Research on Modeling of Adaptive Allocation of Labor Resources Based on Deep Reinforcement Learning

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Abstract. Based on the problem of the unreasonable allocation of labor resources in my country, a modeling method for adaptive allocation of labor resources based on deep reinforcement learning is proposed, combined with deep reinforcement learning algorithms to calculate the distortion of labor resource allocation in my country's primary, secondary, and tertiary industries degree. Analyzed the changing trend of labor resource allocation in urban and rural areas, and proposed an adaptive allocation plan of labor resources based on my country's industrial development structure in recent years to optimize the allocation structure of labor resources. Finally, it was confirmed by experiments that the adaptive allocation model of labor resources based on deep reinforcement learning It has high practicability and can better integrate the actual situation for effective allocation of labor resources.

Keywords: Deep reinforcement learning · Labor resources · Self-adaptation · Resource allocation

1 Introduction

The labor resource market in China is severely fragmented. Before the reform and opening up, it was mainly reflected in the segmentation of the urban and rural labor resource market [1]. After the reform and opening up, with the continuous development of the market economy and the flow of urban and rural labor resources, the segmentation of my country's urban and rural labor resource markets has weakened. Complex market segmentation. The market segmentation of labor resources directly hinders the effective flow of labor resources, causes distortions in the allocation of labor factors and resources, and hinders the healthy development of the economy. Therefore, paying attention to the segmentation of China's labor resource market, the distortion of labor factor allocation, and the impact on economic development is the meaning of the question [2]. Throughout the existing relevant literature, it has conducted a certain research on the state of the labor resource market segmentation in my country, the test of the existence of the labor resource market segmentation, and the impact of labor resource allocation on total factor

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productivity, and the research on the degree of distortion of labor resource allocation in my country Relatively weak, it is generally only involved in the overall research on the distorted variables of labor resource allocation, and simple estimates are used to measure and replace them. There is a lack of systematic research. Therefore, it is necessary to explore the degree of distorted labor factor allocation in my country. Therefore, deep reinforcement learning is proposed. Modeling method for adaptive allocation of labor resources.

This paper firstly analyzes the labor resource allocation mechanism, adopts the labor resource allocation distortion algorithm based on deep reinforcement learning to allocate labor resources adaptively, and establishes a theoretical model of deep reinforcement learning algorithm with reference to the deep reinforcement learning algorithm method to allocate capital and labor. The static analysis of the situation is carried out, and the adaptive allocation model of labor resources is constructed.

2 Modeling of Adaptive Allocation of Labor Resources

2.1 Labor Resource Allocation Mechanism

The macro daily standard for the operation of the labor resource allocation mechanism is an indicator system, not a single indicator. The optimal allocation of human resources is to balance the total amount of human resources production and use, the production structure of human resources is consistent with the demand structure, and the collocation of human resources is reasonable. In order to better guarantee the rationality of labor resource allocation, first, a comprehensive analysis of population resources, human resources, labor resources, and the relationship between people and people is carried out, as shown in Fig. 1:

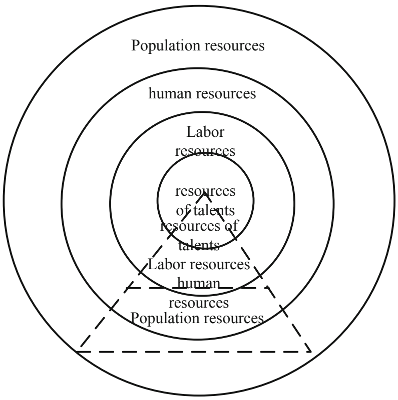

Fig. 1. Population resources, human resources, labor resources, and human relations

Based on the research of the labor resource allocation mechanism of deep reinforcement learning based on the above figure, some people in the theoretical circle believe that only economic benefits can be used as the operating goal of the labor allocation mechanism, ignoring the positive significance of full employment [3, 4]. Under the socialist planned commodity economy, the operating goal of the labor resource mechanism is not a single index, but an index system composed of economic benefits and full employment. Full employment does not necessarily exclude economic benefits, there are many combinations between them. Figure 2 shows the L-S relationship between economic benefits and full employment:

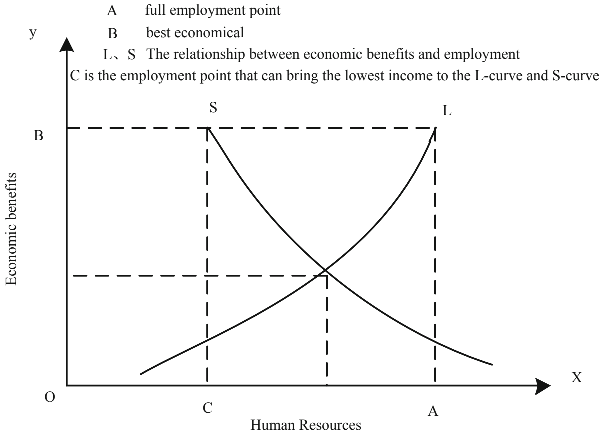

Fig. 2. The L-S relationship curve between economic benefits and human resources

In the figure, the x-axis represents human resources, the y-axis represents economic benefits, point A is the full employment point, point B represents the best economic benefit, and the L and S curves are the relationship between economic benefit and employment under the conditions of two different labor resource allocation mechanisms. For the combination curve, the point C is the employment point that can bring the lowest benefit to the L curve, and the employment point that can bring the most benefit to the S curve. The figure shows that there are countless combinations of employment and economic benefits under each labor allocation mechanism. The best economic benefits may be realized under the condition of less employment, and may also be realized under the condition of full employment [5].

Society and enterprises also play an important role in the optimal allocation of labor resources. The change of employment concepts, the emancipation of the mind, the creation of a cultural atmosphere, the emphasis on skills and knowledge by enterprises, and the adoption of social organizations, non-profit organizations and even for-profit organizations in society Provide employment services, training and recruitment consulting activities, effectively increase employment services, and promote the optimal allocation of labor resources during the transition period [6]. From the analysis below, it can be seen that population management, employment services, training and education, technological innovation, etc. also affect the allocation of labor resources. Government departments are constantly exploring new management methods and macro policies in accordance with the needs of economic development and the trend of population development. Two-way interaction, making full use of the favorable factors provided by internal and external conditions to promote the optimal allocation of labor resources [7]. The specific influencing factors of the optimal allocation of labor resources are specifically discussed from several aspects in Fig. 3.

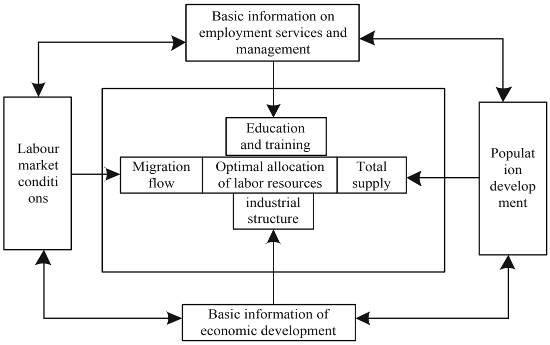

Fig. 3. Micro-influencing factors of optimal allocation of labor resources during the transition period

Economic benefits and employment may be positively correlated or negatively correlated. The key depends on the choice of labor resource allocation mechanism. The specific factors that affect this choice include: accumulation rate, current economic structure and target economic structure, total population and population composition, employment mechanism operation mode and adjustment system. If the employment operation mechanism is temporarily withdrawn, then to achieve higher economic benefits and full employment, it is necessary to choose the accumulation rate and target economic structure suitable for employment according to the specific situation [8].

2.2 The Distortion Degree Algorithm of Labor Resource Allocation Based on Deep Reinforcement Learning

The deep reinforcement learning algorithm is used to calculate the difference between the marginal output of labor and the marginal cost to measure the efficiency of labor resource allocation at the enterprise level. Use the ratio of the difference between the marginal output of labor and the marginal cost to the marginal cost, namely:

$$MISA_{it} = \frac{|MPL_{it} - B_{it}|}{B_{it}} \tag{1}$$

Among them, MPL_{it} is the marginal output of labor employed by firm i in year t, and B_{it} is the marginal cost of labor hired by firm i in year t, where the sum of the average wages and welfare expenditures paid by the enterprise to individuals is substituted [9]. When the resource allocation factors are in the optimal state, the marginal output of labor equals the marginal cost. When the relative difference between the marginal output of labor and the marginal labor cost of an enterprise is greater, that is, the greater the MSA, the higher the level of labor resource misallocation and the lower the efficiency of resource allocation. Therefore, in this article, we mainly focus on the deep reinforcement learning estimation model.

First, we must combine the deep reinforcement learning algorithm to calculate the marginal labor output m of enterprise i in the m-th year. Here, suppose that the production function of the company under the deep reinforcement learning algorithm is in the form of Cob-douglas, and the logarithm on both sides is taken to obtain methods such as deep reinforcement learning, and the theoretical model of deep reinforcement learning algorithm is established to statically analyze the allocation of capital and labor., That is, use the classic Solow model to measure China's TFP, and calculate γ as the balance from the known stock of labor resources and capital and the corresponding output level. Use i to represent a specific area, that is, there are m areas, $i = 1, 2, 3, \ldots, m$ respectively. To facilitate analysis, this article assumes that all different provinces have the same output elasticity. The specific output formula is:

$$Y_m = A_m K_m^{\alpha_n} L_m^{\beta_n}, \; Y_n = A_n K_n^{\alpha_n} L_n^{\beta_e} \tag{2}$$

Among them, the regression estimation coefficient of A_m is β_{m}. If β_{m} is positive, it means that the reduction of intermediate goods tariff L (increased trade liberalization of intermediate goods) reduces the mismatch level of labor resources β_n of the enterprise and improves the efficiency of labor allocation $K_n^{\alpha_n}$, otherwise it reduces the efficiency of labor resource allocation of the enterprise $A.K_n^{\alpha_n}$ In order to obtain the labor resource allocation efficiency of enterprise a in the nth year.

$$\beta = \sum_i \beta_i \frac{\gamma_i}{Y} \tag{3}$$

β_i represents the labor output elasticity of department i, and γ_i represents the output of department i. The degree of distortion of department m salary w_m with department n salary w_n as the reference frame [10]. Based on the above algorithm, the distorted degree of labor resource allocation in the entire society is decomposed into the distortion contribution of the internal labor resource market within each industry and the distorted contribution of inter-industry allocation. Similarly, the degree of distortion in the allocation of labor resources in urban and rural areas and cities can be decomposed into the distortion of the internal labor resource market within the industry and the distortion of the allocation between industries, which will not be repeated here.

2.3 Construction of an Adaptive Allocation Model of Labor Resources

Build an open regional labor resource optimal allocation model, analyze the changes in the labor market supply and demand, so as to realize the effective allocation of human resources.

With reference to the deep reinforcement learning algorithm method, the theoretical model of deep reinforcement learning algorithm is established, and the allocation of capital and labor is statically analyzed. That is, the classic Solow model is used to measure China's TFP, which is based on the known labor resources and capital stock. And the corresponding output level is calculated as L_i^a as the margin. Use i to represent a specific province, that is, there are m provinces, i $=$ 1, 2, 3, ..., m. For ease of analysis, this article assumes that all different provinces have the same output elasticity, and the specific output formula is

$$Y_i = A_i L_i^a K_i^{(1-a)}, 0 < a < 1 \tag{4}$$

Among them: A_i and $K_i^{(1-a)}$ respectively represent the output GDP, total labor resource status, capital stock, labor output share and TFP of province i, and the values of variables ω_i and $1 - \sigma$ are real values. Because it is necessary to measure the TFP of a specific province, for the convenience of analysis, it is assumed that the total output of each province satisfies the constant substitution elastic function between the total output and the total output, namely:

$$Y = \left(\sum_{m}^{i=1} \omega_i Y_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{5}$$

Among them: σ is the substitution elasticity of different provinces, and σ is greater than zero; ω_i is the ratio of the output of province i to the total output, and A_i^* and K_i represent the output level GDP of province i respectively. Capital and labor, which are factors of production, satisfy the condition that the sum of the production factors of each province is equal to the total production factors. The specific formula is:

$$\begin{cases} \Sigma_i L_i = L \\ \sum_i K_i = K \end{cases} \tag{6}$$

Among them, L_i,K_i,L and K represent the labor and capital stock levels of i province and respectively. The resource configuration that meets the following conditions is called effective resource configuration:

$$\begin{cases} \max_{L_i, K_i} Y \dfrac{L_i}{L} = \dfrac{K_i}{K} = \pi_i \\ \pi_i = \dfrac{\omega_i^{\frac{1}{\sigma}} \left(A_i^*\right)^{\frac{1-\sigma}{\sigma}}}{\sum_{m}^{i=1} \omega_i^{\frac{1}{\sigma}} \left(A_i^*\right)^{\frac{1-\sigma}{\sigma}}} \\ A^* = \left[\sum_{m}^{i=1} \omega_i^{\frac{1}{\sigma}} \left(A_i^*\right)^{\frac{1-\sigma}{\sigma}} \right]^{\frac{\sigma}{1-\sigma}} \end{cases} \tag{7}$$

The industrial structure is an important factor that affects the changes in the structure of labor resource allocation. When the level of economic development is at different stages, the industrial structure and employment structure will also be at the corresponding stage. Although the changes in the employment structure lag behind the changes in the industrial structure, the overall trend of the two shows a consistent trend [11–13].

Changes in the industrial structure are the precedent for changes in the employment structure, and adjustments in the industrial structure can lead to continuous optimization of the distribution structure of labor resources among industries. The high-end industrial structure can drive the transfer of workers from low-end industries to high-end industries, and can drive the improvement of the quality of labor resources. The optimal allocation model of labor resources in this paper is

$$S = f(R, E, C, J, A, T, Q, M, P, Z, L, D) \tag{8}$$

Among them: R is a comprehensive factor (factors not listed in the model), E is economic growth, C is urban planning, J is employment policy, A is investment growth, T is technological innovation, Q is reform and opening up, and M is market economy. P is population migration, Z is comprehensive evaluation, L is industrial structure, and D is talent policy. The research on the optimal allocation of labor resources needs to be carried out in the context of economic and social transformation, which is the key point to enhance the significance of the research. The labor resource market, the capital market, and the transformation of government functions are all formed and perfected during the economic and social transformation. Optimizing the allocation of labor resources has the responsibility of the government, and it is inseparable from the role of the market. If the optimal allocation of labor resources is regarded as a system, then the optimal allocation of labor resources is inseparable from the coordination of its own system, and it is also inseparable from the coordination of the external environment of the system and the communication between the internal and external environments of the system [14]. The external environment plays an important role in the optimal allocation of labor resources. Internal and external factors such as economic growth, opening to the outside world, talent policies, infrastructure, employment policies, population policies, technological innovation capabilities, government organization coordination capabilities, and industrial structure are all to a certain extent. The above restricts the advancement of the optimal allocation of labor resources. Based on this, the framework of the optimal allocation of labor resources in the open area is further analyzed as shown in Fig. 4:

In Fig. 4, the influence of population on the quantitative relationship of human resources is mainly manifested in its influence on ordinary labor resources—labor resources. Because ordinary labor resources are the main manifestation of the number of human resources and constitute the main part of human resources. Special labor resources, such as various talents, are a special part of human resources. Their knowledge and talents can only be obtained through long-term accumulation and specialized education and training, which is reflected in the further changes in labor resources. Therefore, changes in the supply of human resources are mainly reflected in changes in labor resources. The supply of labor resources is a major variable that affects the changes in the relationship between supply and demand in the labor market. The supply of labor resources includes actual labor resources and potential labor resources. In this way, the effective allocation of human resources can be realized.

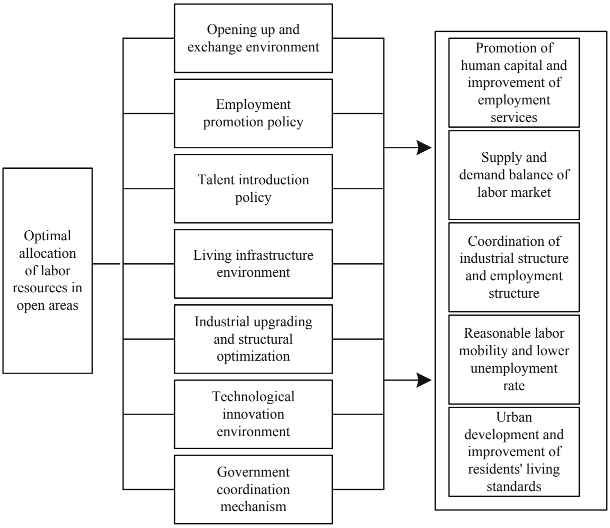

Fig. 4. Model framework for optimal allocation of labor resources in an open area

3 Analysis of Experimental Results

The human resource allocation in a province's statistical yearbook is used to affect the data of various variables, and after standardized collation, it is brought into the model for verification. Among them, human capital is expressed by the weighted product of the laborer's education level, average life expectancy, and skill level; the industrial structure is expressed by the proportion of the tertiary industry; the degree of marketization is expressed by the proportion of the number of employees in non-state-owned enterprises in the total employees. The specific test results are as follows (Table 1).

Table 1. Departure model test of human resource allocation in industrial structure

Classification	Coefficient	Std. error	T-Statistic	Prob.
Human capital	0.039	0.009	9.856	0.000
Industrial structure	0.089	0.277	-7.757	0.000
Degree of marketization	0.356	0.019	5.786	0.001
The degree of distortion in the allocation of rural labor resources	0.209	0.227	13.187	0.000

Table 2 reports the distortion degree of overall labor resource allocation, the degree of distortion of labor resource allocation in urban and rural areas, and the degree of distortion of labor resource allocation in cities in representative years. A further comparison of the overall distortion of the allocation of labor resources, the distortion of the allocation of labor resources in urban and rural areas, and the degree of distortion of the allocation of labor resources in cities shows that the degree of distortion in the allocation of labor resources in my country's urban and rural areas is relatively serious, which is the main factor leading to the distortion of the overall allocation of labor resources; but this is not the case. At the same time, the distortion of the allocation of labor resources in our cities should also arouse great attention, and its influence on the degree of distortion of the allocation of labor resources will be greater and greater.

Table 2. The degree of distortion of overall labor resource allocation, the degree of distortion of labor resources in urban and rural areas, and the degree of distortion of labor resources in cities

Particular year	2017	2018	2019	2020
population	0.653	0.573	0.467	0.469
urban and rural	0.551	0.416	0.385	0.398
Proportion of urban and rural areas (%)	84.321	72.580	82.451	78.961
Within the city	0.103	0.158	0.083	0.100
Proportion in city (%)	15.680	27.420	17.550	21.310

Table 3 reports the decomposition factors of the distorted degree of overall labor resource allocation. The distorted decomposition of labor resource allocation in urban and rural areas and cities are similar and will not be reported. It can be seen from the table that the difference in the marginal productivity of labor between departments directly reflects the distortion of the allocation of labor resources, and has become the main factor of the distortion of the allocation. From an internal perspective of each industry, the wages of labor resources are not determined by the marginal productivity of labor. To varying degrees, it reflects the characteristics of the internal labor resource market in the industry. The reflected labor resource allocation is distorted. For example, in the representative years of the primary industry, the average wage is actually higher than the marginal productivity of labor, while in the secondary industry, the wage is actually lower than the marginal productivity of labor. To a certain extent, the amount of free flow of labor resources between different departments caused by the marginal productivity difference of labor is reduced, and the degree of distortion in the allocation of labor resources is also reduced.

Furthermore, various distortions of labor resource allocation considering the human capital situation are given. Compared with ignoring human capital, when considering human capital, the degree of distortion of overall labor resource allocation, urban and rural labor resource allocation, and labor resource allocation in cities has all decreased. The human capital level of the secondary industry is higher than that of the tertiary industry, and the human capital level of the secondary industry is significantly higher than that of the primary industry, which means that the secondary industry actually uses more labor resources. The primary industry actually uses more labor resources. Fewer labor resources, therefore, the degree of distortion in the allocation of labor resources decreases. Labor resources chase capital, and investment can effectively change the existing industrial structure. Generally speaking, the labor resource allocation structure

Table 3. Decomposition of contributing factors to the degree of distortion of overall labor resource allocation

Particular year	2017	2018	2019	2020
Distorted contribution in the primary industry	−2.085	−0.588	−1.049	−1.068
Proportion of primary industry (%)	−43.521	102.760	−225.071	−228.341
Distorted contribution in the secondary industry	−0.903	−0.777	−0.578	−0.555
Proportion of secondary industry (%)	−138.231	−165.800	−123.891	−118.211
Distorted contribution in tertiary industry	0.0002	−0.071	−0.449	−0.490
Proportion of tertiary industry (%)	0.030	−12.251	−96.411	−104.660
Intersectoral distorted contribution	1.839	2.009	2.539	2.582
Proportion of departments (%)	281.730	350.830	545.390	551.220

is subordinate to the industrial structure. From a regional perspective, due to different development stages, the efficiency of resource allocation in different urban markets in the province is also different, which can be clearly seen in the data in the table. In order to better understand the impact of the distortion of the allocation of production factors in the capital and labor market on TFP, the more efficient resource allocation is selected as a reference. Using the model in this paper and the data used by Garofalo, etc., the distortion of the allocation of resources in the capital and labor market was measured, and the results of the calculation are shown in Fig. 5.

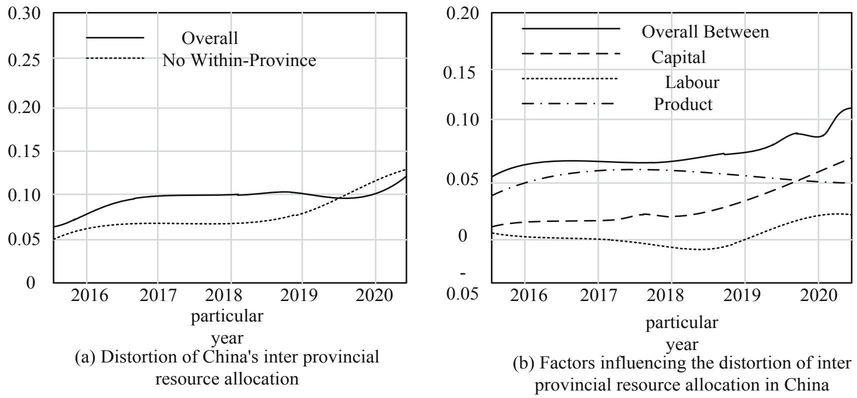

Fig. 5. Distortion of human resource allocation changes with market trends

The overall distortion of capital and labor allocation is relatively small. Based on the above content, the efficiency of resource allocation has experienced a process of initially deteriorating, slightly improving, and then deteriorating. Since the improvement in the middle 10 years is small, the overall allocation efficiency is deteriorating. of. Based on the above information, the data is summarized, and the method in this paper and the traditional method are used for experimental comparison, and the configuration effects of the two methods are recorded. The specific results are shown in Fig. 6.

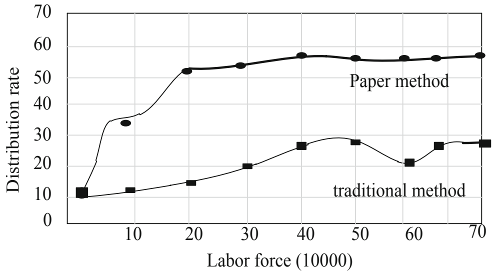

Fig. 6. Different methods of human resource allocation effect detection

Based on the analysis of the detection results in the above figure, it is not difficult to find that, compared with traditional methods, the adaptive configuration modeling of labor resources based on deep reinforcement learning proposed in this article can better realize the reasonable allocation of human resources in the actual application process. Fully meet the research requirements.

4 Concluding

This paper analyzes the impact of China's capital and labor allocation distortions on total factor productivity from 1993 to 2017 by building a model that includes different regions. The current household registration system. The current household registration system hinders the flow of labor resources and causes severe distortions in inter-provincial distribution. On the other hand, the allocation of capital resources among provinces has been deteriorating, mainly because my country's current financial market is not very developed. To solve the problem of distortions in the allocation of resources such as labor and capital between regions in my country, it is necessary to intensify the reform of the household registration system and create a favorable environment for the free flow of labor and the market. Other factors of production.

In future research, it is necessary to further deepen the financial supply. Improve the financing mechanism that meets the development needs of small and medium-sized enterprises to improve the relative shortage of funds in eastern my country.

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