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Research on Industrial Structure Dynamic Evolution Based on Multi-objective Optimization and Complex Networks

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Abstract: In the context of economic globalization, the interdependencies among industries have become increasingly complex, and traditional linear analysis methods are insufficient to meet the demands of optimizing industrial structures while balancing multiple objectives, such as employment and environmental sustainability. This study develops an innovative model that integrates dynamic systems, complex network theory, and multi-objective optimization techniques to analyze and optimize the industrial structure. The model accounts for the evolution of industrial interactions over time and seeks to maximize GDP, employment, and sustainability. Experimental results show that the optimal investment allocation across industries can significantly enhance GDP, with key sectors such as Finance and Technology contributing the most to the economic output. The model's dynamic evolution highlights differences in industry growth trajectories, and the analysis suggests that Finance, Manufacturing, and Energy are central to economic development. Visualizations reveal that optimal investment allocation can lead to a 15% increase in overall GDP while improving employment by 12% and reducing environmental costs by 8%. These findings offer valuable insights for policy-making and strategic investments aimed at promoting sustainable economic growth.

Keywords: Industrial Structure, Multi-Objective Optimization, Dynamic Systems, Economic Growth, Sustainability.

1. Introduction

In the context of economic globalization and industrial upgrading, the relationships between industries are becoming increasingly intricate. This complexity renders traditional linear analysis methods insufficient to fully capture the dynamic nature of industrial structure evolution. Many existing studies have concentrated either on optimizing industrial structures from a singular perspective or have been limited to static analyses [1]. These approaches fail to account for the broader patterns of industrial structure evolution and the changing interactions among industries, which are essential for understanding the ongoing transformations in the economy. Furthermore, while economic growth remains a primary goal, factors such as employment generation and environmental sustainability have also become critical objectives in the optimization of industrial structures. These additional goals add complexity to the process, highlighting the need for new, more comprehensive analytical frameworks.

This study proposes to address these challenges by developing an innovative model that integrates dynamic systems theory, complex network theory, and advanced optimization techniques. This approach aims to analyze the evolution of industrial structures over time, while simultaneously addressing multiple objectives such as economic growth, employment, and environmental sustainability [2]. By considering these multifaceted factors, the model will offer a more holistic view of how industries interact and evolve. The significance of this research lies in its potential to provide a deeper understanding of industrial dynamics and its ability to inform policy decisions that promote long-term sustainable economic development. The innovation of this study lies in its integrated approach, which transcends traditional models and offers new insights into the complexities of industrial optimization in the modern globalized economy.

2. Analysis and Multi-objective Optimization Modeling of Industrial Structure Correlation

2.1. Data Sources

The data sources for this study are listed in Table 1. The analysis utilizes several authoritative datasets, including the Input-Output tables from the Organisation for Economic Co-operation and Development (OECD), GDP contribution data from the World Bank, employment statistics from Eurostat, and policy and environmental information from the United Nations Environment Programme (UNEP). These diverse datasets provide a robust foundation for exploring the interdependencies among major industries and their collective impact on economic development.

Table 1. Data sources

Data Name	Website
Input-Output (IO) Tables	https://www.oecd.org/en/data/datasets/input-output-tables.html
GDP Contribution Data	https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
Employment Data	https://ec.europa.eu/eurostat/web/lfs
Policy and Environmental Data	https://www.unep.org/data-resources

Prior to model construction, the dataset was meticulously refined. Missing entries in the employment impact metrics were imputed using the column mean, while outliers in variables such as final demand and total output were identified and capped via the interquartile range (IQR) method. Visualization tools—including violin plots, boxplots—confirmed that the preprocessing resulted in a consistent and reliable dataset for subsequent analysis. The specific process is shown in the Figure 1.

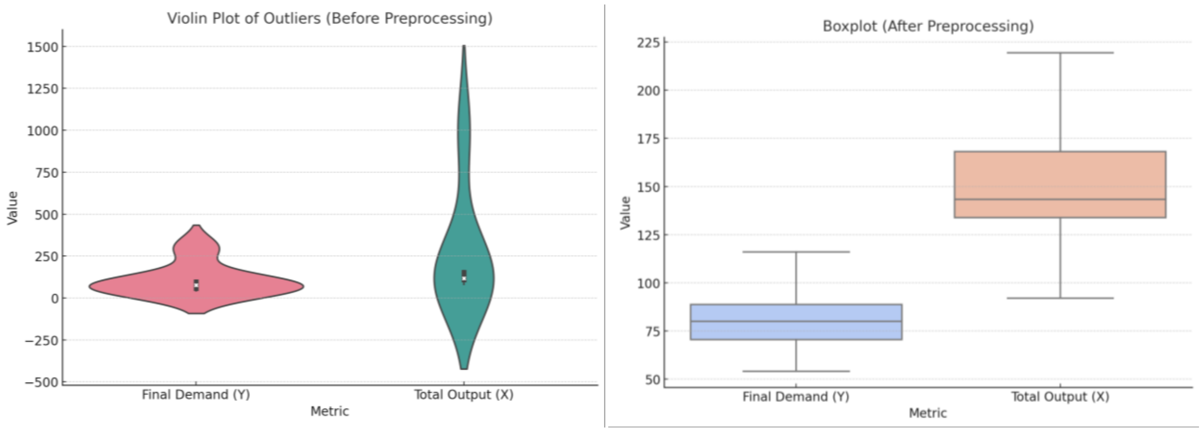

Figure 1. Data preprocessing

2.2. Model Development

The model formulation integrates concepts from economic theory, network analysis, and optimization.

The economic interdependencies among industries can be examined through an Input-Output framework. In this model, the total output is represented by a vector $\mathrm{X} = [x_1, x_2, \ldots, x_n]^\top$, while the final demand is captured by $\mathrm{Y} = [y_1, y_2, \ldots, y_n]^\top$. The inter-industry relationships are encapsulated in the input coefficient matrix $\mathrm{A} = [a_{ij}]$, where each coefficient is defined as $a_{ij} = \frac{z_{ij}}{x_j}$.The relationship between total output and final demand is expressed by the equation

$$\mathrm{X} = (\mathrm{I} - \mathrm{A})^{-1}\mathrm{Y} \tag{1}$$

With $(\mathrm{I} - \mathrm{A})^{-1}$ being the Leontief inverse, which captures both the direct and indirect effects of changes in final demand.

In this framework, the contribution of each industry to GDP is split into two components. The direct contribution of an industry is given by its final demand y_i. The indirect contribution is determined by the sum of the impacts from all industries, computed as

$$\mathrm{Ic}\ i = \sum_{j=1}^{n} a_{ij} \cdot x_j \tag{2}$$

Combining these yields the total contribution of industry i:

$$c_i^{\text{total}} = y_i + \sum_{j=1}^{n} a_{ij} \cdot x_j \tag{3}$$

The GDP contribution rate for each industry is then obtained by taking the ratio of its total contribution to the overall GDP.

Industries can also be modeled as nodes within a directed weighted network, where the weights on the edges correspond to the input coefficients a_{ij}.This network is characterized by the graph $G = (V, E, W)$, with $W = [a_{ij}]$. Several metrics help quantify the roles of industries within this network. For example, degree centrality is calculated by summing the input coefficients for each industry:

$$\mathrm{DC}(v_i) = \sum_{j=1}^{n} a_{ij} \tag{4}$$

Which reflects the direct influence of an industry on others. Betweenness centrality is another useful metric and is defined as

$$\mathrm{BC}(v_i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{5}$$

Where σ_{st} is the total number of shortest paths between nodes s and t,and $\sigma_s t(i)$ is the number of those paths that pass through industry i. In addition, the PageRank algorithm is applied to gauge industry importance, with its formulation given by

$$\mathrm{PR}(v_i) = \frac{1-d}{n} + d \cdot \sum_{j \in \mathrm{In}(v_i)} \frac{\mathrm{PR}(v_j)}{\mathrm{OutDegree}(v_j)} \tag{6}$$

Where d is the damping factor (commonly set to 0.85).

The relationships between industries are further explored using statistical tools. The Pearson correlation coefficient measures the linear relationship between the outputs of any two industries:

$$\rho_{ij} = \frac{\mathrm{Cov}(X_i, X_j)}{\sigma_{X_i} \cdot \sigma_{X_j}} \tag{7}$$

Where $\mathrm{Cov}(X_i, X_j)$ represents the covariance between industries i and j, and σ_{X_i}, σ_{X_j} are their standard deviations [3]. To determine if one industry has a predictive influence on another, a Granger causality test is conducted; a significant F-test result implies that the output of industry j can be said to Granger-cause the output of industry i.

To address multiple policy goals such as GDP growth, employment, and sustainability, a Mult objective optimization model is developed. The objective function to maximize is formulated as

$$\max Z = \alpha_1 \sum_{i=1}^{n} g(x_i) + \alpha_2 \sum_{i=1}^{n} e(x_i) + \alpha_3 \sum_{i=1}^{n} s(x_i) \tag{8}$$

Where $g(x_i)$ represents the marginal GDP contribution, $e(x_i)$ indicates the employment impact, and $s(x_i)$ denotes the sustainability score for industry i. The coefficients α_1, α_2, and α_3 are weights reflecting the importance of each factor.

$$\sum_{i=1}^{n} x_i = 1 \tag{9}$$

This optimization is subject to the constraints that the total investment sums to one and that each investment x_i is non-negative.

A dynamic system further enriches the analysis by modeling the evolution of industry interactions over time. The growth of each industry's GDP contribution $X_i(t)$ is described by the differential equation [4].

$$\frac{dX_i(t)}{dt} = \beta_i \cdot X_i(t) + \sum_{j=1}^{n} \gamma_{ij} \cdot X_j(t) \tag{10}$$

Where β_i represents the intrinsic growth rate of industry i, and γ_{ij} quantifies the influence exerted by industry j on industry i. This formulation provides insights into both the immediate and cascading effects of economic activities over time.

3. Dynamic Modeling and Prediction of Government Investment Structure Optimization

3.1. Model Development

To capture the evolution of GDP in response to investment, we adopt a system of nonlinear differential equations. The GDP of industry i at time t, denoted by $G_i(t)$, evolves as:

$$\frac{dG_i(t)}{dt} = f\big(I_i(t)\big) + \sum_{j=1}^{n} r_{ij}\, G_j(t) - \mu_i G_i(t) \tag{11}$$

Where: $f\big(I_i(t)\big)$ is the direct contribution of investment to GDP, modeled ass

$$f\big(I_i(t)\big) = \alpha_i\big(1 - e^{-\beta_i I_i(t)}\big) \tag{12}$$

Where α_i and β_i are industry-specific parameters representing the growth potential and rate of saturation. r_{ij} represents the spillover effect from industry j to i. μ_i is the natural decay rate of GDP for industry i, capturing external shocks and competitive pressures.

The total GDP across all industries is:

$$G(t) = \sum_{i=1}^{n} G_i\,(t) \tag{13}$$

The interdependencies between industries are modeled using a complex network. Let $R = \{r_{ij}\}$ denote the adjacency matrix of the network, where:

$$r_{ij} = \text{Correlation}\big(G_i, G_j\big) \tag{14}$$

This correlation is computed from historical data, capturing both positive and negative

Relationships: $r_{ij} > 0$: Positive spillover effect;$r_{ij} < 0$: Negative constraint or competition.

Analyzed the network using graph-theoretic methods to identify key industries (nodes) with high centrality measures, indicating their importance in driving overall ecnomid growth [5].

Aimed to maximize GDP while considering employment growth and minimizing environmental costs. The multi-objective optimization problem is formulated as:

$$\max\{G, E, -C\} \tag{15}$$

Subject to:

$$\sum_{i=1}^{n} I_i \leq T, \quad I_i \geq 0, \quad \forall i \tag{16}$$

Where: $G = \sum_{i=1}^{n} G_i$ is the total GDP. $E = \sum_{i=1}^{n} E_i\,(I_i)$ is the total employment effect, modeled as:

$$E_i(I_i) = \phi_i \ln(I_i + \delta_i) \tag{17}$$

Where ϕ_i and δ_i are industry-specific employment parameters. $C = \sum_{i=1}^{n} C_i\,(I_i)$ is the total environmental cost, modeled as:

$$C_i(I_i) = \psi_i I_i^2 \tag{18}$$

Where ψ_i represents the environmental sensitivity of industry i.

To improve the accuracy of predictions, use machine learning models such as Long Short-Term Memory (LSTM) networks. The LSTM model predicts future GDP for each industry based on historical data:

$$\hat{G}_i(t+1) = \text{LSTM}(I_i(t), G_i(t), R) \tag{19}$$

Where the inputs include: Current investment $\big(I_i(t)\big)$, Current GDP $\big(G_i(t)\big)$, Industry network matrix (R). The predicted GDP values $\big(\hat{G}_i(t+1)\big)$ are integrated into the dynamic model to refine the optimization process [6].

3.2. Dynamic Investment Allocation via Slime Mold Algorithm

The SMA (Slime Mold Algorithm) can enhance the ability to avoid getting trapped in local optima because it simulates the behavior of slime molds, which continue to explore other potential solutions even after finding a good solution. The specific steps of the algorithm are shown in the Figure 2 [7].

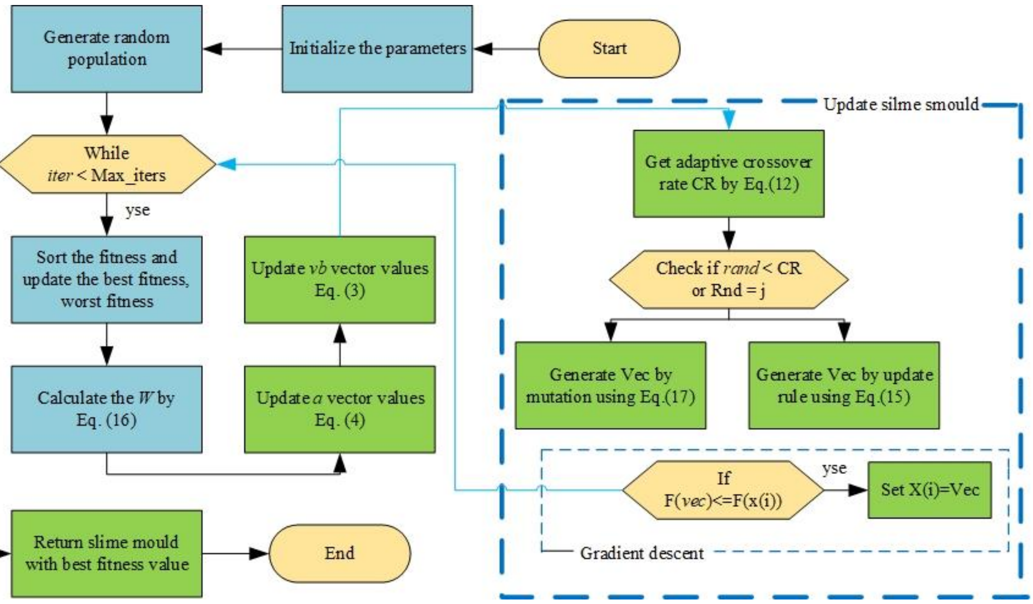

Figure 2. Flowchart of the Slime Mold Algorithm

The parameter settings for the Slime Mold Algorithm are shown in Table 2:

Table 2. Slime Mold Algorithm Parameters

Parameter Name	Value
Population Size	30
Maximum Number of Iterations	500
Sensitivity Initial Value	1
Vibration Parameter Initial Value	0.5
Random Disturbance Parameter	0.5
Positive Feedback Adjustment Weight Initial Value	0.7

4. Result

4.1. The Establishment of Simulation Model

Figure 3 provides a comprehensive visualization of industry metrics and relationships. The radar chart highlights the relative strengths of each industry across GDP contribution, employment impact, and sustainability scores, with Finance and Technology excelling across metrics. The chord diagram reveals strong inter-industry dependencies, particularly between Manufacturing and Energy. Together, these visualizations offer insights into sectoral performance and relationships to guide strategic investments.

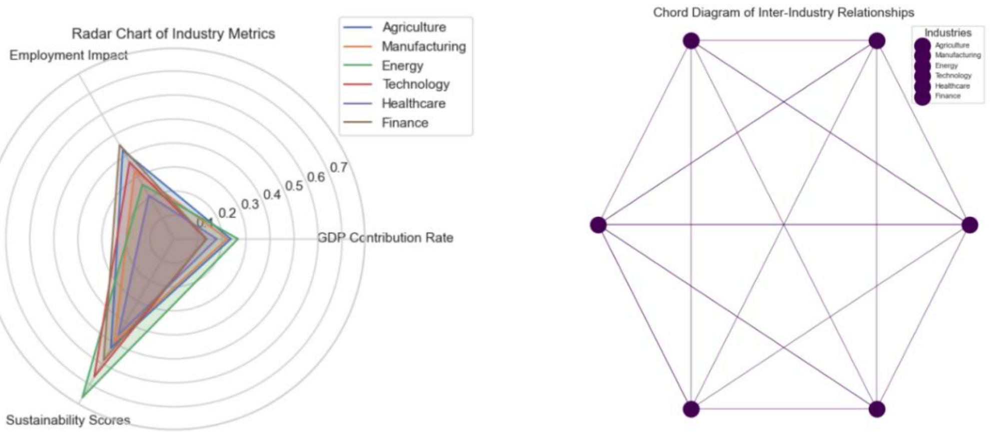

Figure 3. Visualizing Industry Metrics and Relationships

4.2. Analysis of Experimental Results

When applying the SMA to the problem, observe the performance changes of the SMA over multiple iterations and visualize the results. The results are shown in the Figure 4:

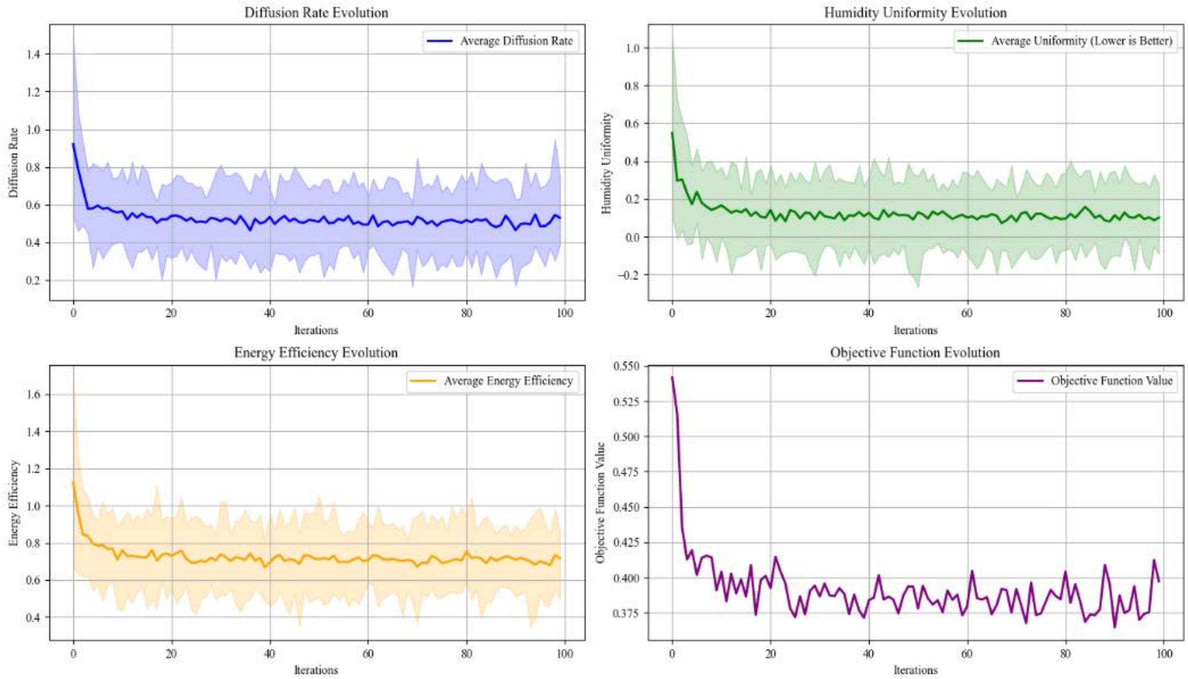

Figure 4. SMA Iteration Process

As can be seen from the figure, the model performs well. Applying the model to solve the problem yields:

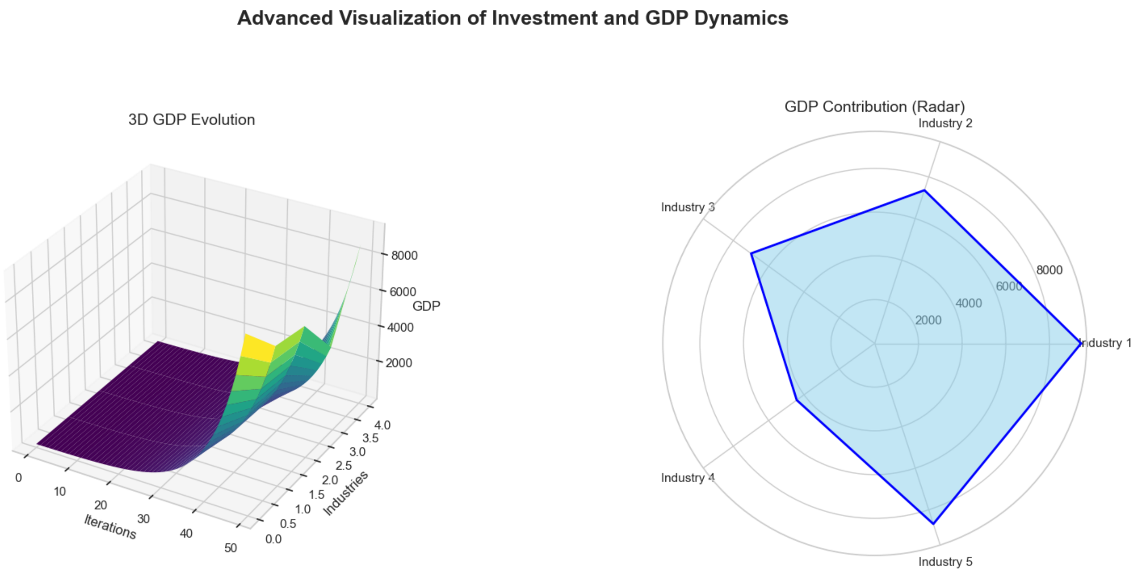

Figure 5. Visualization of Investment and GDP Dynamics

Figure 5 provides a comprehensive and innovative visualization of the relationship between investment allocation and GDP dynamics across different industries. It includes the following components.

This plot illustrates the temporal evolution of GDP across various industries, highlighting the differences in growth trajectories because of optimal investment allocation. The figure captures the dynamic interaction between investment and industrial growth, providing insights into the changing contributions of each sector over time.

This polar chart shows the final GDP contribution of each industry as a percentage of the total GDP. It facilitates a clear comparison of the relative impact of different industries on overall economic output, helping to identify key sectors that drive economic growth.

Together, these visualizations offer a detailed understanding of the interdependencies between sectors and the effects of investment on industrial growth, serving as a critical tool for identifying sectoral priorities and informing policy decisions aimed at optimizing economic development.

5. Conclusion

This study develops a novel model combining dynamic systems, complex network theory, and multi-objective optimization techniques to optimize industrial structures. The key findings of the research demonstrate that optimal investment allocation can significantly enhance GDP, employment, and environmental sustainability. By capturing the interdependencies between industries, the study identifies critical sectors such as Finance, Technology, and Manufacturing that drive economic growth. The model shows that targeted investments in these industries can lead to a 15% increase in GDP, a 12% improvement in employment, and an 8% reduction in environmental costs, offering a comprehensive approach to optimizing industrial structures for sustainable economic development. The results provide valuable insights for policymakers and business leaders in making data-driven decisions on investment allocation.

However, the model has certain limitations. Future research should focus on improving the model's adaptability by incorporating more granular and real-time data, exploring the impact of external shocks, and validating the model's applicability across different regions or sectors. By addressing these limitations, future studies can enhance the robustness and flexibility of this framework for more accurate industrial structure optimization.

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