International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 872-883

https://doi.org/10.70517/ijhsa46480

Optimization of Foreign Trade Industry Chain Value Chain and Analysis of Industrial Upgrading Path Based on Multi-Objective Planning Algorithm

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Abstract The process of global economic integration is deepening, and the international trade network presents a complex and diversified development situation. This paper constructs a value chain optimization model of “Belt and Road” foreign trade industry chain based on multi-objective planning algorithm, adopts complex network analysis method to construct trade network, and applies improved multi-objective Gray Wolf optimization algorithm to solve the industrial upgrading path. By analyzing the data of the United Nations Merchandise Trade Database from 2004 to 2024, it is found that the number of nodes in the trade network of “Belt and Road” has increased from 26 to 49, with a growth rate of 88.5%, and the number of network relations has increased from 28 to 107, which shows the trend of trade diversification. The study establishes a three-dimensional objective function system covering economic production benefits, social life benefits and ecological resource benefits, and designs the corresponding constraints. The empirical analysis shows that under the balanced transformation and upgrading path, the optimized value of industrial added value reaches 22456.4 in 2024, the energy consumption decreases to 16515.2, and the pollution emission index decreases from 21104.9 in 2009 to 18556.The study confirms that the multi-objective optimization algorithm is able to effectively achieve the coordinated development of “three-life space” and provide scientific decision support for the upgrading of the foreign trade industry of the “One Belt, One Road”. The study confirms that the multi-objective optimization algorithm can effectively realize the coordinated development of the “three living spaces” and provide scientific decision support for the upgrading of foreign trade industry in the “Belt and Road”.

Index Terms Multi-objective planning algorithm, Belt and Road, Foreign trade industry chain, Value chain optimization, Industrial upgrading, Triple life space

I. Introduction

Today's world situation is complex and volatile, the economic and social development of countries continue to diverge, the multilateral trading system is subject to the impact of unilateralism and trade protectionism, the international investment and trade pattern is in the stage of deep-seated changes, countries are facing serious development problems [1]-[4]. In this context, China has put forward the cooperative initiatives of building the “New Silk Road Economic Belt” and the “21st Century Maritime Silk Road”, i.e., the “One Belt, One Road” cooperative initiative, which has injected new vitality into the global economy. The Belt and Road Initiative has injected new vitality into global sustainable development. The initiative establishes a multi-level and multi-disciplinary economic cooperation mechanism to jointly explore new ways of innovative development, promote the optimal allocation of regional resources, and further advance the process of globalization [5], [6].

In the context of the “Belt and Road”, the import and export of goods between China and the countries along the routes have continued to grow, which indicates that the economic and trade cooperation between China and the countries along the routes is getting closer and closer, and brings real benefits to the economic and social development of both sides [7]-[9]. From the perspective of the quality of foreign trade industry, China has helped to safeguard domestic production and market demand in terms of imports, while the products exported have been continuously transformed and upgraded to the middle and high end, and the technological content and value-added have been continuously improved [10]-[12]. From the perspective of foreign trade industrial structure, China's foreign trade business entities are developing in the direction of diversification and marketization, which improves the overall vitality of foreign trade [13], [14]. Based on this, it is necessary to promote the optimization of the value chain of the foreign trade industry chain and industrial upgrading in order to enhance the competitiveness and influence of China's foreign trade industry in the global market [15].

In this study, a trade network model of "Belt and Road" is constructed by using complex network analysis method, and the evolution characteristics of trade relations and network structure are analyzed in depth. On this basis, a three-dimensional optimization model covering economic production benefits, social life benefits and ecological resource benefits is established by multi-objective planning theory, and the optimal allocation scheme is solved by the improved multi-objective Gray Wolf optimization algorithm. The validity of the model is verified through empirical analysis, and corresponding industrial upgrading paths are proposed to provide theoretical support and practical guidance for the high-quality development of foreign trade industry in the "Belt and Road".

II. Optimization of the value chain of the "Belt and Road" foreign trade industry chain

II. A. Trade networking

The core concept of complex network analysis is to abstract the linkages between individuals in the real world into a network, and use it to describe and analyze the relationships existing in real systems [16]. In this paper, we select the data in the United Nations Commodity Trade Database (UN Comtrade) from 2004 to 2024, and construct a directed weighted network G' and an un-weighted network G_1^t of the trade relations between China and ASEAN countries by aggregating the trade volumes and trade directions of China and ASEAN countries for a total of 10 countries in the corresponding years. .

(a) The set of import and export nodes of different countries:

$$V_i^t = \{v_1^t, v_2^t, \cdots, v_i^t\} \tag{1}$$

where, V_i^t - set of 10 importing country nodes in year t. v_i^t - i th importing country node in year t. i - importing country node number, $i = 1,2,3,\cdots,10$. t - year number, $t = 2004, 2007, \cdots, 2024$.

Where, V_j^t - set of nodes of 10 exporting countries in year t. v_j^t - j th exporting country node in year t. j - exporter node number, $j = 1,2,3,\cdots,10$.

(b) Weight matrix of different countries in the trade network:

$$W^t = \begin{bmatrix} w_{11}^t & w_{12}^t & \cdots & w_{1j}^t \\ w_{21}^t & w_{22}^t & \cdots & w_{2j}^t \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1}^t & w_{i2}^t & \cdots & w_{ij}^t \end{bmatrix} \tag{2}$$

where, W^t - matrix of intensity of import and export trade between 10 countries in the year t. w_{ij}^t - the average value of import and export trade between node j of the exporting country and node i of the importing country in the year t.

In order to solve the problem of inconsistency between the import and export data published by each country in the trade database, the data published by both countries in the same trade direction are averaged, i.e.:

$$w_{ij}^t = \frac{(e_{ij}^t + m_{ij}^t)}{2} \tag{3}$$

where, e_{ij}^t - the value of country i's imports from country j published by country i in year t. m_{ij}^t - the value of country j's exports to country i published by country j in year t.

(c) Connectivity matrix of different countries in the trade network:

$$A^t = \begin{bmatrix} a_{11}^t & a_{12}^t & \cdots & a_{1j}^t \\ a_{21}^t & a_{22}^t & \cdots & a_{2j}^t \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1}^t & a_{i2}^t & \cdots & a_{ij}^t \end{bmatrix} \tag{4}$$

$$a_{ij}^t = \begin{cases} 1, & \text{if } w_{ij}^t < 0 \\ 0, & \text{if } w_{ij}^t > 0 \end{cases} \tag{5}$$

where, A^t - the trade relationship matrix between China and ASEAN countries in t years. a_{ij}^t - trade relationship between country i and country j in year t, if $w_{ij}^t > 0$, there is a trade relationship between the two countries, and vice versa.

(d) Weighted trade networks:

$$G^t = (V_i^t, V_j^t, W^t, A^t) \tag{6}$$

where, G^t - weighted trade network between China and ASEAN countries.

(e) Unweighted trade network:

$$G_1^t = (V_i^t, V_j^t, A^t) \tag{7}$$

where, G_i^t - unauthorized trade between China and ASEAN countries.

II. B. Characterization of network evolution

II. B. 1) Overall network characteristics

Table 1 shows the measured index values of the Belt and Road trade network from 2004 to 2024. The number of nodes and relationships in the Belt and Road trade network continues to increase, from only 26 countries along the Belt and Road to 49 countries in 2024, with a growth rate of 88.5%. In recent years, the number of trade nodes has basically remained at 40~50, and the number of trade network relationships has increased significantly, indicating that the "Belt and Road" trade is developing in the direction of import and export diversification and marketization [17].

Table 1: 2004-2024 “one belt and one road” trade network measure

Year	Node number	Side number	Network density	Reciprocity
2004	26	28	0.017	0.076
2006	46	59	0.023	0.154
2008	43	50	0.016	0.067
2010	45	55	0.008	0.079
2012	53	75	0.016	0.046
2014	46	77	0.024	0.058
2016	41	62	0.02	0.054
2018	40	68	0.012	0.052
2020	44	94	0.038	0.115
2022	46	100	0.019	0.107
2024	49	107	0.029	0.1

II. B. 2) Network Node Characterization

The node intensity distribution of the trade network of the “Belt and Road” from 2004 to 2024 is shown in Figure 1, which means that only a few countries control a large amount of foreign trade resources. That is to say, only a few countries master and control a large amount of foreign trade resources, and most other countries have small node intensity values. 2004-2024, the power law index of the “Belt and Road” trade network degree distribution decreases year by year, reflecting that the number of countries along the route choosing trade partners is increasing, and the proportion of countries with fewer trade partners is decreasing. The proportion of countries with fewer trading partners is decreasing.

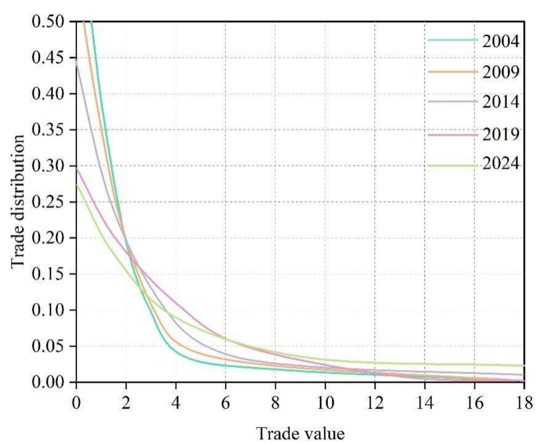

Figure 1: Trade network node intensity distribution

The top 10 countries in terms of trade node outbound and inbound intensity of the “Belt and Road” are shown in Tables 2 and 3, respectively. From the regional and national level, among the countries with the top ranking of node entry intensity, trade is mainly dominated by Asian countries, with fewer European countries. 2024, Asian countries accounted for 7 of the top 10 countries in terms of node entry intensity. China and India have been in the top 2 countries along the Belt and Road since 2009. In addition, although Turkmenistan is not among the top 10 countries in terms of node-out intensity and has very few trading partners, it is in the second position because of its stable and large-scale trade relations with China, with which it has maintained long-standing trade cooperation.

Table 2: Top 10 countries of out degree centrality of the Belt and Road natural trade

Trade node intensity/104t							
2009		2014		2020		2024	
Country	Trade node strength	Country	Trade node strength	Country	Trade node strength	Country	Trade node strength
RUS	5286.8	RUS	6790.2	RUS	3586.5	RUS	3130.1
TKM	2706.6	KAZ	1199.9	TKM	2233.7	TKM	1626.3
KAZ	1200.3	TKM	1194.1	KAZ	1428.4	MMR	997
MMR	914.3	MMR	855.9	MMR	1422.7	AZE	890.6
UZB	477.3	IDN	698.2	IDN	671.6	IDN	622.9
EGY	193.1	UZB	274.9	AZE	556.6	KAZ	355.8
IDN	119.9	AZE	210.5	UZB	304.1	MYS	153.2
AZE	4.8	EGY	108.2	MYS	123.3	UZB	134.9
IRN	0.6	HUN	51.3	CZE	112.4	HUN	129.2
UKR	0.3	CZE	41.2	UKR	85.4	IRN	63.2

Table 3: Top 10 countries of in degree centrality of the Belt and Road natural trade

Trade node intensity/104t							
2009		2014		2020		2024	
Country	Trade node strength	Country	Trade node strength	Country	Trade node strength	Country	Trade node strength
UKR	3416.7	UKR	3279.3	CHN	3154.77	CHN	2723.8
BLR	1426	BLR	1365.7	IND	1548.74	SGP	741.6
THA	914.3	CHN	1036.1	PAK	669.69	TUR	719.3
KAZ	857.7	THA	855.9	THA	433.17	SVK	676.4
HUN	741.6	RUS	800.9	TUR	176.87	CZE	634.7
RUS	629.4	SGP	576	SGP	60.04	THA	574.5
CZE	548.9	CZE	506.7	HRV	36.59	HUN	530.2
SVK	517.3	SVK	472.9	IDN	36.35	BGR	237.3
ROM	404.9	HUN	448.3	LTU	34.52	ROM	234.5
AZE	317	ROM	327	BGD	33.57	ARM	203.5

III. The path of upgrading foreign trade industry in the “Belt and Road” region

Based on the goal of foreign trade industry upgrading from the perspective of "production-living-space", this paper uses nonlinear programming and combinatorial meta-heuristic algorithms and other related system theories to construct a multi-objective optimization model based on the new foreign trade industrial structure, so as to realize the optimal scheduling of "production-life-ecology" and "production-living-living-living" systems.

III. A. Setting of multi-objective coordinated optimization model

Based on the optimization of industrial structure of new foreign trade under the perspective of “three lives”, in the process of model setting, full consideration should be given to echoing with the previous indicators affecting the development level of new foreign trade under the perspective of “three lives”, as well as optimizing the rationalization and advancement of industrial structure. Therefore, in the objective setting of the model, taking the “three living spaces” as the setting perspective, the objectives of the multi-objective optimization model are to maximize the benefits of economic production, social life and ecological resources (i.e., minimize ecological pollution and resource consumption).

III. A. 1) Constructing a system of indicators

Before the establishment of the multi-objective model, due to the consideration that each optimization objective contains multiple indicators, this paper constructs the indicator system according to the principle of indicator screening and the steps of indicator screening, and uses the entropy weight method to calculate the weight of each indicator. The results of the indicator system in the multi-objective optimization model screened by the above method are shown in Table 4. The “three wastes” generally refers to the wastewater, exhaust gas and solid waste produced by industrial pollution sources. The main energy consumption in this paper refers to the consumption of coal, oil and natural gas.

Table 4: Index system for optimizing industrial structure

Target	Index	Attribute
Economic efficiency	Gross domestic product	+
	Investment in fixed assets	+
	Revenue	+
Social life benefits	Employment growth rate	+
	Gross wage growth	+
	Per capita wage growth rate	+
Ecological resource benefit	"Three waste" emissions	-
	Major energy consumption	-

III. A. 2) Decision-making variables

The decision variables in this paper consist of the total output value of primary, secondary and tertiary industry projects. Among them, the primary industry is agriculture, forestry, animal husbandry and fishery. The secondary industry includes industry and construction. The tertiary industry consists of transportation and postal services, wholesale and retail trade, accommodation and catering, finance and insurance, and real estate. The set of decision variables is shown in equation (8):

$$X = \{X_{ij}\} \tag{8}$$

where X_i denotes the j th decision variable for the i th industry.

III. A. 3) Objective function

The goal of optimizing the industrial structure is to maximize the benefits of economic production, social life and ecological resources, with a view to contributing to the development of a new type of foreign trade construction from the perspective of the “Three Life Spaces”.

(a) Economic production efficiency target

The goal of economic production efficiency is to take the three indicators of gross regional product, social fixed asset investment and financial income as the goal of economic production efficiency. The target of economic production efficiency is to obtain the maximum weighted sum of GDP, social fixed asset investment and fiscal revenue per unit of output value of each sector. The calculation formula is shown in equation (9):

$$\begin{aligned}\max f_1 = & w_1 \sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{t_0}^{N}\frac{A_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\} + w_2 \sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{t_0}^{N}\frac{B_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\} \\ & + w_3 \sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{t_0}^{N}\frac{C_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\}\end{aligned} \tag{9}$$

where $A_{ij}^{(t)}$ is the gross regional product of the j decision variable of the i industry in the t year. $B_{ij}^{(t)}$ is fixed asset investment in year t for the j th decision variable of the i th industry. $C_{ij}^{(t)}$ is the local revenue of the j th decision variable of the i th industry in year t. $Z_{ij}^{(t)}$ is the gross output value of the i th industry in the j th year of the decision variable t. t is the year of calculation.

(b) Social life benefit objective

The social life benefits studied in this paper are mainly considered from the perspective of residents' income. Therefore, the maximization of the cumulative value of employment growth rate, total wage growth rate and average wage growth rate can be regarded as the second objective, as shown in equation (10):

$$\begin{aligned}\max f_2 = & w_4 \sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{t_0}^{N}\frac{D_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\} + w_5 \sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{t_0}^{N}\frac{E_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\} \\ & + w_6 \sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{t_0}^{N}\frac{M_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\}\end{aligned} \tag{10}$$

where, $D_{ij}^{(t)}$ denotes the growth rate of employment for the j decision variable in the i industry in year t. $E_{ij}^{(t)}$ denotes the growth rate of per capita wages for the j decision variable in the i industry in year t. $M_{ij}^{(t)}$ denotes the growth rate of total wages for the j decision variable in the i industry in the t year.

(c) Eco-efficiency resource objective

The eco-efficiency resource objective mainly considers both resource conservation and environmental protection. That is, minimizing energy use and pollution emissions is the third objective of the model. Specifically, it is to minimize solid, liquid and gaseous pollutant emissions and energy utilization of coal, oil and natural gas in each industrial sector, as shown in equation (11):

$$\begin{aligned}\min f_3 = {} & w_7\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{i_0}^{N}\frac{F_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\}+w_8\sum_{i=1}^{3}\sum_{j=1}^{n}\left\{\left[\sum_{i_0}^{N}\frac{P_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\} \\ & +w_9\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{i_0}^{N}\frac{Q_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\}+w_{10}\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{i_0}^{N}\frac{Q_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\} \\ & +w_{11}\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{i_0}^{N}\frac{H_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\}+w_{12}\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\sum_{i_0}^{N}\frac{U_{ij}^{(t)}}{Z_{ij}^{(t)}}/T\right]X_{ij}\right\}\end{aligned} \tag{11}$$

where $F_{ij}^{(t)}$ denotes the solid pollutant emissions of the j decision variable of the i industry in the t year. $P_{ij}^{(t)}$ denotes the liquid pollutant emissions of the j th decision variable of the i th industry in the t th year. $Q_{ij}^{(t)}$ denotes the gaseous pollutant emissions of the j th decision variable of the i th industry in year t. $O_{ij}^{(t)}$ denotes the oil consumption of the j decision variable in the i industry in year t. $H_{ij}^{(t)}$ denotes the coal consumption of the j decision variable in the i industry in year t. $U_{ij}^{(t)}$ denotes the natural gas consumption of the j decision variable for the i industry in year t.

III. A. 4) Constraints

(a) Resource constraints

a) Energy consumption constraint: Energy has always been an important resource for economic development. Effective optimization of industrial structure can save energy. Therefore, the rationality of energy utilization needs to be considered in the process of industrial structure optimization. In order to maintain economic security, the total energy consumption of each industrial sector is less than the total available energy. See equation (12):

$$\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\left(\sum_{t_0}^{N}\frac{G_{ij}^{(t)}}{Z_{ij}^{(t)}}\right)/T\right]X_{ij}\right\}\le R_1 \tag{12}$$

where $G_{ij}^{(t)}$ denotes the energy consumption of the j decision variable for the i industry in year t. R_1 is the maximum available amount of energy.

b) Industry production capacity constraint: in order to maintain the stability of the economic system and the availability of resources, sectoral production capacity should be taken into account in the industrial reconstruction process. That is, the annual gross output of each industry cannot be higher than the upper limit of the growth rate of each sector, nor lower than the lower limit of the growth rate of the total output of the sector. See equation (13):

$$\alpha_{ij}Z_{ij}^{(N)} < X_{ij} < \beta_{ij}Z_{ij}^{(N)} \tag{13}$$

where, $\alpha_{ij} < 1 < \beta_{ij}$, α_{ij} and β_{ij} are the lower and upper bounds on the growth rate of output for each industry, respectively.

(b) Ecological and environmental constraints

The ecological environment constraints are mainly to control the emission of pollutants, including solid pollutants, liquid pollutants and gaseous pollutants.

a) Solid pollutant constraints: the total solid pollutant emissions of each industrial sector are less than the allowable emissions. See equation (14) shown:

$$\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\left(\sum_{t_0}^{N}\frac{F_{ij}^{(t)}}{Z_{ij}^{(t)}}\right)/T\right]X_{ij}\right\}\le S_1 \tag{14}$$

where, S_1 denotes the maximum emission limit for solid pollutants in the base year.

b) Liquid pollutant limitation: the total liquid pollutant emission from each industrial sector is less than the permitted emission. See equation (15) shown:

$$\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\left(\sum_{t_0}^{N}\frac{P_{ij}^{(t)}}{Z_{ij}^{(t)}}\right)/T\right]X_{ij}\right\}\le S_2 \tag{15}$$

where, S_2 denotes the maximum emission limit for liquid pollutants in the base year.

c) Limitation of gaseous pollutants: the total emissions of gaseous pollutants from each industrial sector are less than the allowable emissions. See equation (16) for an illustration:

$$\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\left(\sum_{t_0}^{N}\frac{Q_{ij}^{(t)}}{Z_{ij}^{(t)}}\right)/T\right]X_{ij}\right\}\le S_3 \tag{16}$$

where, S_3 denotes the constrained maximum emissions of liquid pollutants in the base year.

(c) Labor force constraint

The labor force constraint refers to the total amount of labor used in each industry sector that is less than the number of employable people in the area. See equation (17):

$$\sum_{i=1}^{3}\sum_{j=1}^{n_i}\left\{\left[\left(\sum_{t_0}^{N}\frac{D_{ij}^{(t)}}{Z_{ij}^{(t)}}\right)/T\right]X_{ij}\right\}\le K \tag{17}$$

where, K represents the number of employable people in the region.

(d) Non-negative constraints

Non-negative constraints are applied to the independent variables in the model. See equation (18):

$$X_{ij}\ge 0\forall i,j \tag{18}$$

III. B. Multi-objective Gray Wolf Optimization Algorithm and Improvements

III. B. 1) Multi-objective optimization algorithm

A single scheduling objective is no longer sufficient to meet the practical needs of the integrated energy system optimal scheduling problem, and in real cases, a certain system optimal scheduling problem usually has more than one optimization direction, and the accompanying optimal solution often has more than one. Therefore, it is crucial for the optimization problem to be solved to obtain the optimization results needed for the study.

After the concept of Pareto, the gray wolf optimization algorithm combined with Pareto theory proposed multi-objective gray wolf optimization algorithm [18], this paper in the improvement of the gray wolf algorithm based on the combination of Pareto theory, the application of improved multi-objective gray wolf algorithm for solving the foreign trade industry upgrading path problem. The general mathematical model of multi-objective optimization is as follows:

$$\begin{gathered}\min \quad p=F(X)=(f_1(X),f_2(X),\cdots,f_m(X))\\ s.t \quad g_i(X)\le 0, i=1,2,\cdots,q\\ h_j(X)=0, j=1,2,\cdots p\\ X=(1,2,\cdots,n); p=(1,2,\cdots,m)\end{gathered} \tag{19}$$

X belongs to the decision vector space and p belongs to the objective vector space, and they are mapped by f -objective relations.

In multi-objective problems, there is usually no two good cases, and the optimization of one objective is often accompanied by the deterioration of the other objectives, which is also in line with the actual situation. For the solutions that satisfy the constraints of this paper are called feasible solutions, but these solutions are often not what this paper wants, so this paper needs to find out those solutions that the current objective is optimal and the other objectives do not deteriorate, and this paper refers to the set of these solutions as the non-dominated solution set.

In a multi-objective optimization problem, consider an objective whose optimal solution can be defined as follows:

$$\underset{X\in\Omega}{opt}f(X)=f(X') \tag{20}$$

Among them:

$$f:\Omega\rightarrow\mathbb{R}^m \tag{21}$$

where Ω is the set of feasible solutions that satisfy the constraints. That is:

$$\Omega=\{X\in\mathbb{R}^n \mid g_i(X)\ge 0, h_j(X)=0 \quad i=(1,2,\cdots,q); j=(1,2,\cdots,p)\} \tag{22}$$

The set of Pareto optimal solutions is a subset of the decision vector space, the Pareto optimal frontier is a subset of the objective vector space of the function, and the mathematical problem of multi-objective optimization is a mapping of the decision space to the objective space.

III. B. 2) Rapid sorting

There are various relationships between individuals in a population, such as dominance relationship between individuals, aggregation relationship within the same habitat, crowding degree between individuals, and so on. In this paper, the relationship "$\succ$" is often used to indicate that one individual performs better than another. $a \succ b$ indicates that b is dominated by a. However, for two independent individuals i.e. when a,b are irrelevant, i.e. not dominated by each other, "$\succ$" is not able to describe the relationship. Here in this paper, we introduce the "$\succ_d$" relationship, where $a \succ_d b$ is denoted as either a dominates b in a certain performance or a,b is irrelevant.

Rapid sorting is a non-transitive sorting method. In a population obtained in this paper, an individual φ is randomly selected, and the first individual in the population can generally be chosen for comparison. After a sorting, this paper takes φ through the entire population, selects the individuals in the population that are inferior to φ, and concentrates them in set A, and selects the individuals that are superior to φ, or unrelated individuals, and concentrates them in set B. Up to this point, this paper has delineated a population through the "$\succ_d$" relation, with φ as the dividing line. For the A-set, since it is a dominating set, it is directly discarded in this paper in the downward sorting. After this the first round of fast sorting was completed. Next, this paper repeats the above operation on the second non-dominated set, "Set B". When φ is not dominated by other individuals in the set, this paper selects φ and incorporates it into the external non-dominated set. If φ is dominated by other individuals in the set, it discards φ. Re-select the first individual in the set and repeat the above sorting until there is only one individual left in the second part of the set.

Let $P=\{\alpha_1,\alpha_2,\cdots,\alpha_n\},\forall\varphi\in P$, φ divides P into two subsets, delimited by φ, i.e., $\{\varphi_1,\varphi_2,\cdots,\varphi_i\}$ and $\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$ and $\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$. Make $\forall x\in\{\alpha_1,\alpha_2,\cdots,\alpha_i\}, y\in\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$, with $y\succ_d\varphi$, and $\varphi\succ x$, then:

(1) The set $\{\varphi_1,\varphi_2,\cdots,\varphi_i\}$ is the dominating set, and each individual is inferior to φ.

(2) If $\forall y\in\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$, φ is not dominated by y, i.e. $\neg(y\succ\varphi)$, then φ is a nondominated solution of the population P.

(3) $\forall y\in\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$, if γ is $\{\varphi_i+2,\varphi_{i+3},cdots,\varphi_n\}$ of nondominated individuals, then y is also a nondominated solution of the population P.

It is worth clarifying that in the process of sorting, let the second part of the set be $\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$, and if none of the individual elements in the set are associated with φ, then φ must belong to the current nondominant individual of the population, but the individual elements in the set are not all nondominant individuals. Especially at the beginning of the sorting iteration, the relationship between the individuals of the multi-objective population is shown in Figure 2. If the set of individuals at this time is $\phi=\{A,B,C,D,E,a,b,c,d,e\}$, $\phi\in\{\varphi_{i+2},\varphi_{i+3},\cdots,\varphi_n\}$, the individuals φ are not related to individuals of the set ϕ are not related to the individuals in the set φ, but it is clear that $A\succ\{a,b\},B\succ\{c,d\},c\succ\{d\},C\succ\{e\}$.

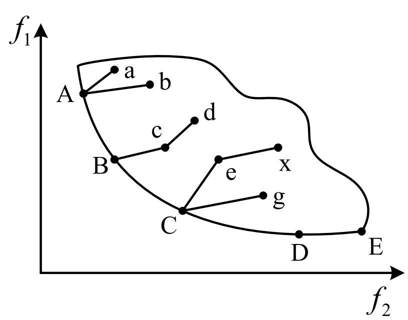

Figure 2: Individual Relationships in multi-objective populations

III. B. 3) Improvement of stock diversity and distribution

The grid method can well capture the distributivity of the nondominated set, and the distribution of individuals can be clearly described by the gridding of the external set, and a good distribution of individuals can optimize the final result derived from the algorithm.

For an optimization model with r objectives, there are generally $2r$ boundaries, and the boundaries of the grid are divided into the upper boundary ub and the lower boundary lb. In this paper, we describe a mesh in terms of the diagonal of a hypercube. An optimization model with m objectives in general has its lattice denoted

$\{(lb_1, lb_2, \cdots, lb_m), (ub_1, ub_2, \cdots, ub_m)\}$. A grid can be divided into multiple chunks, depending on the problem being optimized and the size of the population individuals. For the chunks ∂^j in the grid are described as follows:

$$\forall p \in \{1, 2, \cdots, m\}, \partial lb_j^p = lb^p + j_p \cdot \delta_p \tag{23}$$

$$\partial ub_j^p = lb^p + (j_p - 1) \cdot \delta_p \tag{24}$$

$$\delta_p = \frac{range_p}{d} \tag{25}$$

where, δ_p - denotes the length of each chunk in the pth dimension, d - denotes the number of divisions of the grid in each dimension, $range_p$ - denotes the width of the grid in the pth dimension.

III. C. Analysis of the upgrading path of foreign trade industry

III. C. 1) Analysis of Pareto solutions

The dynamic multi-objective optimization model is solved by applying genetic algorithm NSGA-II through MATLAB software version R2014b. The Pareto front surface is obtained as shown in Figure 3. The three axes represent the sum of five years of industrial added value, energy consumption and pollution emission, i.e. the values of the three objective functions. Since the first objective function is to maximize the value added of industry in the planning period, it is transformed into a problem of finding the minimum value, and thus the values on the axes are shown as negative numbers.Each point on the Pareto front corresponds to a Pareto solution, and the distribution of each point is more uniform, not concentrated in a local range, and the boundary is clearer, and the population is converged to a smaller range.

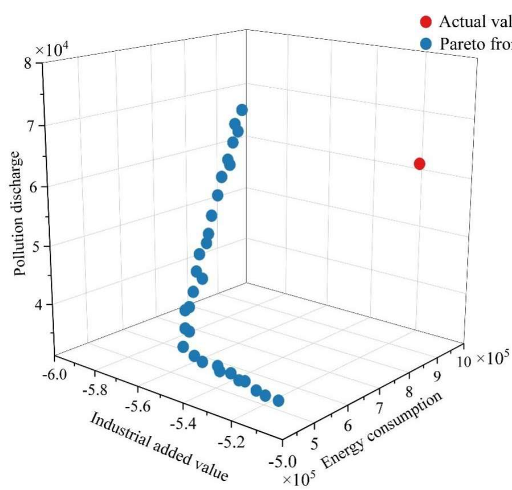

Figure 3: Pareto front and the actual value in 2004-2024 optimizing

III. C. 2) Transformation and upgrading path

All of the above 3 types of transformation and upgrading respectively take the 3 objectives in the dynamic multi-objective optimization model as the only goal, and the optimization values obtained can be said to be the 3 most extreme cases. In actual production, the development of the industrial sector cannot favor only one aspect, but also take into account the 3 objectives. Then, for the case where the 3 objectives are equally important, i.e., the weights of the 3 objectives are 1/3 respectively, the optimized industrial value added optimization results obtained after optimization are shown in Table 5. The optimization results of the value added of each industrial industry are still divided into 3 cases, some industrial value added of the industry maintains the trend of increasing year by year, some industrial value added of the industry decreases year by year, and some industrial value added of the industry increases first and then decreases. Among them, the oil and gas extraction industry (13), agricultural and food processing industry (7) and electrical machinery and equipment and other manufacturing industries (5) and computers and other electronic equipment manufacturing industry (3) of the optimization of the value of industrial added value is higher. On the other hand, the ferrous metal mining industry (8), non-ferrous metal mining industry (2) and chemical fiber manufacturing industry (14) have lower optimized industrial added value, which is lower than the actual value.

Table 5: The optimized value of added-value under balanced upgrading

Industry	2009	2014	2020	2024
1	1507.2	312.6	1618.4	1186.7
2	429.1	927.9	915.3	1191.8
3	1085.3	1802.5	1493.3	1924.3
4	1369.7	411.5	1131.6	1616.5
5	373.9	1428	2166.5	2357.6
6	1646.4	2108.5	311.1	1825.5
7	1724.5	2207.7	2177.5	812.5
8	383.4	1076.7	643.4	928.7
9	1944	2050.8	533.6	2419.6
10	1050.8	1615	1167.1	1958
11	1621.2	1727.8	1969.4	958.2
12	1539.4	2014.3	2410.6	2180.9
13	2156.4	1757.8	715.9	2307
14	490.5	1683.2	1183.7	789.1
Total	17321.8	21124.3	18437.4	22456.4

According to the optimization results of industrial added value multiplied by the energy consumption coefficient, the optimized value of energy consumption of each industrial industry is obtained, and the specific results are shown in Table 6. Compared with the optimization results under the three types of transformation and upgrading paths, under the balanced transformation and upgrading path, the sum of the energy consumption values of industrial industries in each year is smaller than the actual value of the year, which is slightly higher than the optimized value under the energy-saving transformation and upgrading path, but still significantly lower than the optimized value under the value-enhancing and environment-friendly transformation and upgrading path.

Table 6: The optimized value of energy consumption under balanced upgrading

Industry	2009	2014	2020	2024
1	2184.8	1444.7	1028.8	1309.1
2	2065	1601.1	713.6	1733.8
3	2298.1	1367.4	1369.5	451.5
4	1291.5	1499.8	1674.7	1200.4
5	1896.9	2216.3	2290.9	2422.6
6	1729.3	1235.3	1019.4	419
7	703.3	899.6	789	1518.5
8	1205.6	2012.8	422.5	447.1
9	1321.5	1042.8	1914.5	1483.9
10	1755.1	1471.7	805.1	610.4
11	780.7	1584.4	985	504.5
12	989.5	1891.9	1035.9	2197.8
13	2444.6	1515.4	1433.1	1714.9
14	2337.1	1903.4	1334.4	501.7
Total	23003	21686.6	16816.4	16515.2

Finally, according to the optimization results of industrial added value multiplied by the pollution emission coefficient, the optimized value of pollution emission index of each industrial industry is obtained, and the specific results are shown in Table 7. Compared with the optimization results under the transformation and upgrading paths of the previous three scenarios, under the balanced transformation and upgrading path, the sum of the optimized values of the pollution emission composite index of industrial industries in each year is smaller than the actual value of that year, slightly higher than the optimized value under the environment-friendly transformation and upgrading path, but still significantly lower than the optimized value under the value-enhancing and energy-saving transformation and upgrading path. From 21,104.9 in 2009, it decreases year by year to 18,556 in 2024, with a significant decrease.

Table 7: The optimized value of waste discharge under balanced upgrading

Industry	2009	2014	2020	2024
1	2201.2	2037.1	1785.5	1050.7
2	2231.3	1140.7	2145.7	546.6
3	345.7	694.3	2296.8	2437.2
4	1677.2	2290	1414.3	887.7
5	1043.8	862.5	1048.4	801.2
6	955.5	1229.7	2249.2	2485.9
7	635.5	1984.5	1141	736.2
8	1978.1	1666.2	1107.1	323
9	2373.2	1160.4	662.1	1941.6
10	1829.3	2355.7	966.2	2196.5
11	1825.2	317.1	997.8	1542
12	1668.1	2478.6	2394.4	1304.6
13	1282.4	1571	1725.7	1156.5
14	1058.4	2122.5	2139.8	1146.3
Total	21104.9	21910.3	22074	18556

In summary, under the balanced transformation and upgrading path, the industrial industry in the case of value enhancement, energy saving and environmental friendly three objectives are equally important, through the dynamic multi-objective optimization model to solve, get the optimized value of industrial added value of each industrial industry as well as the optimized value of energy consumption and pollution emissions, the optimization results are between the three types of optimization results of transformation and upgrading, the method in this paper can effectively promote the industrial Transformation.

IV. Conclusion

By constructing a value chain optimization model for the foreign trade industry chain of “Belt and Road” based on multi-objective planning algorithm, this study analyzes the characteristics of trade network evolution and proposes industrial upgrading paths. It is found that the trade network of “Belt and Road” shows significant agglomeration effect and diversification development trend, in which Asian countries dominate in the ranking of node entry intensity, and seven of the top ten countries in 2024 are occupied by Asian countries. The application of the multi-objective optimization model effectively realizes the coordinated development of economic, social and ecological benefits, and under the balanced transformation and upgrading path, the total added value of each industrial sector is raised from 17,321.8 in 2009 to 22,456.4 in 2024, which reflects a significant economic growth effect. Outstanding results have been achieved in environmental protection, with total energy consumption decreasing from 23,003 in 2009 to 16,515.2 in 2024, and the composite index of pollution emission showing a continuous decline, indicating that industrial upgrading plays an important role in the construction of ecological civilization. The changes in network density and reciprocity index reflect the deepening of trade relations, laying the foundation for building a closer economic and trade cooperation pattern. This study verifies the effectiveness of the multi-objective optimization algorithm in solving complex industrial upgrading problems, and provides a scientific basis for countries along the “Belt and Road” to formulate foreign trade development strategies.

Funding

This work was supported by Key provincial scientific research projects: (2023AH052817) Research on Industrial Upgrading in Anhui Province Driven by the Integration of RCEP and "Belt and Road".

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