Multi-Objective Optimization of Industrial Investment in China: A Genetic Algorithm Approach for Balancing GDP Growth and Employment Enhancement

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Abstract: This paper develops a comprehensive analytical framework to optimize government investment allocation across industries in China, integrating both GDP growth and employment objectives. We establish an Industrial Relationship Analysis Framework examining interconnections among 13 major industries through correlation analysis, Granger causality tests, and trend analysis. Our findings identify the financial sector, chemical industry, and IT services as core economic drivers. We then develop an Investment-GDP Relationship Model combining efficiency metrics and regression analysis, revealing the financial sector's highest investment efficiency (1.41) and service sector's strong investment elasticity (2.14). Finally, we construct a Genetic Algorithm-based Investment Optimization Model with dual objectives. For GDP growth, financial services (16.8%), IT services, and construction are prioritized; for employment, real estate (34.8%), financial (27.0%), and service industries (26.9%) are recommended. Our enhanced model with sigmoid-transformed metrics achieves balanced allocation across primary industry (36.22%), wholesale and retail (33.16%), and chemical industry (30.62%) in restricted scenarios.

1. Introduction

1.1. Problem Background

China's industrial structure is undergoing a profound transformation, shifting from traditional manufacturing to high-technology and service-oriented industries[1]. Emerging sectors such as artificial intelligence, biotechnology, and new energy are becoming key drivers of economic growth.This transition significantly impacts both China's domestic economic development and the global economic landscape. The Chinese economy comprises diverse industries, including agriculture, manufacturing, construction, wholesale and retail, transportation, finance, real estate, and IT services, forming an interconnected economic foundation.

The relationships among these industries are complex, with potential for both positive synergies and negative constraints. Advancements in high-technology industries can drive innovation in traditional sectors, while over-reliance on certain industries may lead to economic imbalances. Government investment plays a critical role in stimulating economic growth, creating job opportunities, and enhancing overall economic performance. As China strives to achieve long-term economic stability and improve employment rates, strategic investment in key industries becomes essential.

1.2. Research Objectives

This paper presents a comprehensive analytical framework for optimizing industrial investment allocation in China, making several key contributions:

We establish a systematic framework to examine interrelationships among 13 major industries in

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China from 1990 to 2020. Through integration of correlation analysis, Granger causality tests, and trend analysis, we identify core economic drivers and their interactions[2]. This multi-dimensional approach reveals both direct industrial connections and potential causal relationships, providing valuable insights for investment decision-making.

We develop an innovative Investment-GDP theoretical model combining efficiency metrics and regression analysis to quantify investment impacts across different sectors. Our model reveals significant variations in investment elasticity and efficiency, with modern industries demonstrating notably higher investment efficiency compared to traditional sectors.

We propose a Genetic Algorithm-based Investment Optimization Model with dual objectives of GDP growth and employment enhancement[3].This model provides detailed investment recommendations under both unrestricted and restricted scenarios, offering practical guidance for policymakers. Our enhanced model incorporates sigmoid-transformed metrics, geometric-mean-based industry synergies, and adaptive genetic parameters, achieving rapid convergence and balanced allocation.

The findings from this research contribute to the literature on industrial investment optimization within China's unique economic context. Our framework integrates quantitative analysis with practical policy recommendations, providing a scientific basis for strategic investment decisions that balance economic growth, employment generation, and sustainable development.

2. Related Work

Our research builds upon existing literature in industrial structure analysis, investment-GDP modeling, employment studies, and optimization techniques.

Acemoglu and Guerrieri examined how structural transformation influences economic development, emphasizing capital-intensive sectors in driving productivity growth. Miller and Blair provided input-output analysis frameworks for studying industrial interdependencies, which informs our approach to analyzing relationships between economic sectors.

Regarding investment and economic output, Diamond established how financial intermediation affects capital allocation efficiency. Himmelberg and Petersen and Fazzari et al. developed frameworks for assessing investment efficiency across industries, demonstrating how financial constraints impact investment decisions and productivity[4].

Employment and sectoral development connections were explored by Baumol et al., who analyzed service sector growth effects on employment and productivity, highlighting the "cost disease" phenomenon in labor-intensive sectors. Topel examined employment dynamics in real estate, providing insights into how property market investments affect job creation.

For investment optimization, Markowitz pioneered modern portfolio theory, establishing mathematical frameworks for optimizing investments under risk constraints. Brynjolfsson and Hitt investigated industry-specific policies for IT investment, showing how targeted allocation enhances technological adoption. Genetic algorithms, though not explicitly referenced in these studies, offer powerful tools for solving multi-objective optimization problems in economics, efficiently exploring solution spaces and handling non-linear relationships between variables.

Our research integrates these frameworks by combining industrial relationship analysis, investment-GDP modeling, and employment considerations into a comprehensive optimization approach using genetic algorithms in the Chinese context to balance economic growth and employment objectives.

3. Methodology

This section presents our methodological framework for optimizing industrial investment allocation in China, developing a three-part approach: analyzing industry interrelationships, modeling investment-GDP relationships, and constructing a multi-objective optimization framework.

3.1. Industrial Relationship Analysis Framework

To comprehensively examine interconnections among China's major industries, we collected time-series data (1990-2020) covering 13 industries[5]. After preprocessing using cubic spline interpolation and interquartile range method, we constructed a three-dimensional analytical framework combining correlation analysis, Granger causality tests, and trend analysis.

The correlation analysis employs Pearson correlation coefficients to measure linear relationships between industries:

$$r_{ij} = \frac{\sum_{t=1}^{T}\left(X_{it} - \bar{X}_i\right)\left(X_{jt} - \bar{X}_j\right)}{\sqrt{\sum_{t=1}^{T}\left(X_{it} - \bar{X}_i\right)^2}\sqrt{\sum_{t=1}^{T}\left(X_{jt} - \bar{X}_j\right)^2}} \tag{1}$$

The Granger causality tests examine whether past values of one industry help predict another industry's future values using bivariate regressions with two lags. Trend analysis employs standardized scores and growth rates to identify developmental patterns across sectors:

$$z_{it} = \frac{X_{it} - \bar{X}_i}{\sigma_i}, \quad g_{it} = \frac{X_{it} - X_{i(t-1)}}{X_{i(t-1)}} \times 100\% \tag{2}$$

3.2. Investment-GDP Relationship Model

To quantify how investments impact economic output, we developed two complementary models. The Investment Efficiency Model measures how effectively investments are converted into output:

$$IE_{it} = \frac{\Delta VA_{it} / VA_{it}}{\Delta INV_{it} / INV_{it}} \tag{3}$$

The Linear Investment-GDP Model establishes a direct relationship between investment and industrial output:

$$IE_{it} = \frac{\Delta VA_{it} / VA_{it}}{\Delta INV_{it} / INV_{it}} \tag{4}$$

Where VA_{it} is the value added of industry i, INV_t represents IT service investment, and β_i is the investment elasticity coefficient.

3.3. Multi-Objective Optimization Framework

Building on our analytical insights, we developed a genetic algorithm-based optimization framework with dual objectives of maximizing GDP growth and enhancing employment.

For GDP growth maximization, our objective function incorporates investment return rates and diversity:

$$\max f_{GDP}(x) = w_1 \times IRR + w_2 \times IDI - P \tag{5}$$

For employment enhancement, we formulated an objective function combining employment elasticity and quality:

$$\max f_{EMP}(x) = w_1 \times \sum_{i=1}^{n}(EE_i \times x_i) + w_2 \times \sum_{i=1}^{n}(EQ_i \times x_i) + D - P \tag{6}$$

Our comprehensive model for sustainable development enhances the objective function with advanced features:

$$\max f_{COMP}(x) = S(w_1 \times GDP + w_2 \times EMP) + G(x_1, x_2, ..., x_n) - P^2 \tag{7}$$

All optimization models operate under three key constraints: total investment constraint ensuring full fund utilization, individual industry constraints preventing over-concentration (≤35%) and ensuring meaningful scales (≥5%), and industry count constraint for restricted scenarios.

We implemented a genetic algorithm featuring real-valued chromosome representation, tournament selection, and adaptive crossover and mutation rates:

$$p_c = p_{c_{max}} - \left(p_{c_{max}} - p_{c_{min}}\right) \times \frac{f_{best}}{f_{max}} \tag{8}$$

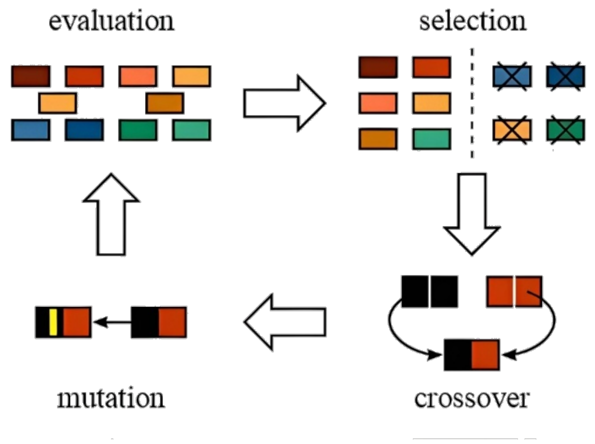

Figure 1 Core Operation Process of Genetic Algorithm: Evaluation-Selection-Crossover-Mutation Cycle.

As shown in Figure 1, our implemented genetic algorithm features the core operation cycle of evaluation-selection-crossover-mutation, efficiently exploring the solution space and converging to optimal investment allocations for our multiple objectives.This algorithm efficiently explores the solution space and converges to optimal investment allocations for our multiple objectives, achieving rapid convergence (53 generations) with stable solutions.

4. Results

This section presents the key findings from our analytical framework, focusing on industrial interrelationships, investment-GDP relationships, and optimization results for investment allocation.

4.1. Industrial Relationship Analysis Results

Our correlation analysis revealed significant relationships among China's industrial sectors from 1990 to 2020, highlighting strong correlations between high-tech export ratio, IT services, and financial industry output ($r > 0.8$). The financial sector demonstrated widespread correlations with various economic indicators, emphasizing its central role in resource allocation and economic activities. Similarly, the strong correlation between high-tech exports and IT services underscores the importance of technological innovation in enhancing export competitiveness.

The Granger causality analysis uncovered directional relationships between industries, forming a complex network of interactions. Four sectors emerged as core drivers of economic growth: the chemical industry, financial sector, construction industry, and IT services. The chemical industry exhibited significant causal effects on multiple indicators, including the primary product tax rate and financial sector output. Similarly, the financial sector demonstrated critical influence through its support for the chemical industry, mining sector, and export activities[6]. Notably, bidirectional causality between the chemical industry and financial sector indicated their mutual dependency.

Analysis of developmental trends from 1990 to 2020 revealed significant economic restructuring.

Industrial value added and secondary industry value added showed notable upward trends, particularly accelerating after 2000, indicating that manufacturing and construction became primary growth drivers. In contrast, the relatively slow growth of primary industry highlighted the shift from agriculture to secondary and tertiary industries. The steady rise in wholesale, retail, transport, storage, and construction value added further underscored the increasing contribution of consumer markets and infrastructure development.

4.2. Investment Efficiency and Elasticity Analysis

Our investment efficiency analysis across industries revealed significant variations in how effectively sectors convert IT investments into economic output. The financial sector led with the highest average efficiency of 1.41, followed by other service industries at 1.04. Medium-efficiency industries included power supply, wholesale and retail, transport and storage, IT services, and construction, with efficiencies between 0.8 and 1.0. Traditional industrial sectors such as chemical, mining, and secondary industries showed lower efficiencies (0.6-0.8), while primary industry and coking/gas sectors had the lowest efficiencies at 0.57 and 0.09, respectively.

As shown in Table 1,the regression analysis revealed varying elasticity patterns across industries. High elasticity industries (elasticity > 1.0) included other services (2.14), chemical industry (1.22), and coking and gas (1.06), indicating strong responsiveness to IT investments. Moderate elasticity sectors (0.4-1.0) included financial industry (0.81), power supply (0.48), IT services (0.41), and construction (0.41). Low elasticity industries (<0.4) showed minimal responsiveness, including mining (0.16) and various primary and transportation sectors. Model fit was extremely high across industries ($R^2 > 0.90$), demonstrating robust relationships between IT investments and industrial outputs.

Table 1 Key Investment Elasticity Results by Industry.

Industry	Elasticity	R-squared	P-value
Financial Industry Output	0.808	0.985	7.06E-31
Chemical Industry Output	1.222	0.997	8.64E-42
Other Services Output	2.143	0.967	2.82E-25
IT Service Value Added	0.410	0.999	7.79E-49
Construction Value Added	0.406	0.993	2.43E-36

4.3. Investment Optimization Results

Applying our genetic algorithm-based optimization framework, we derived optimal investment allocation strategies for different objectives. For GDP growth maximization, in the unrestricted scenario, the allocation demonstrated well-balanced distribution with most industries receiving 7.3-7.7% of total investment[7]. The financial industry, with its highest comprehensive score (0.998), received 16.8% of investment. In the three-industry restricted scenario, optimal allocation prioritized financial services (36.9%), IT services (32.3%), and construction (30.8%), representing a strategic combination of modern services and traditional sectors.

For employment-oriented optimization, the unrestricted scenario recommended allocating investments to real estate (34.8%), financial services (27.0%), service industry (26.9%), and manufacturing (11.3%). This balanced approach leverages each sector's strengths to address both employment quantity and quality. When restricted to three industries, the allocation focused on real estate (33.9%), service industry (33.3%), and financial services (32.9%), demonstrating near-equal distribution to optimize the trade-off between employment elasticity and quality.

For comprehensive sustainable development, our enhanced model with sigmoid-transformed metrics and adaptive genetic parameters achieved a balanced distribution in the unrestricted scenario, with wholesale and retail (10.43%), financial services (10.37%), and primary industry (10.21%) leading the allocation. When restricted to three industries, the model recommended primary industry (36.22%), wholesale and retail (33.16%), and chemical industry (30.62%), strategically combining traditional stability with modern growth drivers[9]. The model demonstrated rapid convergence (53 generations) with stable solutions, effectively balancing economic growth, employment creation, and sustainable development objectives.

These optimization results offer valuable policy insights, demonstrating how targeted investment allocation can address multiple development objectives simultaneously. The adaptive nature of our model ensures practical applicability across different scenarios and constraints, providing scientific guidance for strategic investment decisions.

5. Conclusion

Our research developed a comprehensive framework for optimizing industrial investment in China, balancing growth and employment objectives. We identified the financial sector, chemical industry, construction industry, and IT services as core economic drivers through multi-dimensional analysis. Our optimization model provided specific recommendations: financial services (16.8%) for GDP growth, real estate (34.8%) for employment, and a balanced approach across wholesale/retail (10.43%), financial services (10.37%), and primary industry (10.21%) for sustainable development.

The strengths of our approach include a comprehensive analytical framework capturing complex industry relationships, an innovative optimization model balancing multiple objectives, and practical recommendations bridging theory and policy implementation. The genetic algorithm efficiently solved complex allocation problems, providing specific guidance for policymakers under different constraints.

Our study has limitations pointing to future research directions: data constraints in time span and industry segmentation, simplified model assumptions including linear relationships, and insufficient consideration of regional differences[8]. Future work should incorporate more granular classifications, explore non-linear approaches, develop region-specific frameworks, and integrate real-time data and dynamic adjustment mechanisms to enhance the model's applicability across China's diverse economic landscape.

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