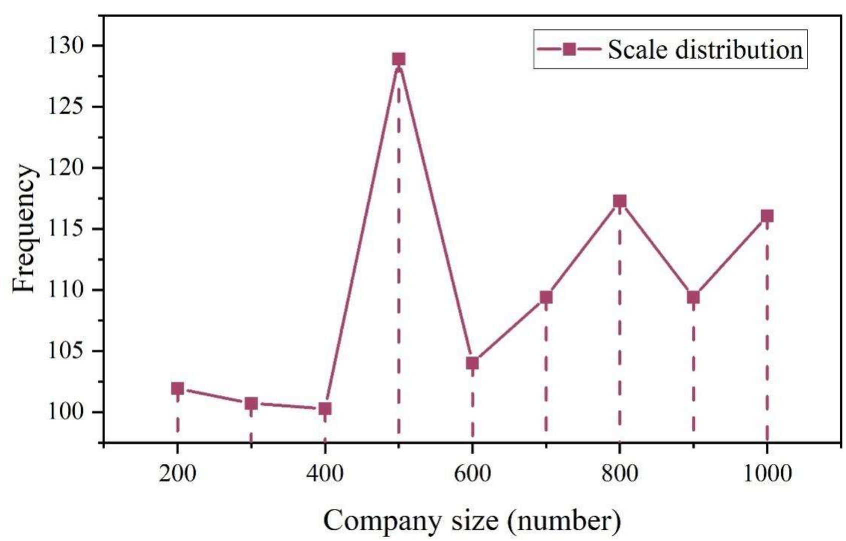
Considering the impact of various types of features on the model prediction results, the impact of different elements on human resources demand is organized, and the results are shown in Figure 8, with Figure (a) showing the number of recruits, Figure (b) showing the size of the company, Figure (c) showing the type of the industry, and Figure (d) showing the future demand for recruitment.

All types of data features are roughly evenly distributed, the size of the number of recruits of different enterprises in the past few years is relatively balanced, and there is a more even distribution, the number of recruits is mainly concentrated between 50 and 200 people, of which the number of recruits of 60-80 people has the highest frequency of enterprises, a total of 158 times. In addition, small to medium-sized enterprises (less than 1,000 employees) also show a balanced distribution, and also show a more even distribution in terms of industry types. Since these characteristics exist in the historical data and reflect the different types of enterprises and their demand conditions in real scenarios, the good sampling results obtained based on such a good data structure and statistical properties have reliability and corresponding value, which can effectively reduce the sampling error and ensure that the prediction model built is more representative.

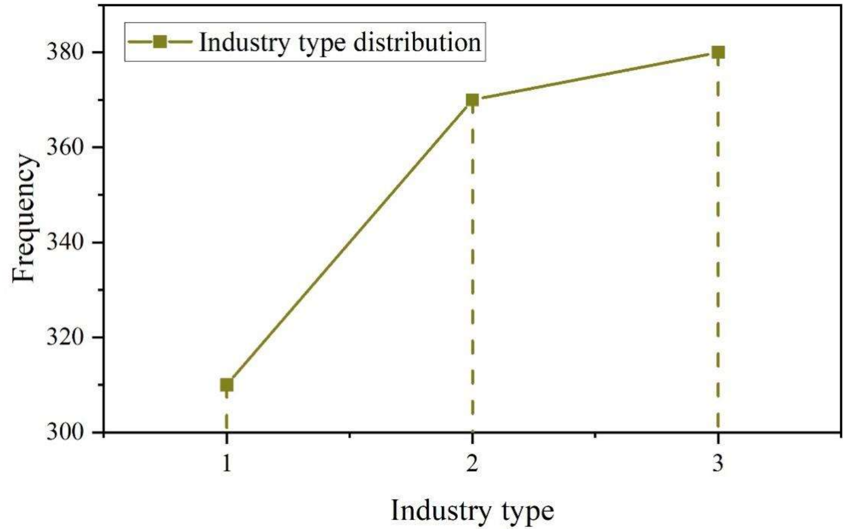
The results of the analysis based on this sample data show that the demand for future hires is generally characterized by a normal distribution. This means that in most cases, for all companies or industries considered as a whole, changes in headcount will be concentrated around an average of around 100 to 120 employees, decreasing in both directions, with a few extreme cases moving away from this average, such as below 20 or above 180. This data reflects the relatively stable and high rate of personnel turnover in most enterprises, and the recruitment scale of enterprises is often more than 10% or even 20% of the total size of the staff, and the normal curve reflects the universality of the sample, that is, this type of curve is usually considered to be one of the most common, typical, and in line with the description of the state of things that are most commonly observed when the results of the joint action of a large number of stochastic variables in the natural world and the types of social life. In the context of data mining techniques, they also present a higher quality of existing samples and predictions.



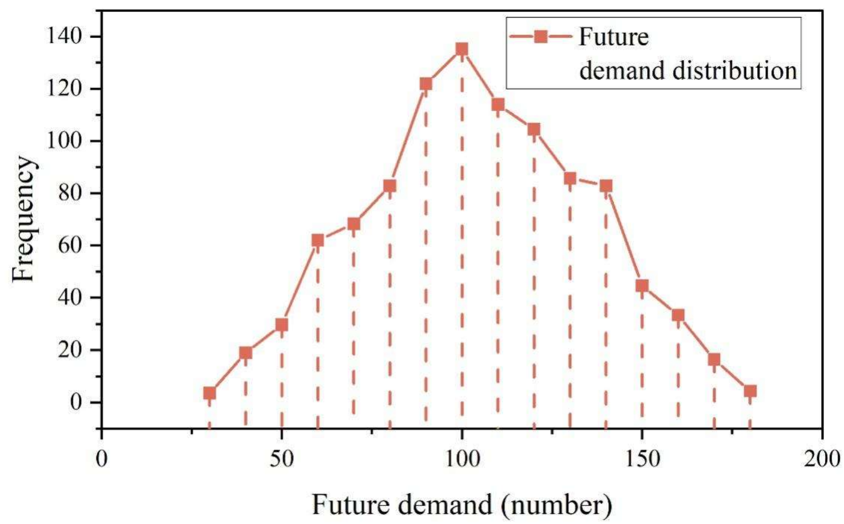
(a) The number of recruits



(b) Company size



(c) Industry type



(d) Future demand

Figure 8: Item combination situation

IV. Conclusion

This paper associates the grey correlation degree and BP neural network model, optimizes these two models respectively, and constructs the human resource demand prediction model based on grey BP neural network. Enterprise A is selected as the test enterprise, and the human resource demand model is applied to this enterprise to predict the human resource demand of this enterprise in the future. A preliminary analysis of the profile of enterprise A. The electricity sales of enterprise A slipped by 2,240 degrees in the year 2019, except for the rest of the year, the electricity sales and the number of employees maintained the trend of growth. Screening the relevant indicators affecting the human resources demand of Enterprise A, after correlation analysis, it is learned that the four indicators of the transmission network length, the number of substations under the jurisdiction, the total number of users, and the power sales on the Internet have a greater impact on the analysis of human resources demand, and the values of these four indicators in 2023 are 4,905.987 kilometers, 193 seats, 6,903,480 people, and 5,556,969.614 Million degrees. Comparing the prediction effect of gray BP neural network and gray prediction model, the average value of error between gray BP neural network and the actual value is -12.343, and the predicted value of gray prediction model is -84, the predicted value of gray BP neural network model is closer to the actual value, and the model has a better prediction accuracy.

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