An ACP-Based Parallel Economic System Framework for Economic Analysis

Shi Luo[a*], Linyao Yang[b], Xi Cheng[c]

Zhejiang Lab, Hangzhou, Zhejiang, 311121, China

[a*]luoshi0801@zhejianglab.org, [b]yangly@zhejianglab.org, [c]chengxi@zhejianglab.org

Abstract. Economic analysis plays a vital role in policy-making and economic optimization. Traditional economic analysis methods rely on predefined models to fit economic operation data and simulate the economic evolution process, but these methods suffer from insufficient flexibility and scalability. To address these challenges, we propose a parallel economic system based on the ACP (Artificial systems, Computational experiments, Parallel execution) approach. Specifically, we develop three types of intelligent agents—government, enterprise, and resident—based on the real business cycle model. Using these agents, an artificial economic system is created, capable of generating extensive data for diverse scenarios with various goals and parameters. Computational experiments are then conducted to analyze the generated data, learning optimal solutions for different scenarios. Finally, the learned solutions are applied to reveal economic laws and optimize physical economic systems through parallel execution. The proposed parallel economic system can accurately simulate economic activities under different tax rates and subsidy conditions, providing effective support for decision-makers in formulating economic adjustment policies.

Keywords: Parallel Economy, Simulation, ACP Approach, Agent, Reinforcement Learning.

1 Introduction

Economic activities are the foundation and driving force of social development. Economic analysis plays a vital role in policy-making and economic optimization. To assist economic decision-makers in evaluating the potential impacts of different policies and making optimal decisions, various economic simulation models have been developed. Along with these models, a classic experimental process has been established. This process begins with clarifying the analysis objectives and problem hypotheses, followed by collecting and processing relevant economic data. Models are then constructed based on economic theories to ensure they accurately reflect specific economic scenarios and phenomena. Finally, appropriate simulators are used to verify and interpret the results. Despite the continuous development of economic theories, economic analysis still faces several challenges.

© The Author(s) 2025

B. Siuta-Tokarska et al. (eds.), *Proceedings of the 2025 3rd International Academic Conference on Management Innovation and Economic Development (MIED 2025)*, Advances in Economics, Business and Management Research 348,
https://doi.org/10.2991/978-94-6463-835-6_78

Limited modeling scope: Traditional economic analysis often needs to choose between focusing on broad macroeconomic trends (such as GDP growth, inflation rates, and employment levels) and individual behaviors at the microeconomic level (such as personal consumption choices and enterprise production decisions). This choice results in models that cannot objectively describe economic phenomena and details at both interacting levels.

Data diversity and inefficient fusion: Economic analysis and simulation require handling data from diverse sources with varying characteristics. While macroeconomic indicators are relatively easy to access, detailed micro-level data on individuals and enterprises are often challenging to collect due to security concerns. Additionally, data integration and utilization face challenges related to different scenarios, granularity and timeliness.

Enormous complexity: The nonlinear characteristics and complex interactions of economic systems often make analysis and simulation difficult to manage and interpret. Currently, there is a lack of effective means to describe and understand the generation mechanisms and evolution processes of complex economic phenomena from the collaborative perspective of multiple agents such as governments, enterprises, and residents.

Insufficient flexibility and adaptability: The economic environment and policy conditions are constantly changing, requiring models to have adaptive evolution mechanisms to dynamically adjust parameters and structures to maintain long-term effectiveness and relevance. Different policy scenarios need to be simulated and fed back into the environment, and their impacts need to be analyzed and evaluated continuously to optimize policies. Unfortunately, traditional analysis methods are static and cannot dynamically adjust to changing economic environments, limiting their ability to continuously optimize.

Parallel systems, an innovative technology proposed at the beginning of this century, include Artificial Systems (A), Computational Experiments (C), and Parallel Execution (P). Through a set of parallel interactions between physical and artificial systems, this approach provides solutions for complex problems with high social and engineering complexity. This methodology has been widely researched and has achieved excellent results in many fields. Parallel systems organically combine macro-level modeling of emergence and evolution laws with micro-level detailed characterization and interaction modeling. By comprehensively and accurately depicting the characteristics, behaviors, and interactions of participating individuals, they achieve the modeling of complex wholes, leading to the emergence and evolution of complex system laws.

To address the challenges of traditional methods, this paper proposes a parallel economic system based on the ACP approach. It develops an artificial economic system by modeling three types of agents, i.e., government, enterprise, and resident, based on the real business cycle model [1]. Various economic scenarios are then simulated in the artificial economic system, generating extensive artificial data. Based on these data, optimal economic adjustment policies for specific scenarios are learned. Finally, the corresponding policy for the real-world economic system can be recommended to decision-makers, optimizing the physical economic system in a virtual-real interactive

way based on parallel execution. This proposed parallel economic system provides effective support for the formulation of financial subsidies and tax policies, better addressing the challenges faced by current economic analysis and simulation. This interdisciplinary integration not only promotes the development of economics but also provides strong technical support for social governance and policy formulation.

2 Related Word

2.1 Economic Analysis

Economic analysis involves collecting and organizing data, constructing models based on economic theories and assumptions, calibrating and validating these models using historical data, and conducting simulations to analyze the impact of different policies or external shocks. Economic models for policy analysis include econometric models, structural macroeconomic models, computable general equilibrium (CGE) models, and dynamic stochastic general equilibrium (DSGE) models.

Econometric models use statistical techniques to analyze the relationships between economic variables and the impacts of economic policies. For instance, Borojo et al. [2] provided a new perspective on how economic policy uncertainty affects global supply chains by influencing trade flows through static analysis of data from different countries and periods. Structural macroeconomic models are built on specific economic theories and structures, incorporating detailed relationships and behaviors within the economy to simulate the effects of economic policies. For example, Christiano et al. [3] investigated the impact of risk shocks on the economy using a structural model that integrates financial market frictions, highlighting the importance of financial markets in macroeconomic fluctuations.

CGE models use computational techniques to simulate the general equilibrium effects of economic policies on various markets and sectors within an economy. For example, Hertel et al. [4] developed a global CGE model framework to analyze the impact of trade policies and globalization on the economy, providing a powerful tool for decision-makers to evaluate the impact of trade agreements and global economic changes on national economies. DSGE models integrate microeconomic foundations with dynamic and stochastic processes to analyze how economic policies affect macroeconomic variables over time. Compared to CGE models, DSGE models offer significant advantages due to their ability to incorporate dynamics and uncertainty. They particularly excel in analyzing the interactions between macroeconomic characteristics and the decision-making behaviors of microeconomic agents. For instance, Christiano et al. [5] incorporated nominal rigidities into a DSGE model to study the dynamic effects of monetary policy shocks on output and inflation, showing the importance of price and wage stickiness in macroeconomic dynamics.

With the development of artificial intelligence, technologies such as big data, machine learning, and reinforcement learning continue to achieve significant results in the field of economic analysis. Susan Athey [6] discussed how machine learning techniques were transforming economic research and practice by enhancing predictive accuracy, uncovering complex patterns in data, and offering new tools for causal inference and

policy analysis. Zheng et al. [7] developed an intelligent framework based on two-level deep reinforcement learning and demonstrated its efficacy in the problem of optimal taxation.

Each of these models has unique characteristics and applications in economic policy analysis. However, the data and models used in their analyses are often overly simplified and singular, typically based on assumptions of fully rational economic agents or perpetually balanced markets, without considering various scenarios in the environment. This simplification does not align with the complex reality. Additionally, these models are relatively static or remain unchanged within a simulation cycle, making it difficult to capture dynamic changes in time series. Most importantly, economic activities are a balanced process of multi-party interactions, and traditional methods are usually linear and discrete, considering only deterministic outcomes and lacking mechanisms for real-time interaction and continuous feedback with the physical economic environment.

2.2 Parallel Systems

Parallel systems are an approach designed to manage and control complex systems by operating a virtual or artificial system alongside the physical system. This methodology is grounded in the ACP approach, which stands for artificial systems, computational experiments, and parallel execution. Artificial systems are detailed simulations that mirror the physical system's characteristics, computational experiments involve running various scenarios on these simulations to explore potential outcomes, and parallel execution integrates these insights back into the physical system for real-time optimization and control. The advantages of parallel systems include dynamic adaptability to changing conditions, proactive risk management, optimized decision-making, improved efficiency, and the facilitation of innovation, all of which contribute to a comprehensive understanding and effective management of complex systems. In recent years, ACP approach has been successfully applied in various fields such as transportation [8-10], healthcare [11,12], environment [13,14], and energy [15,16], providing comprehensive solutions for research on complex social problems centered around human beings. Inspired by the significant success of parallel systems across various domains, we propose the implementation of a parallel economic system to achieve automatic optimization of economic processes.

3 Parallel Economic System

The framework of the proposed parallel economic system is depicted in Fig. 1, encompassing a software-defined model that corresponds to the physical economic system, referred to as an artificial economic system. Within this artificial system, multi-agent simulations of economic activities are performed via computational experiments. Optimized policy schemes are derived through data analysis. This new research framework enables the simulation, prediction, and guidance of the economic system by facilitating

collaborative evolution and parallel feedback between the artificial economic system and the physical economic system.

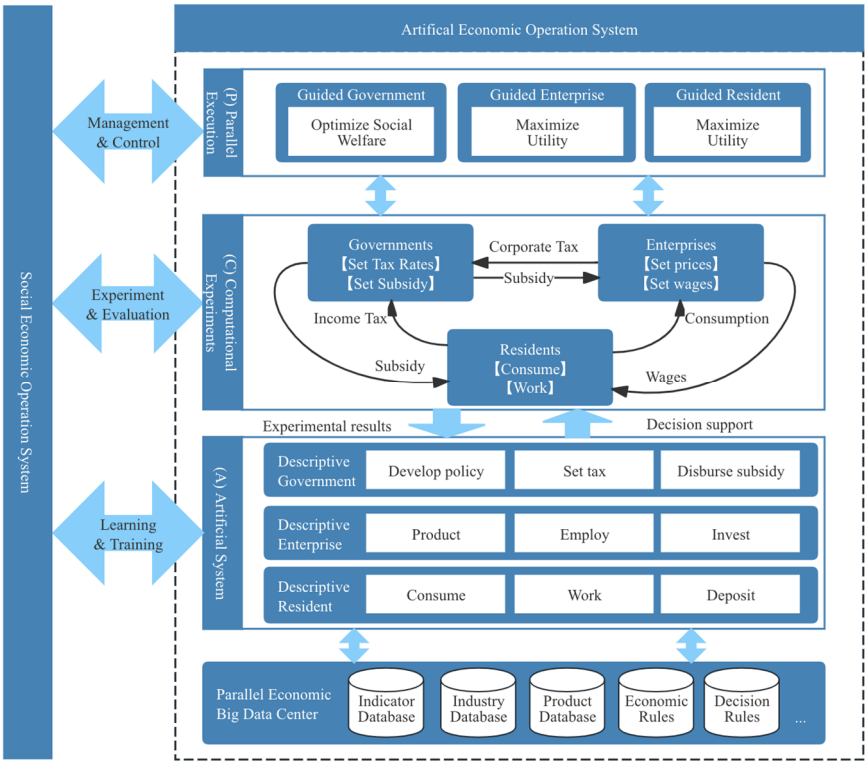

Fig. 1. The overview of parallel economic system.

3.1 Artificial Economic Systems

Initially, the agents were trained directly within the RBC environment, and the reward function was designed to either increase GDP or reduce the Gini coefficient. When reducing the Gini coefficient was set as the objective, the reward curve consistently improved as training progressed. However, when increasing GDP was the target, the reward curve failed to converge. This issue arose because tax rates did not directly affect GDP, resulting in no significant impact. To address this limitation, the previous RBC environment was simplified into a mini model (see Fig. 2). In this revised framework, the tax rate set by the government influences residents' income, which, in turn, affects their willingness to work. Willingness to work impacts working hours, which subsequently determine wages. Wages, in turn, influence both individual income and tax revenue, thereby creating a feedback loop.

In this miniRBC environment, each resident aims to maximize their standard of living and will imitate and learn from others with the same talent level. Talent, a fundamental attribute of residents, represents the varying abilities of individuals and is the original source of the wealth gap.

Utility reflects residents' willingness to work in this simulated environment. Currently, the factors affecting utility only include income, which is determined by working hours, talent, tax rates, and subsidies. Based on these hypotheses, we derive the following calculation formulas.

$$income = subsidy + talent * working_hour - wages * tax_rate \tag{1}$$

Residents' income comprises three components: subsidies, taxes, and wages. Residents operate under certain rule-based rational assumptions, gradually converging through imitation learning. The foundation of this imitation learning is their willingness to work, which is a function that initially increases with income and then gradually decreases. Specifically, when residents' income is too low, they struggle to meet basic needs for food and clothing, leading to a significant increase in their willingness to work as income rises. Conversely, when income is relatively high, residents tend to experience a comfortable lifestyle, resulting in a diminished desire to strive for more. At this point, the marginal benefit of additional income declines, causing utility to plateau or even decrease slightly. In our environment, each resident maximizes their utility through imitation learning, ultimately achieving an appropriate income level.

Finally, the income of all residents directly influences GDP and the Gini coefficient, playing a critical role in the reward structure of reinforcement learning.

$$reward = \frac{GDP}{GDP_{\{baseline\}-1}}, \quad GDP = \sum\{income_i\} \tag{2}$$

$$reward = (1 - Gini) * 0.5 \tag{3}$$

Formula 3 posits that larger rewards produce more substantial effects. The reward values are fed back into the neural network and aggregated into a global value function by separately calculating the contributions of seven agents (each corresponding to a distinct tax rate). The global state value function computes the loss function according to the Bellman equation, enabling backpropagation to update the local value function networks. Notably, the utility functions of the seven government agents are summed.

$$Q_{tot}(s,a) =: Q_1(s,a) + \cdots + Q_7(s,a) \tag{4}$$

$$\mathscr{L}oss_{tot} = \mathbb{E}_{\mathcal{D}}[(r + \gamma \max_{a'} \overline{Q}_{tot}(s',a') - Q_{tot}(s,a))^2] \tag{5}$$

In this context, $\mathscr{L}oss_{tot}$ represents the total loss of the global value function, while $\mathbb{E}_{\mathcal{D}}$ refers to the experience pool. The variable r denotes the immediate reward returned by the environment at the current moment. The discount factor γ, set to 0.99 in this experiment, modulates the influence of future rewards. Q_{tot} is the target value produced by the target network, where s' represents the global state at the net moment, obtained through state transition. Similarly, a' refers to the action vector of N agents at next moment, as determined by the target network. At the current moment, s represents

the global state, while a denotes the action vectors of the current N agents, which are involved in the summation operation.

3.2 Computational Experiments

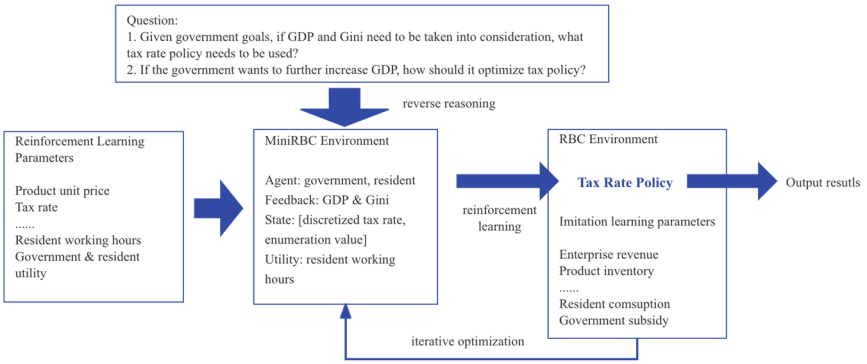

Fig. 2. The computational experiment process of economic simulation.

Fig.2 illustrates the computational experiment process of economic simulation. Based on existing prior knowledge, we develop the following experimental procedure.

Step 1, Initial. Based on environmental assumptions, we construct a miniRBC environment. An initial tax rate is developed with reference to the national standard tax rate, and the number of residents is set at 100.

Step 2, Update. The neural network is updated according to the value function, utilizing the VDN algorithm [17].

Step 3, Imitation. We conduct 10 rounds of imitation learning under the current tax rate, producing average GDP and Gini coefficients. The residuals are calculated by comparing the initial GDP and Gini values, which serve as reward feedback.

Step 4, Adjust. The tax rate value is adjusted, and steps 2 and 3 are repeated. Each episode has a step size of 50, resulting in a total of 2400 episode iterations.

Step 5, Backward. The tax rate results are substituted into the miniRBC environment to run simulation learning, followed by comparative experiments with the results from the standard tax rate.

3.3 Parallel Execution

In the developed artificial economic system (see Fig. 3), economic simulation trends under different tax rates and subsidy policies are simulated. We visualize the experimental process through three dimensions: government statistics, enterprise statistics, and resident statistics. For example, GDP data fluctuates significantly at the beginning due to the model's initial exploration capabilities and parameter learning. Once stabi-

lized, GDP and the Gini coefficient exhibit a smooth decline under the existing economic policies. Income distribution analysis reveals changes in the incremental wealth gap, showing a pyramid-shaped income structure with a concentration of low-income individuals, which aligns with the current domestic economic situation.

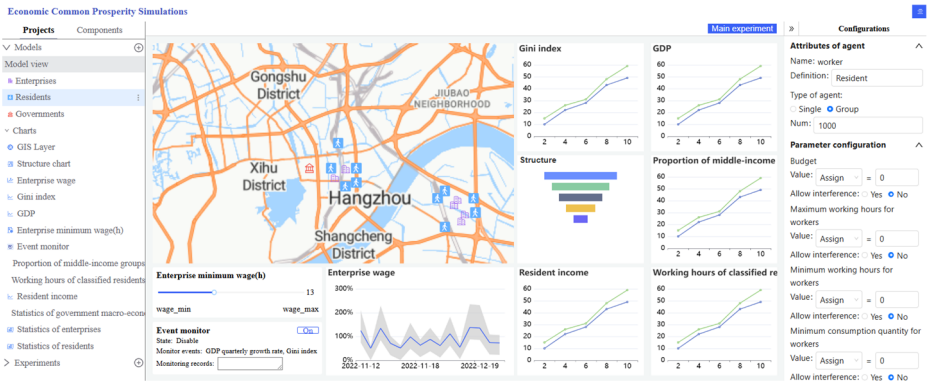

Fig. 3. The artificial system software of economic simulation.

Using the national standard tax rate as a benchmark and targeting GDP and the Gini coefficient as optimization objectives, we adjust the learned tax rate values in the agent configuration for effect simulation. Experiments demonstrate that the tax rate derived from the reinforcement learning method can increase GDP while slightly reducing the Gini coefficient compared to the national standard tax rate.

The simulation results from these computational experiments in the artificial system are fed back in real-time to the physical economic system, guiding decision-makers in managing and controlling the actual complex system based on optimal solutions. By analyzing the differences between the physical economic system and the evaluation state of the artificial economic system, new changes and trends (such as unexpected events like pandemics) are incorporated into the artificial economic system. Through repeated experiments, evaluations, and refinements, optimized new results and solutions are obtained, which then guide the development and evolution of the physical economic system. This synchronous operation and real-time interaction between the physical and artificial systems enable continuous data exchange and decision adjustments, thereby achieving ongoing optimization of the physical economic system.

4 Conclusion

This paper extends the application of the ACP approach to the field of social economics and proposes a parallel economic system. By integrating interdisciplinary innovations that combine economics with artificial intelligence technologies, we constructed a parallel economic system. This system has been developed and successfully applied in the digital reform of Zhejiang Province to explore potential policies for economic common prosperity. After numerous simulations of different policy combinations, we designed

a non-uniform fiscal and tax regulation mechanism that comprehensively considers residents' talents and working hours. This mechanism aims to transform the income distribution structure from a "pyramid" shape to an "olive" shape, providing a valuable reference for policy formulation.

References

1. Rebelo, Sergio. "Real business cycle models: past, present, and future." (2005).
2. Borojo, Dinkneh Gebre, Jiang Yushi, and Miao Miao. "The impacts of economic policy uncertainty on trade flow." Emerging Markets Finance and Trade 58.8 (2022): 2258-2272.
3. Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. "Risk shocks." American Economic Review 104.1 (2014): 27-65.
4. Hertel, Thomas W. Global Trade Analysis: Modeling and Applications. Cambridge University Press, 1997.
5. Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. "Nominal rigidities and the dynamic effects of a shock to monetary policy." Journal of political Economy 113.1 (2005): 1-45.
6. Athey, Susan. "The impact of machine learning on economics." The economics of artificial intelligence: An agenda (2018): 507-547.
7. Zheng, Stephan, et al. "The AI Economist: Taxation policy design via two-level deep multiagent reinforcement learning." Science advances 8.18 (2022): eabk2607.
8. Chen, Jicheng, et al. "ACP-based energy-efficient schemes for sustainable intelligent transportation systems." IEEE Transactions on Intelligent Vehicles 8.5 (2023): 3224-3227.
9. Luo, Guiyang, et al. "ACP based large-scale coordinated route planning: from perspective of Cyber-Physical-Social Systems." 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2022.
10. Ren, Yilong, et al. "ACP-based modeling of the parallel vehicular crowd sensing system: Framework, components and an application example." IEEE Transactions on Intelligent Vehicles 8.2 (2022): 1536-1548.
11. Ge, Lin, et al. "A hypertension parallel healthcare system based on the ACP approach." IEEE Journal of Radio Frequency Identification 6 (2022): 724-728.
12. Lv, Xinyi, et al. "Optimize the accessibility of healthcare facilities via ACP-based approach." 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2023.
13. Jiao, Yuantao, et al. "Intelligent Generation of Test Cases for a Parallel Testing System: A Case Study on Railway Systems." IEEE Intelligent Transportation Systems Magazine (2024).
14. Guo, Jianqun, et al. "Parallel intelligent monitoring system of port water quality based on the ACP method." Journal of Marine Science and Engineering 12.2 (2024): 218.
15. Chen, Jicheng, et al. "ACP-based energy-efficient schemes for sustainable intelligent transportation systems." IEEE Transactions on Intelligent Vehicles 8.5 (2023): 3224-3227.
16. Gong, Linjuan, et al. "Parallel Control of Supercritical Thermal Power Unit based on the ACP Method." 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI). IEEE, 2021.
17. Sunehag, Peter, et al. "Value-decomposition networks for cooperative multi-agent learning." arXiv preprint arXiv:1706.05296 (2017).

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.