ISSN 2616-5902 Vol. 5, Issue 26: 172-178, DOI: 10.25236/AJBM.2023.052626

# Research on Intelligent Manpower Forecasting Model of Dalian International Hub Port

**Guangying Jin[1,*], Chunhui Yang[1], Qingpu Meng[1], Wei Feng[1]**

[1]*School of Maritime Economics and Management, Dalian Maritime University, Dalian, China*
[*]*Corresponding author*

***Abstract:*** *Human resources constitute the core assets of enterprises, and effective forecasting methods for manpower demand can significantly reduce labor costs, enhance production efficiency, and drive the transformation and high-quality development of port enterprises. However, the large scale and complex operations of port enterprises, coupled with numerous internal and external factors to be considered during manpower demand forecasting, pose significant challenges and result in lower accuracy. Consequently, there is a lack of research on manpower demand forecasting specifically tailored to port enterprises. This paper analyzes the actual situation of Dalian International Hub Port (DIHP), summarizes and establishes an indicators system of influencing factors for human resources in Dalian International Hub Port. Afterward, A GM-BP forecasting model is established for port enterprises. Furthermore, we conduct a comparative analysis on the prediction effects of three different models, including GM, BP and GM-BP. The comparison results validate the rationality and reliability of the proposed model, providing a basis for port manpower management from an enterprise perspective.*

***Keywords:*** *Manpower forecast; Grey system; Back propagation neural network; Dalian international hub port*

## 1. Introduction

More than 80% of the international merchandise trade volume is transported by shipping[1]. The ports of any country are the window to the world[2]. With the realization and deepening of the internationalization process, the disadvantages of traditional personnel port management have become increasingly prominent [3] It has become an inevitable trend change to replace traditional personnel management with modern manpower management [4]. Therefore, it is imperative to establish a practical and powerful manpower management system in the port enterprises. The business routes of Dalian International Hub Port cover Asia, Europe, North America and other regions, and it is an important hub connecting Northeast China to the world. DIHP is not only an important port in China, but also an important support for China's maritime economic development. DIHP actively promotes the construction of intelligent, green and digital ports, strives to build a world-class port, and has made important contributions to the development of China's marine economy. Therefore, analyzing the Dalian International Hub Port and establishing an intelligent prediction model can help DIHP achieve intelligent port management and help the port achieve intelligent transformation and upgrading.

According to the statistical data of DIHP in China, we can conclude that the profits of enterprises and the number of employees in enterprises have basically changed in the same range. Therefore, the prediction of the demand number of employees can indirectly reflect the operating conditions of enterprises and have guiding significance for the development trend of enterprises. Meanwhile, port manpower prediction directly affects the planning, management and utilization of labor force for port enterprises[5]. As the rate of intelligent has increased in recent years, the intelligent management of ports is becoming more and more feasible [6]. In these increasingly complex logistics networks, effective management of human resources is becoming more and more important to improve work efficiency, reduce waste and save costs[7].

However, the traditional port industry is a typical labor-intensive industry and port operations are seasonally prominent [8]. This leads to the port human demand prediction being conceived as a complex forecasting system, strongly linked to the various factors of port enterprises and in close relationship with the external environment of the port. Through the investigation and study of port enterprises, we can understand the characteristics of port enterprises, thus helping us to choose the factors that have a greater impact on port manpower[9]. Meanwhile, when establishing the indicators system for forecasting, it is necessary to consider various factors affecting human demand and choose important factors to study[10]. Grey system theory is an effective method of studying and modeling systems consisting of small sample sizes that contain a limited amount of information and is widely used in many fields[11]. Based on literature review and indicator select method, this paper analyzes the factors influencing the manpower demand of port enterprises, establishes a prediction index system for port enterprises, and uses grey correlation method to screen the indicators.

Additionally, neural networks have a strong learning ability[12]. It has good approximation ability and high robustness on high-complexity nonlinear problems, and can better deal with many factors and noise data in port enterprise human demand forecasting[13]. In this paper, GM-BP neural network combines grey system theory and neural network technology, which can improve the stability and robustness of the prediction model while ensuring the accuracy of human demand prediction results.

Hence, this paper helps port enterprises to select key indicators that affect human resources, and use BP neural network to predict manpower demand. At the same time, taking DIHP as an example, we analyze the characteristics of port enterprises, collect data, establish a prediction indicator system, and then a GM-BP prediction model for the port's manpower is established. Finally, the accuracy of the prediction method proposed in this article was analyzed by comparing the prediction accuracy of different models.

## 2. Construction of Port Manpower Demand Forecasting Model

### *2.1. Grey Correlation Analysis*

Grey correlation analysis is a quantitative method used to analyze the degree of correlation between various factors in a grey system, aiming to identify numerical relationships among subsystems (or factors) within the system. Through grey correlation analysis, the selected indicators related to port manpower demand are screened, and key indicators are identified to effectively enhance the predictive accuracy of the model. Grey correlation analysis consists of the following steps:

(1) Determination of reference sequence and comparison sequence: The comparison sequence is denoted as $X_i = X_i\left(k\right) | k = 1,2,\ldots n, i = 1,2,\ldots m$ , and the reference sequence is denoted as $Y = Y\left(k\right) | k = 1,2,\ldots n$ .

(2) Calculation of grey correlation coefficient: The grey correlation coefficient represents the degree of correlation between the reference sequence and the comparison sequence at each moment. The calculation formula is as Formula (1):

$$\zeta_i\left(k\right) = \frac{\min\limits_i \min\limits_k T + \rho \max\limits_i \max\limits_k T}{T + \rho \max\limits_i \max\limits_k T} \qquad T = \left|y\left(k\right) - x_i\left(k\right)\right| \tag{1}$$

Where: $\rho$ is the resolution coefficient, taking values between (0, 1), commonly set $\rho = 0.5$ .

(3) Calculation of grey correlation degree: As correlation coefficients may not provide an intuitive understanding of specific correlation degrees, the average value, i.e., the grey correlation degree, is calculated to comprehend the specific correlation degrees. The grey correlation degrees are sorted based on their magnitude, and those with higher values are selected as key indicators. The calculation formula for grey correlation degree is as follows:

$$r_i = \frac{1}{n}\sum_{k=1}^{n} \zeta_i\left(k\right), k = 1,2,\ldots n \tag{2}$$

### *2.2. GM (1,1) Model*

The research focus of the Grey System Theory is on systems characterized by "partial information known, partial information unknown," referred to as "scarce data" or "poor information" uncertain systems. Constructing a Grey prediction model to forecast the values of key indicators for the next three years serves as preparation for the BP neural network prediction. The GM series models are fundamental models in Grey prediction theory and find widespread application. The basic modeling process for GM(1,1) is as follows:

(1) Determination of the original data sequence: Generally, let the original data be $Y^{(0)} = \{y^{(0)}(1), y^{(0)}(2), y^{(0)}(3), \cdots y^{(0)}(n)\}$. Where, $Y^{(0)}(k) \geq 0, k = 1, 2, 3, \cdots, n$.

(2) Generation of the cumulative data sequence 1-AGO: $Y^{(1)} = \{y^{(1)}(1), y^{(1)}(2), y^{(1)}(3), \cdots y^{(1)}(n)\}$. Where, $Y^{(1)}(k) = \sum_{i-1}^{k} Y^{(0)}(\mathrm{i})$.

(3) Generation of the background value sequence $Z^{(1)}(k)$, here, $\alpha = 0.5$.

$$Z^{(1)}(k) = \alpha Y^{(1)}(k-1) + (1-\alpha) Y^{(1)}(k) \tag{3}$$

(4) Establishment of the first-order, single-variable differential equation concerning t: Based on the above information, establish the first-order, single-variable differential equation as in Formula (4):

$$\frac{\mathrm{dY}^{(1)}}{\mathrm{dt}} + aY^{(1)} = b \tag{4}$$

Where $a$ and $b$ are undetermined parameters.

Discretizing the equation by turning the differential into a difference, we obtain Formula (5):

$$Y^{(0)}(k) + aZ^{(1)}(k) = b \tag{5}$$

Using the least squares method to solve the equation, we get the parameter sequence. $\hat{a} = [a, b]^T = \left(A^T, A\right)^{-1} A^T Y_N$.

(5) Establishment of the GM(1,1) forecasting formula: The forecasting formula is given by Formula (6):

$$\hat{Y}^{(1)}(k+1) = \left[Y^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \tag{6}$$

For the above formula, cumulative subtraction and restoration are applied to obtain the forecasting formula as in (7):

$$\hat{Y}^{(0)}(k+1) = Y^{(1)}(k+1) - Y^{(1)}(k) \tag{7}$$

### *2.3. BP Neural Network*

BP neural networks excel in handling nonlinear relationships, allowing for multiple input variables to find the connection weight relationships between inputs and outputs using existing data for predictions. BP neural networks possess excellent self-learning and strong fault-tolerance capabilities. The standard three-layer BP neural network structure is illustrated in Figure 1.

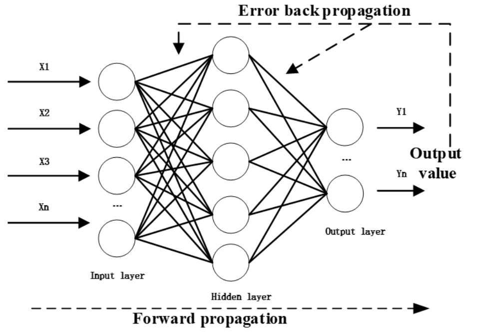


*Figure 1: Schematic diagram of forward propagation and back propagation of BP neural network*

The learning process of BP neural network is divided into two stages: forward propagation and back propagation. The direction of forward propagation is propagated from the input layer to the output layer

ISSN 2616-5902 Vol. 5, Issue 26: 172-178, DOI: 10.25236/AJBM.2023.052626

through the hidden layer, and is passed to the next layer through the weight, threshold, activation function, etc. of the network. After forward propagation, the error between the predicted value and the actual value is calculated. The error signal returns along the original connection route, and the weights and thresholds of nodes in each layer are modified to reduce the error. Until the error is reduced to the target value or the training reaches the preset number of iterations.

In here, grey correlation analysis, GM (1,1) and BP neural network are combined and applied to the port manpower forecasting problem, and a GM-BP model based on grey theory and neural network is established.

## 3. Establishment process and comparative evaluation of intelligent manpower demand forecasting model for DIHP

### *3.1. Data collection and indicators screening*

The establishment of port manpower demand forecasting indicators should fully consider the external and internal factors that affect the company's manpower. External factors include market demand, government policies and corporate development strategies, etc., and internal factors include the internal environment of the company and the personal conditions of the company's employees. We summarized the influencing factors of DIHP's manpower demand through expert interviews and literature research, and screened all indicators based on grey correlation analysis to determine the key indicators that are ultimately used to predict the port's manpower demand.

After investigation, based on the actual situation of DIHP, we selected 14 indicators to establish an initial indicator system for port manpower demand forecasting, as shown in the following Table 1. After the prediction indicator system is established, the grey correlation method is used to calculate the correlation of each indicator, and the factors that have a greater impact on the port's manpower demand are screened out, that is, the key indicators. The calculation results of the grey correlation degree of each indicator are shown in Table1.

*Table 1: The forecast indicator system of DIHP and the summary of correlation coefficients between various indicators and the number of employees.*

| First-level indicators | Second-level indicators | Third-level indicators | $\rho$ |
|---|---|---|---|
| DIHP external factors | Regional labor force status | Regional average salary ( $f_1$ ) | 0.64 |
| | | Regional labor productivity ( $f_2$ ) | 0.62 |
| | | Number of local labor force ( $f_3$ ) | 0.62 |
| DIHP internal factors | Port enterprise scale | Total assets ( $f_4$ ) | 0.65 |
| | | Net assets ( $f_5$ ) | 0.66 |
| | | Market share ( $f_6$ ) | 0.63 |
| | Port operating status | Total enterprise output value ( $f_7$ ) | 0.77 |
| | | Profit ( $f_8$ ) | 0.62 |
| | | Operating income ( $f_9$ ) | 0.77 |
| | Port enterprise employee structure | Proportion of operators ( $f_{10}$ ) | 0.94 |
| | | Proportion of skilled workers ( $f_{11}$ ) | 0.80 |
| | | Proportion of company administrative personnel ( $f_{12}$ ) | 0.50 |
| | | Proportion of highly educated employees ( $f_{13}$ ) | 0.66 |
| | | Proportion of employees of the parent company ( $f_{14}$ ) | 0.93 |

The greater the correlation value, the greater the impact of this indicator on port manpower demand. Therefore, sort the above correlation values to get the top five ranked indicators: $f_8$ $f_{11}$ $f_9$ $f_7$ $f_5$ . Therefore, these five indicators have a greater impact on port manpower changes, and these five indicators are regarded as key indicators for port prediction.

ISSN 2616-5902 Vol. 5, Issue 26: 172-178, DOI: 10.25236/AJBM.2023.052626

### *3.2. Establishment of GM-BP prediction model*

The overall process of modeling is described as follows: Firstly, establish the GM (1,1) model, predict the data of the key indicators in the next five years based on the selected key indicators, Secondly, the GM (1,1) output value is used as the input sample for BP neural network training, a neural network model is established. Finally, the future manpower demand quantity predicted by the GM-BP is finally obtained.

Use the GM (1,1) model to predict the future values of key indicators as input values for the future trained neural network model. The predicted values of five key indicators of DIHP were obtained. Afterward, a three-layer BP neural network model is built. The selected key indicators are used as input variables of the input layer, so the number of neurons in the input layer is 5; Then, determine the number of hidden layer neurons according to the empirical formula $p = \sqrt{m+n} + a$ (n is the number of input layer neurons, m is the number of output layer neurons, a is a constant between [1,10]), and through training, statistics of different hidden layers. The prediction error of the number of nodes is shown in Table 2. We can see that the prediction effect is best when the number of nodes is 5, so we set the hidden layer nodes to 5;

*Table 2: Root Mean Square Error (RMSE) values of different hidden layer nodes.*

| Hidden layer nodes | Error |
|---|---|
| 3 | 178.89 |
| 4 | 186.54 |
| 5 | 135.98 |
| 6 | 165.33 |
| 7 | 175.62 |

Meanwhile, the value of the output layer is the predicted value of the enterprise's manpower demand, so the number of neurons in the output layer is 1.

Since different indicators have different dimensions and dimensional units, in order to avoid affecting the data analysis results, the data are standardized to eliminate the influence of dimensions between indicators.

The parameters of the BP neural network are set as follows: the maximum number of training times is 10,000 times, the target error value is 0.000001, and the learning rate is 0.01. In Figure 2, we can see that the optimum is obtained in the ninth round.

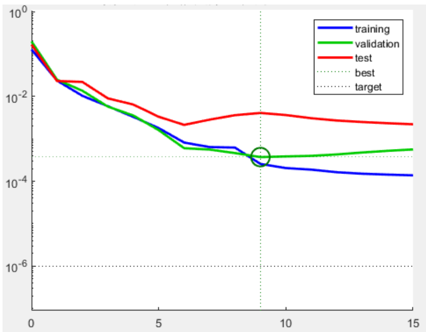


*Figure 2: Neural network training state diagram, reaching the optimum in the ninth round.*

Finally, Root Mean Square Error (RMSE, Root Mean Square Error), Mean Absolute Error (MAE, Mean Absolute Error), and coefficient of determination (R2) are used to evaluate the model. The obtained values are: RMSE=135.98, MAE=78.56, $R^2$=0.90

### *3.3. Comparison of prediction results of GM model, BP neural network and GM-BP model*

In order to compare the prediction performance of different models, GM, BP and GM-BP were used to predict port manpower demand, and the prediction error was compared with the actual true value. Here, the data from 2007-2017 are used to calculate the number of port employees from 2018-2022, and the results in Figure 3 are obtained.

ISSN 2616-5902 Vol. 5, Issue 26: 172-178, DOI: 10.25236/AJBM.2023.052626

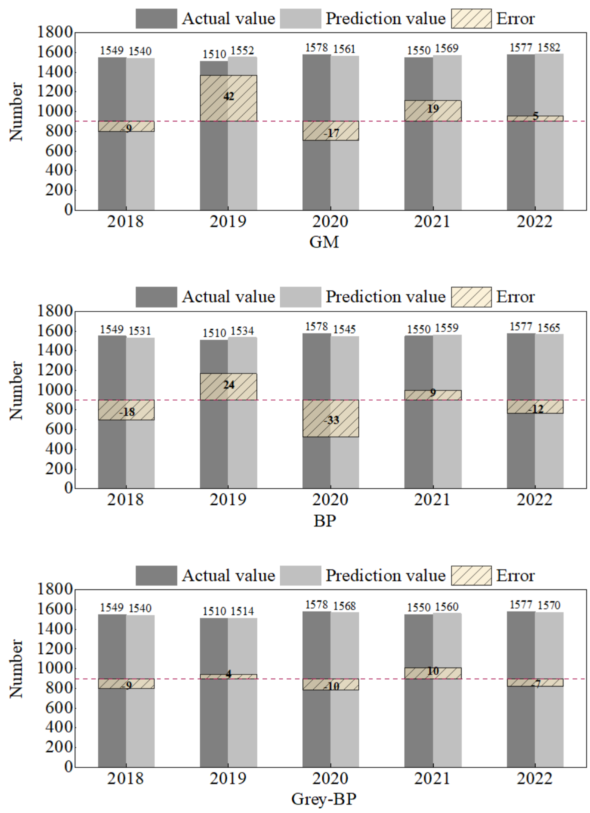


*Figure 3: Comparison of prediction results and errors between GM prediction, BP network and grey BP prediction model from 2018 to 2022.*

In Figure 3, the yellow shaded area is the error value vector. We can see that the errors of BP and GM are larger and the prediction results are not stable enough. The prediction error of GM-BP is smaller and each error value is also more stable. This shows that the prediction effect of the improved model has been improved.

## 4. Conclusion

This article summarizes the relevant factors that affect DIHP manpower demand, constructs an indicator system for manpower demand forecasting from the perspective of port enterprises, and analyzes the nonlinear changes in the number of port manpower. The grey prediction model is simple to calculate and has a small amount of data. BP neural network has good approximation ability when dealing with nonlinear problems, and has a high degree of self-learning, adaptive ability and good robustness. Therefore, this paper builds a GM-BP combined forecasting model to predict future port manpower needs.

Through grey correlation analysis, the key indicators of the prediction model are screened out. The prediction of key indicator values is then realized through the GM model. Finally, the future manpower demand of DIHP is predicted through BP neural network. Then three different models are used to predict manpower demand. Comparing different prediction results, the GM-BP combined prediction model is better in terms of prediction accuracy. It can accurately predict future port manpower needs. This method can be used to solve other similar prediction problems. In terms of manpower allocation, this study can provide theoretical and practical basis for building smart DIHP.

The manpower management of port enterprises needs to consider many aspects: number of personnel, staff changes, staffing, department management, etc. Manpower demand forecasting is only the first step in studying manpower allocation. Factors such as employees' personal situation, personal satisfaction, and whether employees' personal needs are met are also important factors affecting the stability of port personnel. Therefore, considering the personal factors of employees and studying the changes and predictions of corporate manpower from the perspective of employees is a future research direction to provide support for the construction of intelligent DIHP.

ISSN 2616-5902 Vol. 5, Issue 26: 172-178, DOI: 10.25236/AJBM.2023.052626

**Acknowledgements**

This research was funded by Liaoning Social Science Planning Fund Project, grant number L22BGL008.

**References**

*[1] Bjerkan, K. Y., & Seter, H. (2019). Reviewing tools and technologies for sustainable ports: Does research enable decision making in ports? Transportation Research Part D: Transport and Environment, 72, 243-260.*
*[2] AlRukaibi, F., AlKheder, S., & AlMashan, N. (2020). Sustainable port management in Kuwait: Shuwaikh port system. The Asian Journal of Shipping and Logistics, 36(1), 20-33.*
*[3] Shen, B. (2020). Construction of performance evaluation system of human resource management in port foreign trade enterprises. Journal of Coastal Research, 103(SI), 217-221.*
*[4] Bali, A. S. (2019). An analytical study of applications of human resource information system in modern human resources management. International Journal of Sustainable Agricultural Management and Informatics, 5(4), 216-229.*
*[5] Harel, G. H., & Tzafrir, S. S. (1999). The effect of human resource management practices on the perceptions of organizational and market performance of the firm. Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management, 38(3), 185-199.*
*[6] Wang, S., Zhen, L., Xiao, L., & Attard, M. (2021). Data-driven intelligent port management based on blockchain. Asia-Pacific Journal of Operational Research, 38(03), 2040017.*
*[7] Saeed, B. B., Afsar, B., Hafeez, S., Khan, I., Tahir, M., & Afridi, M. A. (2019). Promoting employee's proenvironmental behavior through green human resource management practices. Corporate Social Responsibility and Environmental Management, 26(2), 424-438.*
*[8] Hu, H. (2022). Assessment of the measures by ports against the impact of the Covid-19 pandemic: a case study of Jiujiang Port.*
*[9] Arshed, N., & Danson, M. (2015). The literature review. Research methods for business and management: a guide to writing your dissertation, 31-49.*
*[10] Ding, Z. Y., Jo, G. S., Wang, Y., & Yeo, G. T. (2015). The relative efficiency of container terminals in small and medium-sized ports in China. The Asian Journal of Shipping and Logistics, 31(2), 231-251.*
*[11] Julong, D. (1989). Introduction to grey system theory. The Journal of grey system, 1(1), 1-24.*
*[12] Wu, Y. C., & Feng, J. W. (2018). Development and application of artificial neural network. Wireless Personal Communications, 102, 1645-1656.*
*[13] Li, J., Cheng, J. H., Shi, J. Y., & Huang, F. (2012). Brief introduction of back propagation (BP) neural network algorithm and its improvement. In Advances in Computer Science and Information Engineering: Volume 2 (pp. 553-558). Springer Berlin Heidelberg.*