Methods to Improve Company Maturity Based on Analytic Hierarchy Process, Entropy Weight Method and Visual Radar Map

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Abstract. With the development of 5G, the Internet of Things, and other technologies, data needs to be analyzed and sorted in a larger way, so as to obtain more valuable information from it. In order to address the problem that the maturity of different companies is difficult to analyze due to business factors, in this paper, we show the AHP-EWM combined weight analysis method and visual radar to find the model of the optimal solution, and design a system of maturity index that is suitable for companies. Subsequently, the degree of KPI of the company is shown through a radar map, and find out the optimal direction of the internal system of enterprise development. By increasing the weight ratio of optimal development factors, the maturity of the company can be improved. Finally, this model is used to simulate the application degree of port industries of different sizes and different enterprises. The results of the radar map show that even enterprises of different sizes and properties can be normalized by this model according to their internal KPIs, and the optimization suggestions given by the radar map can improve the maturity of the company, which is of great significance for the company to integrate internal resources and find the development direction of the company.

Keywords: Weight analysis · Radar map · Optimum maturity solution · KPI

1 Introduction

The development of enterprises needs perfect and reliable internal decision-making and analysis systems to put forward effective suggestions for the development of the company in real time. In recent years, some methods have also gradually emerged in the aspect of enterprise data governance. For example, the Delphi method [1, 2] reflects the opinions of experts by virtue of its anonymity and multiple rounds of feedback, and finally obtains the final index system of the company through statistical analysis. Machine learning [3] has been applied to risk assessment [4], financial performance [5], fault network management [6], and other fields due to its ability to constantly learn and adapt to the development of enterprises.

However, these methods have many problems. For example, the Delphi method will have too much interference of subjective consciousness; Although the neural network

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system has the function of adaptive adjustment, the “Black Box Model” [7] hides the internal flow logic of the network, resulting in reduced reliability of the model.

2 Maturity Analysis Model Architecture

2.1 AHP-EWM Weight Distribution Evaluation Index Model

To measure the maturity level L of Intercontinental Freight Company’s current system, secondary KPIs were defined based on three key performance indicators: personnel, technology, and processes, to measure the system from these aspects. Figure 1 is a demonstration of this model.

The value of L is equal to the sum of the performance indicators of personnel, technology, and process multiplied by their respective weights.

$$L = \mathrm{W_P} * P + \mathrm{W_t} * T + \mathrm{W_s} * S \tag{1}$$

where L represents maturity value, P represents the key performance indicators of personnel, $\mathrm{W_P}$ represents the weight of personnel, T represents the key performance indicators of technology, $\mathrm{W_t}$ represents the weight of technology, S represents the key performance indicators of process, $\mathrm{W_s}$ represents the weight of process. $\mathrm{W_P} = \mathrm{W_t} = \mathrm{W_s} = 1/3$.

We determine the final weight allocation by means of the average weight assigned by AHP and EWM. First, Analytic Hierarchy Process (AHP) is employed, which relies on experts to score KPIs for each component. Then, the Entropy Weight Method is used to calculate the weight of KPI again, which is more objective. Finally, in order to make the weight more convincing, after determining the weight of each KPI of the two methods, the average value is taken as the final weight value.

A Measure of Personnel Performance.

(1) Skill effectiveness

Skill effectiveness describes the situation of employees’ basic skills and reflects their work efficiency to some extent. We define skill effectiveness as:

$$P_1 = e/100 \tag{2}$$

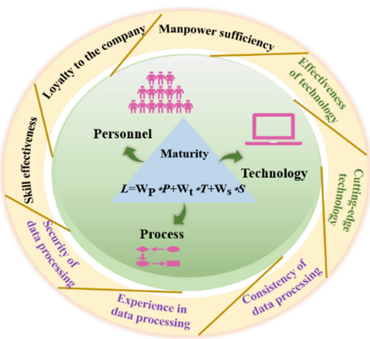


Fig. 1. AHP-EWM weight distribution diagram

where P_1 corresponds to the skill effectiveness of personnel, and e is the score of work efficiency.

(2) Loyalty to the company

Hired employees and outsourced employees have different levels of loyalty to the company, which will be reflected in their work attitude, which will affect the employee's output. Therefore, the manager can grade the employees' working attitude. It is defined as follows:

$$P_2 = a/100 \tag{3}$$

where P_2 corresponds to the degree of employee loyalty to the company, and a is the rating of work attitude.

(3) Manpower adequacy

The adequacy of manpower can be equivalent to the completion rate of the company's work. The higher the completion rate, the higher the manpower adequacy of the company. Its definition is as follows:

$$P_3 = c/100 \tag{4}$$

where, P_3 corresponds to the adequacy of manpower, and c is the score of the company's work completion rate.

To sum up, the functional relationship between personnel key performance indicator P and the above secondary indicators is as follows:

$$P = P_1 * W_{p_1} + P_2 * W_{p_2} + P_3 * W_{p_3} \tag{5}$$

where, W_{p_1}, W_{p_2}, and W_{p_3} respectively represent the weight of personnel skill effectiveness, loyalty to the company and manpower adequacy.

A Measure of Technology.

A company's advanced technology T_1 determines whether the company has a development prospect, and cutting-edge evaluation can be conducted based on the proportion of the technology currently used by the company and the new technologies of the times. The effectiveness of technology, T_2, reflects, to some extent, the operational efficiency of the technology. Through the above two, the key performance indicator T of technology can be formed into the following functional relationship.

$$T = T_1 * W_{t_1} + T_2 * W_{t_2} \tag{6}$$

T_1 and T_2 correspond to the frontier and effectiveness of the technology respectively, and W_{t_1} and W_{t_2} correspond to the weight of the frontier and effectiveness of the technology respectively.

A Measure of Technology Process.

s_1 Indicates the consistency of data processing. Data may change during transmission. This requires managers to calculate the proportion of the number of times data inconsistency occurred in their past work to the total number of times.

s_2 represents the experience in data processing. With the increase of time, s_2 value will rise, and to measure it at this time, it is necessary to measure a company's experience in data processing by calculating the proportion of employees with previous experience in data processing as a percentage of all employees in the team.

s_3 represents the security of the data processing, because no data system can run well under the risk of data insecurity.

According to the above description, the functional relationship of key performance indicator S of the process is as follows:

$$S = W_{s_1} * S_1 + W_{s_2} * S_2 + W_{s_3} * S_3 \tag{7}$$

where W_{s_1}, W_{s_2}, and W_{s_3} are the weight ratios of data processing consistency, data processing experience, and data processing process security, respectively.

The Weight Was Calculated by AHP.

Analytic hierarchy process (AHP) [8] decomposes elements related to decisions into multiple levels, such as objective, criterion and scheme, and makes qualitative and quantitative analysis on this basis.

In this model, the objective of our evaluation is to achieve the best maturity of Intercontinental Freight Company. In order to achieve this goal, we set three key indicators: personnel, technology and process, and the evaluation criteria are determined by expert rating.

(1) Construct a hierarchical evaluation model, as shown in Fig. 2.

(2) Perform AHP analysis on personnel, technology, and processes through SPSS to obtain weight values.

Table 1, Fig. 3, and Table 2 show the weight calculation results of the analytic hierarchy process. By showing the consistency test results, the weight of each indicator is analyzed to determine whether there is a logical problem in constructing a judgment matrix. Then, the three built a judgment matrix with the number of leaf node indicators through the weight calculation results of the scheme layer of the analytic hierarchy process (namely, the total hierarchy ranking) to analyze the weight of each indicator, and passed the consistency test. Finally, the ownership reweighting ratio was sorted out as shown in Table 3 with the rounding principle:

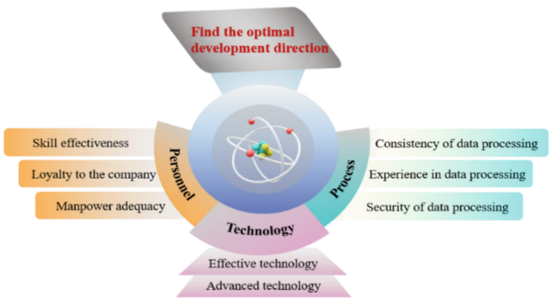


Fig. 2. AHP Hierarchical analysis model diagram

Table 1. Summary results of personnel judgment matrix

	P_1	P_2	P_3	Feature vector	Weight value (%)
P_1	1	7	0.2	1.119	23.991
P_2	5	7	1	3.271	70.149
P_3	0.143	1	0.143	0.273	5.86

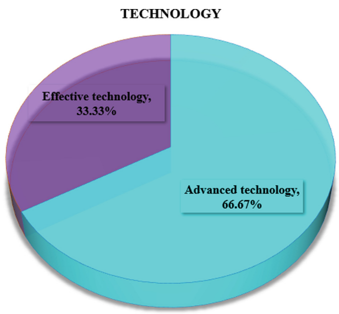


Fig. 3. Summary diagram of technical judgment

Table 2. Summary results of process judgment matrix

	s_1	s_2	s_3	Feature vector	Weight value (%)
s_1	1	0.5	0.5	0.63	19.58
s_2	2	1	2	1.587	49.339
s_3	2	0.5	1	1	31.081

Table 3. Weight table of key indicators of AHP model

i	W_{P_i}	W_{t_i}	W_{s_i}
1	0.24	0.67	0.20
2	0.70	0.33	0.49
3	0.06		0.31

Entropy Weight Method (EWM) Calculates the Weight.

Entropy weight method (EWM) [8] is an objective weighting method based on the principle that the greater the dispersion, the greater the degree of differentiation, and therefore the more information available. We use EWM to determine the weights of standardized indicators.

Table 4. Weight distribution table of entropy weight method

i	W_{P_i}	W_{t_i}	W_{s_i}
1	0.61	0.50	0.29
2	0.19	0.50	0.40
3	0.20		0.31

Due to the unpredictability of data, the random number generated by the random number function is used as the initial data of personnel, technology and process.

For the standardization process there is:

$$x_{ij} = 0.998\frac{x_{ij} - \min\{x_{1j}, x_{2j}, \ldots\ldots, x_{nj}\}}{\max\{x_{1j}, x_{2j}, \ldots\ldots, x_{nj}\} - \min\{x_{1j}, x_{2j}, \ldots\ldots, x_{nj}\}} + 0.002 \tag{8}$$

The purpose of the coefficients 0.998 and 0.002 is to make the value of x_{ij} greater than 0, so as to prevent ln0 in the subsequent calculation of lnx_{ij}. Here, 0.998 can be changed to any number closer to 1, such as 0.999, 0.997, etc.

The proportion of index value of the i-th scheme of the j-th index:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{9}$$

The information entropy of the j-th index:

$$e_j = -k\sum_{i=1}^{n} P_{ij} lnP_{ij} \tag{10}$$

among them $k = \frac{1}{lnn}$,

The weight of each index is obtained:

$$\omega_j = \frac{1 - e_j}{\sum_{j=1}^{n}(1 - e_j)} \tag{11}$$

The weights of indicators obtained through calculation are shown in Table 4:

Finally, the average value of AHP and EWM is used as the final weight distribution, and the weight distribution result is shown in Fig. 4.

2.2 Confirm the Maturity Level

All parameters need to be calculated by the company according to the manager's data, and the obtained L is a value between [0, 1], which can measure the maturity of the company. That is, the closer to 1, the higher the maturity of the company.

Here, the capacity maturity model for software (CMM-SW) researched by the Software Engineering Institute (SEI) of Carnegie Mellon University was adopted [9].

CMM model defines five software process maturity levels, which are initial level, repeatable level, defined level, managed level and optimized level. Table 5 shows the situation at each stage.

Finally, the maturity level of Intercontinental Freight Company is determined by the value of L, and then the key indicators that the company should improve most need to be found according to this maturity level.

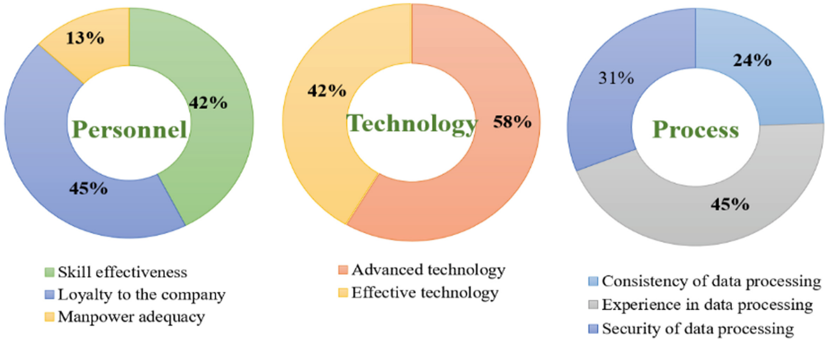


Fig. 4. Final weight distribution diagram

Table 5. CMM Model Maturity Level Table

Maturity grade	Numerical interval	Characteristics
Initial level	$0 < L < 0.2$	Data management processes are disorganized, even chaotic, and few processes are properly defined.
Repeatable level	$0.2 \leq L < 0.4$	The company has established a fundamental process for data management based on basic work requirements, which can be able to track cost, schedule and functionality, and developed the necessary process discipline based on repeated early success with similar application data.
Defined level	$0.4 \leq L < 0.6$	The company documents and standardizes data processing processes in management and engineering activities and integrates them into the agency's standard data processing processes.
Managed level	$0.6 \leq L < 0.8$	The data processing process has detailed measurement values, and the data processing process has quantitative understanding and control, so the information resources of this part of the data face less danger.
Optimized level	$0.8 \leq L \leq 1$	The company is able to continuously improve the data processing process and can strategically come up with corresponding strategies. Data processing is highly confidential.

2.3 System Optimization Model

For specific optimization decisions, it is necessary to consider the values that can directly reflect personnel, technology and process, namely P_i, T_i, S_i. It is the evaluation index that measures all aspects of the company system in the model. Radar map [10] is the preferred scheme of this model because it can comprehensively analyze multiple indicators and has the advantages of completeness, clarity and intuition. According to the radar map, we can judge whether the system should be optimized by the step length of each indicator in its direction. The flow chart of this optimization model is shown in Fig. 5.

We adopt the principle of optimization scheme as follows: The score of each measurement index changes after the weight is added. The greater the change is compared with other indicators, the more obvious the weakness of a more important project is, and the greater the impact on the whole system, and it should be optimized first.

Due to the confidentiality of company data, Excel random number generation function is used to generate columns of data P_1, P_2, P_3, T_1, T_2, S_1, S_2, S_3. Let's take random row data as an example. First, each column of data is normalized, and then the original data radar map is drawn and compared with the weighted radar map.

According to Table 6 and Eq. (1), we will get L = 0.64885, which is in the managed level of CMM model. Then we make model optimization.

In Fig. 6, inside the red box line is the radar map formed by each indicator without adding the weight. Inside the blue box line is the radar map generated after adding the weight. When studying how to measure the level of indicators in the system through them, it is necessary to refer to the step length of each value, that is, the length of indicators on their respective axes.

According to the red box display area of the radar map above, it can be seen that parts of P_1, P_2, P_3, T_1, T_2, S_2, S_3 should be optimized. After adding weight, the blue block diagram is obtained, and the largest difference between the red peripheral lines and the

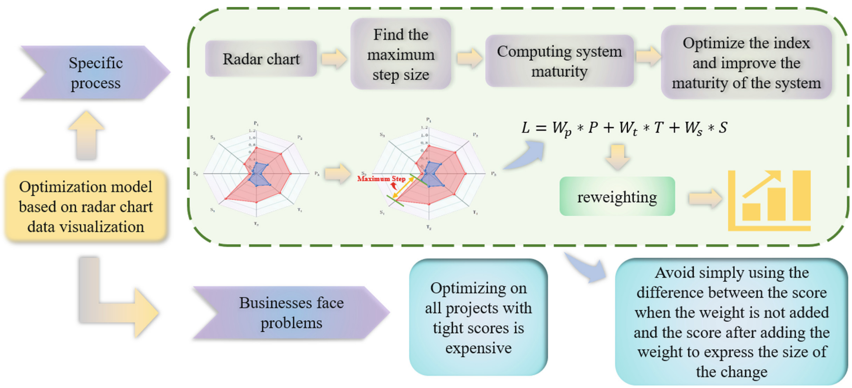


Fig. 5. Flow chart of the visual radar map

Table 6. Random row data and random row data after adding weights

KPI	P_1	P_2	P_3	T_1	T_2	S_1	S_2	S_3
Random row data	0.724	0.78	0.77	0.752	0.791	0.979	0.154	0.383
random data after adding weights	0.304	0.351	0.100	0.436	0.332	0.235	0.069	0.119

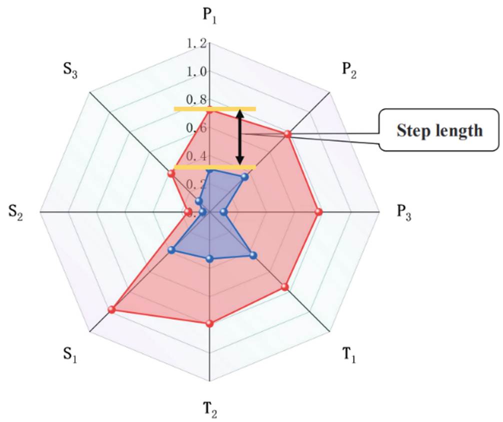


Fig. 6. Random row data and random row data radar map after adding weights

blue peripheral lines is S_1. According to the above optimization scheme principle, it can be concluded that S_1 should be optimized the most. Therefore, when selecting this row of data, they should give priority to improving the consistency of data processing.

Then, the weight of consistency factors in data processing in the process is increased through AHP, and Table 7 (it has passed the consistency test) is obtained. Then, Table 7 is used to determine a new weight distribution table, as shown in Table 8. Through calculation, we can get L = 0.6873. The calculation shows that the maturity of the system increases after the weight changes, which proves the feasibility of the model.

Table 7. Summary results of process judgment matrix -- Increase the consistency proportion of data processing

	s_1	s_1	s_1	Feature vector	Weight value (%)
s_1	1	2	2	1.587	50
s_1	0.5	1	1	0.794	25
s_1	0.5	1	1	0.794	25

Table 8. Weight distribution table after the consistency ratio of data processing is increased

i	W_{P_i}	W_{t_i}	W_{s_i}
1	0.42	0.58	0.37
2	0.45	0.42	0.35
3	0.13		0.28

3 Analysis of the Possibility of Model Extension

3.1 Applicable to Seaports of Different Sizes

To apply our evaluation model to seaports of different sizes and businesses in different industries, we reconsidered the relationship between personnel, technology and process. Large seaport companies contain a large amount of data and have high requirements for technical safety, effectiveness and processing experience in terms of technology. In terms of personnel, they have a high degree of skill effectiveness, loyalty to the company and sufficient personnel. Small seaport companies have fewer data and do not have too many requirements for data processing. Moreover, they have fewer personnel and have higher requirements of personnel's ability. Therefore, companies of different sizes have different emphases on maturity evaluation.

The weights of different seaports are redistributed through AHP-EWM model, and the weights of big and small seaports are obtained in an evaluation, as shown in Table 9. The values of ports of different sizes after adding weights to the original data are shown in Table 10.

According to formula (1), the maturity of a large sea port is L = 0.65986, and that of small sea port is L = 0.66197, both of which are in the managed level of CMM maturity level. Next, the maturity of large and small seaports is increased respectively.

It can be seen from Fig. 7 that, with the change in port size, the inner area of the final radar map is not significantly different from that of the original model, indicating that the model has good applicability to port companies of different sizes. According to the data in this paper, it is necessary to improve the consistency of data processing for both large and small seaports. According to this conclusion, the AHP of the large sea port and small sea port is reassigned. Table 11 shows the specific weight allocation table.

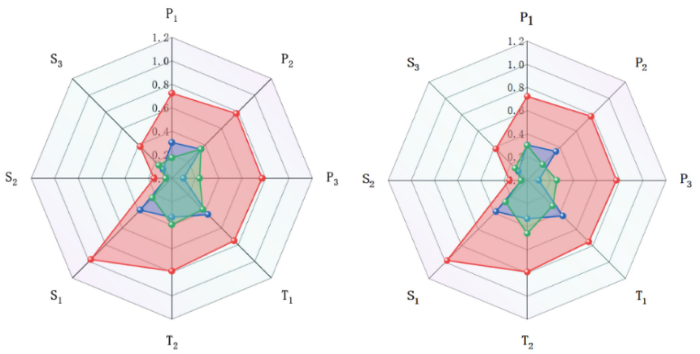
After calculation, we can get: Large seaport maturity $L = W_p * P + W_t * T + W_s * S = 0.71833 > 0.659856$, and small seaport maturity $L = W_p * P + W_t * T + W_s * S = 0.71408 > 0.66197$.

Table 9. Weight distribution table of seaports of different sizes (AHP + EMA)

KPI	P_1	P_2	P_3	T_1	T_2	S_1	S_2	S_3
Large seaport	0.24	0.45	0.31	0.50	0.50	0.24	0.35	0.41
Small seaport	0.42	0.25	0.33	0.42	0.58	0.52	0.27	0.21

Table 10. Random rows of seaports of different sizes are added to the calculated data table

KPI	P_1	P_2	P_3	T_1	T_2	S_1	S_2	S_3
Large seaport data (add weight)	0.175	0.351	0.237	0.376	0.396	0.235	0.054	0.155
Small seaport data (add weight)	0.302	0.191	0.256	0.312	0.459	0.510	0.041	0.081



a) Large seaport radar map b) Small seaport radar map

Fig. 7. Visual radar map of port data of different sizes, raw data and raw data after adding weights

Table 11. Weight distribution table of large seaports and small seaports (AHP + EMA) -- optimized radar map

KPI	P_1	P_2	P_3	T_1	T_2	S_1	S_2	S_3
large seaport	0.24	0.45	0.31	0.50	0.50	0.49	0.23	0.29
small seaport	0.42	0.25	0.33	0.42	0.58	0.50	0.29	0.21

It can be seen that the maturity increases after radar map optimization, so it can be considered that the model is correct.

3.2 Applicable to Other Enterprises

Our assessment model can be used to analyze the maturity of industries other than the seaport industry. However, there are some differences to point out:

(1) When the AHP-EWM model is applied for weight distribution, the key performance of another industry is different from that of a seaport, so KPI and weight need to be redistributed.
(2) In this paper, the visual radar map is used to find the KPI that needs to be improved first. Instead of using the specific transportation data of Intercontinental Freight Company, random data is used to evaluate and model from the perspective of personnel, technology and process. Therefore, the model can be used in other industries.

4 Maturity Model Analysis Results

4.1 Maturity Analysis

Regarding the maturity of the company, the formula is as follows, based on the product of key performance indicators and weight:

$$L = W_P * P + W_t * T + W_s * S \quad (1)$$

Here, the key performance indicators are mainly determined by expert scores. This method is simple and feasible, and there is no need to worry too much about financial problems so that relatively accurate data can be obtained for maturity calculation, so as to determine the maturity level of the company and prepare for the next analysis. However, if the sample collection times of this method are few, there will be personnel errors to some extent.

4.2 Weight Allocation

AHP has the disadvantage of less quantitative data and more qualitative components, while EWM solves this problem. The smaller the variation degree of the index, the less information reflected, and the lower the corresponding weight. In addition, AHP has an advantage over EWM in that it makes decisions according to the intention of the decision-maker, but its objectivity is relatively poor and its subjectivity is stronger. Therefore, in this paper, AHP and EMA are combined to complement each other's advantages, and the median value is finally adopted for weight allocation.

4.3 Visual Radar Map

In this paper, a set of data is selected by random numbers for simulation test, in which the red part is the layer after weight is added to the original data, the blue part is the layer after weight is added to the big port, and the green part is the layer after weight is added to the small port, as shown in Fig. 8. This paper assumes that due to the large amount of data in the big port and the need for stable staff, therefore, the important factors are determined from the six main factors of technology and personnel. For small seaports, the effectiveness analysis of personnel skills is mainly focused. Through the determination of these key factors, the consistency of data processing should be improved for large seaports, and the loyalty of personnel to the company should be improved for small seaports. Since the area of blue and green layers is roughly equal to that of red layers, it can be considered that this model can be applied to large or small seaports. According to the suggestions given by radar map, the weights of different factors of the harbor are re-assigned. The results show that the maturity of the company is improved after the modification of this model.

5 Conclusion

Nowadays, reasonable allocation of resources, real-time updates of technology and stability of data systems have become important factors for the sustainable development of a company. In this environment, the company's internal data analysis must quickly and accurately analyze the shortcomings of the company and give strategic adjustment suggestions. In this paper, we show AHP-EWM mixed distribution weight model and visual radar map optimization system model. Compared with fuzzy analysis and other models with complex calculations, this model can better meet the requirements of the existing companies that need to make fast decisions. Moreover, the combined use of

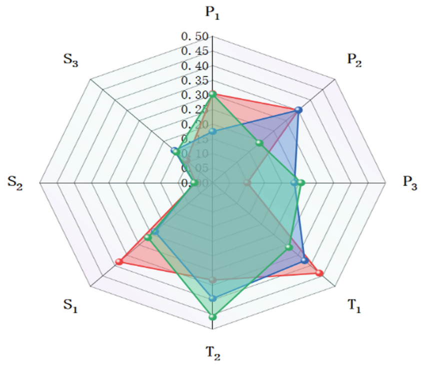


Fig. 8. Comparative analysis diagram of original data, large seaport and small seaport after adding weights respectively

AHP and EMA model to determine the weight value can realize the real-time adjustment of the parameters of the model data. When the weight ratio is re-assigned to the model after optimizing the radar map, EMA model does not need to be calculated again, because EWM is not affected by subjective factors and only related to the original data in the calculation. Therefore, when the weight is re-allocated, the proportion of weight allocated by EWM method remains unchanged. This method greatly reduces the amount of computation. Then, on the basis of this model, the radar map is used to find the biggest factors affecting the maturity of the company, and through these factors, the distribution target is refined to give the company a feasible way to improve. This is optimized in such a way that the operational structure can be understood by non-specialists. Finally, through a random number test, it is proved that the model can be effectively applied to seaports of different sizes and other industries.

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References

1. Wang C. J. (2022). *Based on AHP and BP neural network of public sports service performance evaluation studies* (Master's degree thesis, huaibei normal university). https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202202&filename=1022597125.nh.
2. Miller, K. A., Prieto, M. M., Wing, R., Goldman, M. P., Polikoff, L. A., Nishisaki, A., & Nagler, J. (2023). Development of a paediatric airway management checklist for the emergency department: a modified Delphi approach. Emergency medicine journal: EMJ, 40(4), 287–292. doi: https://doi.org/10.1136/emermed-2022-212758.

3. Tang C. Z., Wang Z. G. & Chen H. B. (2023). Empowering system software with machine learning techniques: Challenges, Practice, and Prospects. *Journal of Computer Research and Development*.
4. Ma G. H., Gao T. L. & Ma C. H. (2023). Research on business data security risk prevention based on machine learning. *Journal of Management* (01), 70–83. doi: https://doi.org/10.19808/j.cnki.41-1408/F.2023.0006.
5. Wang A. J. (2021). Construction and test of financial performance evaluation model based on EM-BP neural network. *Technology and Market* (03), 13–16.
6. Lei Z. L., Su J. & Guo W. (2022). Survey of cellular network fault management framework and methods based on machine learning. *Application Research of Computer*(12), 3521–3533. doi: https://doi.org/10.19734/j.issn.1001-3695.2022.04.0217.
7. Dou H., Zhang L. M., Han F., Shen F. S, & Zhao J. (2023). Survey on convolutional neural network interpretability. *Journal of Software*. doi: https://doi.org/10.13328/j.cnki.jos.006758.
8. Zhang S., Zhang S. L., Zou D., He M.Y., & Nan H. (2023). The weight of Qi and Yin deficiency syndrome of IgA nephropathy was constructed based on Delphi method and analytic hierarchy process. *Modernization of Traditional Chinese Medicine and Materia Medica-World Science and Technology*. https://kns.cnki.net/kcms/detail/11.5699.R.20230318.1352.004.html.
9. Qian S. Y. (2022). The research on ability evaluation of financial sharing center of D company based on capability maturity model (Master's Thesis, Hebei University of Technology). https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD202301&filename=1022726250.nh.
10. Bento, L. C., Correia, R. P., de Sousa, F. A., & Bacal, N. S. (2023). A novel approach for MRD assessment by high-sensitivity flow cytometry and multidimensional radar visualization. *International journal of laboratory hematology*.