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Research on Distributed Content Collaborative Caching Optimization Based on Multi-Agent Reinforcement Learning in Intelligent Identification Network

Zhenlin Jin

Computer science department, University of Arkansas at Little Rock
Little Rock, 72204, Arkansas, USA

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Abstract: In the context of the integration of distributed cloud computing and SDN, artificial intelligence driven network architecture faces challenges such as inefficient dynamic resource allocation, difficulties in cross domain collaboration, and privacy utility imbalance. This study is based on game theory and generative AI to construct an analytical framework. By comparing Nash non cooperative, Stackelberg master-slave, and collaborative R&D models with the HJB equation using differential game models, it is found that R&D investment subsidies can enhance the R&D efforts and returns of enterprises and academic research institutions, and government R&D efforts are not affected by cost sharing; The collaborative cooperation model achieves Pareto optimality between the three parties' R&D efforts and total revenue. Combine Shapley value method to optimize the profit distribution of collaborative mode, and verify the theoretical consistency through Matlab simulation. Research the construction of three collaborative mechanisms: coordination of benefit distribution, sharing of resource investment, and incentive constraint guarantee, and propose multi-party countermeasures. The study found that the profit distribution ratio of the collaborative mode is about 24:24:52, and the profits of all parties are higher than those of other modes; In the future, it is necessary to expand the optimization of generative AI and distributed cloud computing SDN architecture to enhance the efficiency of technological collaborative innovation.

1. Introduction

In the context of the deep integration of distributed cloud computing [1] and SDN, artificial intelligence has become the core engine driving the intelligence of network architecture. With the popularization of 5G/6G IoT, traditional SDN faces challenges such as inefficient dynamic resource allocation, difficulties in cross domain collaboration, and an imbalance between privacy protection and data utility. Existing research has shown that game theory has theoretical advantages in resource allocation optimization, and generative AI can achieve intelligent generation and dynamic adjustment of network configuration. However, the integration of the two poses three major challenges: traditional game models are difficult to adapt to the dynamic decision-making characteristics of generative AI, generative AI suffers from data utility loss under privacy protection mechanisms, and privacy budget allocation and user preference response need to be balanced in multi-agent collaboration. This study aims to construct an SDN intelligent architecture optimization solution through the deep integration of game theory and generative AI. Specific motivations include breaking through the limitations of traditional SDN static configuration to achieve dynamic resource allocation and network topology intelligent optimization, solving the utility decay problem of generative AI in privacy scenarios to enhance privacy utility balance, and building a multi-agent collaborative dynamic game mechanism to adapt to the strategic interaction needs of heterogeneous entities such as government/enterprises/users. The research objectives are divided into three levels: at the theoretical level, constructing an intelligent architecture model based on game theory and generative AI to deconstruct the dynamic evolution mechanism of multi-agent collaborative innovation; At the methodological level, innovative methods such as dynamic privacy budget allocation, user preference modeling, and generative network configuration are proposed; The performance improvement of application level verification schemes in terms of privacy protection strength, data utility, and operational efficiency provides a scalable intelligent architecture solution for large-scale distributed cloud computing scenarios. The research contribution includes four points: proposing a "game theory generative AI" dual drive architecture to achieve dynamic game and intelligent generation of SDN resource allocation; Design a dynamic privacy budget allocation mechanism to balance privacy protection and data utility; Building personalized privacy configuration strategies driven by user preferences to improve service accuracy; Through numerical simulation and experimental verification, it has been proven that the scheme significantly optimizes indicators such as privacy budget, access time, and operational efficiency.

2. Correlation theory

2.1. Game driven dynamic mechanism for collaborative innovation of key AI technologies

Collaborative innovation [2] originated from Ansoff's collaborative theory, developed by Haken's collaborative theory and Tidd's integrated innovation theory, forming a theoretical framework for multiple subjects to achieve technological breakthroughs and results transformation through resource integration, knowledge sharing, and technological cooperation. Its core features include holism (risk sharing and complementary advantages), dynamism (evolution over time and market conditions), complexity (interaction between multiple subjects and factors), and dissipativity (balance between resource consumption and external exchange). Differential game theory, as a method for studying multi-agent dynamic decision-making, is widely used in supply chain cooperation and collaborative innovation. Through Nash non cooperative game, Stackelberg master-slave game, and collaborative cooperative game models, the optimal strategy of the subject is explored, which is applicable to the nonlinearity, coupling, and dynamic complexity of collaborative innovation. It can handle dynamic equilibrium problems under information asymmetry and differences in interest demands. The key technologies of artificial intelligence, as a core set of technologies supporting intelligent decision-making, cover eight categories including natural language processing, machine learning, and deep learning. Its collaborative innovation emphasizes the ecological integration of multiple subjects and elements (knowledge, technology, data, algorithms), with the complexity of interdisciplinary integration and the dynamic adaptability to external changes. Although existing research has focused on mechanism construction and evolution, the dynamic evolution mechanism of subject strategy interaction still needs to be further explored.

2.2. Research on the Collaborative Innovation Mechanism of Game Triple Helix Double Drive AI

The theory of collaborative innovation emphasizes the joint effect of "1+1>2" achieved by multiple entities through resource integration, knowledge sharing, and technological cooperation. External collaborative innovation involves the non-linear interaction process of multiple entities such as enterprises, research institutions, and governments, as well as the collaboration of knowledge, technology, and capital. The Triple Helix Theory [4] provides a research paradigm for collaborative innovation among multiple subjects, forming an interactive mode of tripartite overlap and intersection through structural and institutional coordination among government, enterprises, and research institutions. It is divided into three modes: laissez faire, government led, and interactive overlap. The focus is on studying the cooperative relationship between the three to promote technology sharing and resource complementarity. Differential game theory, as a combination of game theory and optimal control theory, deals with multi-agent dynamic decision-making problems. Its objective function is:

$$E_{t_o}^{T}\left[\int_{t_o}^{T} g_i(t,x(t),E_1(t),\cdots,E_n(t))dt + Q_i(x(T))\right](i=1,\cdots,n) \tag{1}$$

the state transition equation is:

$$\frac{dx(t)}{dt} = f(t,x(t),E_1(t),\cdots,E_n(t)), x(t_o) = x_o \tag{2}$$

It is necessary to meet the conditions that the participants aim to maximize their own interests, have common information to calculate optimal returns, have decision-making priorities, and control variables to affect returns. It is suitable for Nash non cooperative games, Stackelberg master-slave games, and collaborative cooperative games. Existing research focuses more on strategic emerging industries at the research object level, and there is insufficient integration of the dynamic and complex technical characteristics of key artificial intelligence technologies; The research perspective relies heavily on innovative network theory, which makes it difficult to reveal the micro mechanisms of multi-agent strategy interaction; At the level of research content, there is insufficient exploration of the collaborative model of "core enterprise leadership government policy guidance academic research institution knowledge spillover", and the characteristics of rapid technological iteration have not been fully considered, resulting in deviations between strategy optimization and real-world scenarios. Therefore, it is necessary to conduct in-depth research on collaborative innovation of key technologies in artificial intelligence based on differential game theory, combined with its dynamic and complex characteristics, identify the multi-agent and interactive relationships of collaborative innovation of key technologies in artificial intelligence, summarize the characteristics of collaborative innovation, and deepen theoretical understanding.

3. Research method

3.1. Theoretical framework and subject interaction for collaborative innovation of key technologies in artificial intelligence

Collaborative innovation of key technologies in artificial intelligence is a complex system process in which multiple innovation entities (artificial intelligence enterprises, research institutions, and governments) jointly promote technological breakthroughs, applications, and transformations through resource sharing and technological complementarity. Its essence is to achieve non-linear technological innovation transitions through resource integration, dynamic optimization of research and development strategies, collaborative conflicts of interest, and institutional design (as shown in Figure 1).

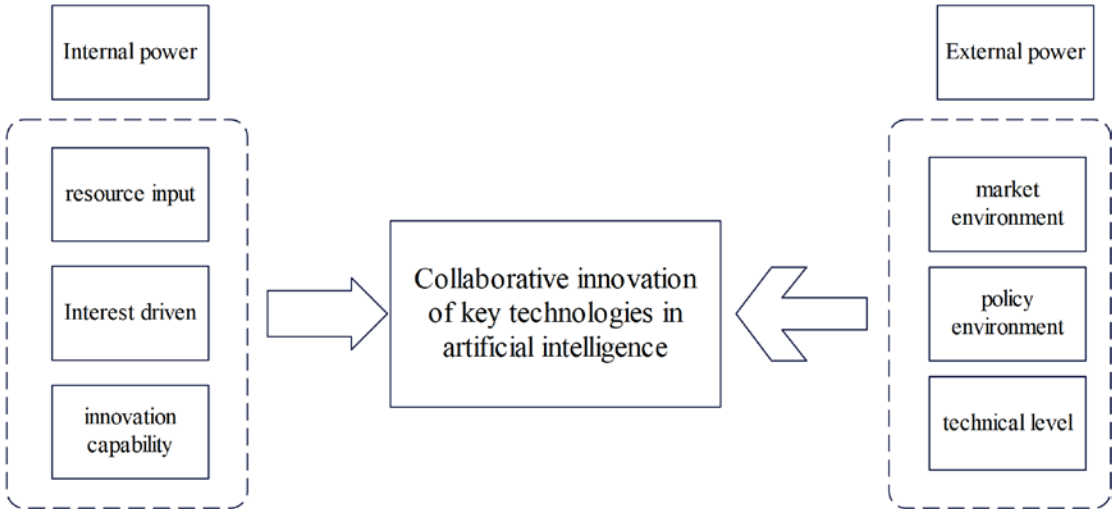

Figure 1 Model diagram of collaborative innovation driving environment for key artificial intelligence technologies

Among the core entities, artificial intelligence enterprises serve as the core carriers of technological innovation, promoting technological breakthroughs and achievement transformation through knowledge sharing, collaborative research and development, and resource integration, possessing characteristics of technological cooperation, resource allocation, and risk management; As a source of knowledge innovation, academic research institutions support innovative development through basic research supply, professional talent cultivation, and technology resource sharing; The government, as a guide and supervisor, ensures the stable operation of collaborative innovation through policy formulation, resource allocation, and innovative ecological construction. Three parties build an innovative consortium based on the triple helix coupling mechanism: enterprises drive technology direction based on market demand and provide computing power/data resources, research institutions enhance international competitiveness through cutting-edge technology supply and talent cultivation, and the government optimizes resource allocation and strengthens data security supervision through policy tools. The interactive relationship between entities is manifested as: enterprises and research institutions achieve resource sharing and technological complementarity through knowledge technology talent supply and demand matching; The government and enterprises promote collaborative innovation through policies, regulations, financial support, and application scenarios; Academic research institutions and the government form a two-way interaction through feedback on cutting-edge technological achievements and policy decision-making support, jointly promoting breakthroughs in key artificial intelligence technologies.

3.2. Construction of Differential Game Model for Collaborative Innovation of Key Technologies in Artificial Intelligence

Collaborative innovation of key technologies in artificial intelligence is a complex dynamic system mainly composed of enterprises, research institutions, and governments, which achieves technological breakthroughs through resource integration and risk sharing. This article introduces differential game equations from a dynamic perspective, and uses the Hamilton Jacobi Bellman equation[6] to analyze the optimal R&D effort, benefits, and total benefits of each subject in three modes: Nash non cooperative game, Stackelberg master-slave game, and collaborative cooperative game. It explores the mechanism and long-term coordination strategy of government R&D

investment subsidies, and uses the Sharpley value method to optimize the distribution of benefits in the collaborative cooperative mode. In the model setting, the R&D efforts of enterprises, academic research institutions, and governments are E1 (t), E2 (t), and E3 (t), respectively. The cost function is a quadratic convex function [7]:

$$C_1(t)=\frac{1}{2}u_1E_1^2(t)、C_2(t)=\frac{1}{2}u_2E_1^2(t)、C_3(t)=\frac{1}{2}u_3E_3^2(t) \quad (u_1,u_2,u_3 \text{for cost coefficient}) \tag{3}$$

the dynamic equation for the level of technological innovation is:

$$\frac{dK(t)}{dt}=\lambda_1E_1(t)+\lambda_2E_2(t)+\lambda_3E_3(t)-\alpha K(t) \tag{4}$$

The total benefit function is: $V(t)=\theta_1E_1(t)+\theta_2E_2(t)+\theta_3E_3(t)+\beta K(t)$ is the marginal benefit coefficient and β is the impact coefficient). The objective functions of each subject are calculated through discount rates.Maximizing profits, the objective function of enterprises and research institutions includes the profit distribution coefficient ω i and government subsidies σ i, and the government objective function includes subsidy costs. This model provides a theoretical framework for analyzing multi-agent dynamic strategy interactions and profit distribution.

3.3. Differential game model and synergistic effects of collaborative innovation in key technologies of artificial intelligence

In the Nash non cooperative game scenario, independent decision-making among three parties[8]constitutes Nash equilibrium, and the feedback solution is

$$E_1^N=\frac{(1-\omega_1)[\theta_1(\rho+\alpha)+\beta\lambda_1]}{u_1(\rho+\alpha)}、E_2^N=\frac{(1-\omega_2)[\theta_2(\rho+\alpha)+\beta\lambda_2]}{u_2(\rho+\alpha)}、 \tag{5}$$

$$E_3^N=\frac{(1-\omega_3)[\theta_3(\rho+\alpha)+\beta\lambda_3]}{u_3(\rho+\alpha)} \tag{6}$$

Corresponding to the optimal return function, such as

$$V_1^N=\frac{(1-\omega_1)^2x[\theta_1(\rho+\alpha)+\beta\lambda_1]^2}{2u_1(\rho+\alpha)^2}+\cdots. \tag{7}$$

comparing three modes (Nash non cooperative, Stackelberg master-slave, collaborative), it is found that the level of R&D effort meets the requirements

$$E_i^C\geq E_i^s>E_i^N(i=1,2,3) \tag{8}$$

the level of technological breakthrough is $k^c\geq k^s>k^N$, and the R&D revenue shows $V_i^s>V_i^N(i=1,2,3)$and$V^C>V^s>V^N$. The government subsidy coefficient satisfies

$$\sigma_1^S=\frac{\omega_1\theta_1E_1+\omega_2\theta_2E_2}{2} \tag{9}$$

$$\sigma_2^S=\frac{\omega_1\theta_1E_1+\omega_2\theta_2E_2}{2} \tag{10}$$

The inference suggests that subsidies can stimulate the R&D drive of enterprises and academic research institutions, while collaborative cooperation maximizes R&D potential through resource sharing and knowledge integration, promoting efficient breakthroughs and profit optimization of key technologies in artificial intelligence.

4. Results and discussion

4.1. Numerical simulation analysis of collaborative innovation of key technologies in artificial intelligence

This section verifies the effectiveness of the tripartite differential game model through numerical simulation, and selects an artificial intelligence technology limited company, an industrial Internet research institute of a university, and a financial technology service center as the case objects. The parameter settings are as follows: discount rate

$\rho=0.8$ (calculated from the formula $\rho=\frac{\text{Regular lending rate}}{\text{1+discount period x general loan interest rate}}$), initial technical level $k_0 = 0.5$, Cost coefficient $u_1 = u_2 = u_3 = 2$ innovation capability coefficient $\lambda_1 = \lambda_2 = 2, \lambda_3 = 1$, technology intergenerational transition rate α =0.2, The marginal revenue coefficient $\theta_1 = \theta_2 = 2.5$、$\theta_3 = 2$, the revenue impact coefficient β =2, and the revenue distribution coefficient $\omega_1 = \omega_2 = 0.6$. The simulation results show that there are significant differences in the optimal R&D effort, technological breakthrough level, and R&D benefits among the three modes of Nash non cooperation, Stackelberg master-slave, and collaborative cooperation. Specifically, under the collaborative cooperation model, the effort level of enterprises and research institutions reached 7.00 (an increase of 42.8% compared to the Stackelberg model), and the effort level of the government reached 4.00 (an increase of 40%); The trajectory of technological breakthrough level is $K^C(t) = e^{-0.2t}(160t - 155)$, significantly higher than other modes; The total revenue trajectory is $e^{-0.2t}(782.5t - 620)$, achieving Pareto optimality. The Stackelberg model increases the profits of enterprises and research institutions through government subsidies compared to the Nash model, while collaborative cooperation maximizes research and development potential through resource sharing. The simulation results have verified the effectiveness of the model, indicating that collaborative cooperation is the optimal path to promote breakthroughs in key technologies of artificial intelligence.

4.2. Model experiment

The optimal total R&D revenue limits for Nash non cooperative, Stackelberg master-slave, and collaborative R&D game models are 220, 568, and 782, respectively. In the Nash model, the three party benefits of enterprises, academic research institutions, and governments are 44, 44, and 133, respectively; In Stackelberg mode, it is 118, 118, and 331. Calculate the profit distribution under the collaborative cooperation mode using the Shapley value method, as shown in Table 1:

Table 1 Calculation of R&D income distribution for artificial intelligence enterprises

Parameter values	i_1	i_1□i_2	i_1□i_3	i_1□i_2□i_3
V(F)	44	88	449	782
V(F\{i})	0	44	133	449
$\omega(F)$	1/3	1/6	1/6	1/3
$\omega(F)[V(F)$-V(F\{i})]	14.67	7.33	52.67	111

The calculation of R&D income distribution in academic research institutions shows that when the parameter value V (F) is 44, 88, 449, 782, V (F \ {i}) is 0, 44, 133, 449, and the weight ω (F) is 1/3, 1/6, 1/6, 1/3, the corresponding calculation results are 14.67, 7.33, 52.67, 111, and the total is 185.67; In the calculation of government R&D revenue distribution, V (F) is taken as 133, 449, 449, 782, and V (F \ {i}) is taken as 0, 44, 44, 88. Under the same weight, the calculated results are 44.33, 67.5, 67.5, 231.33, and the total is 410.66. The R&D revenue distribution values of artificial intelligence enterprises, academic research institutions, and governments are 185.67, 185.67, and 410.66, respectively, totaling 782, which is consistent with the total revenue of collaborative cooperation. The tripartite distribution ratio is about 24:24:52, and the revenue of all parties is higher than the optimal revenue under other modes, verifying the effectiveness of revenue distribution under the collaborative cooperation mode.

4.3. Effect analysis

The benefit distribution and coordination mechanism dynamically adjusts the profit distribution coefficient and cost sharing ratio through institutional level (innovation contribution oriented distribution system, collaborative innovation governance structure and performance evaluation system), organizational level (government led coordination mechanism and full life cycle management system), and trust mechanism (government industry university research trust community, information sharing network and risk warning system), combined with self fulfillment mechanism and multi-dimensional risk compensation mechanism [9] to ensure incentive compatibility and effective contract execution. The resource investment and sharing mechanism relies on diversified innovative resource integration (knowledge, technology, talent, funds) and resource sharing platforms (comprehensive platforms integrating data, computing power, algorithms, and elastic configuration networks), using generative artificial intelligence to optimize dynamic resource allocation, and combining distributed cloud computing and SDN architecture to enhance resource utilization efficiency and collaborative innovation capabilities. The innovation incentive and constraint mechanism incentivizes innovative behavior through policy tools such as government subsidies and tax incentives, and strengthens system stability through default penalties, risk control, and risk sharing mechanisms. Specific measures include: optimizing the allocation of innovation resources by the government, promoting the open sharing of computing power platforms and common technology platforms, and improving policy, regulatory, and institutional systems; Enterprises should strengthen the collaboration of innovation elements, utilize generative AI to optimize R&D funding and talent allocation, and establish effective communication, coordination, and risk prevention mechanisms; Academic research institutions should strengthen the cultivation of innovative talents, build cross subject knowledge sharing networks, and promote the efficient transformation of technological achievements to match market demand. This framework clarifies the optimal strategy through game theory methods, combines generative artificial intelligence with distributed cloud computing SDN architecture to achieve dynamic optimization, and improves the efficiency and sustainability of collaborative innovation of key artificial intelligence technologies.

5. Conclusion

Exploring the collaborative innovation of key technologies in artificial intelligence is of great significance for promoting technological research and development, breaking through technological blockades, and strengthening strategic technological capabilities. Based on game theory methods, an analytical framework is constructed. By comparing the optimal strategies and benefits of Nash non cooperative, Stackelberg master-slave, and collaborative R&D models using differential game models and HJB equations[9], it was found that R&D investment subsidies can effectively enhance the R&D efforts and benefits of enterprises and academic research institutions, and the government's own R&D efforts are not affected by cost sharing; The collaborative cooperation model achieves the optimal balance between the three parties' R&D efforts and total revenue, achieving Pareto optimality. Combining Shapley value method to optimize profit distribution in collaborative mode [10], and verifying theoretical consistency through Matlab simulation. Based on this, three collaborative mechanisms will be constructed: coordination of benefit distribution, sharing of resource investment, and incentive constraint guarantee, and specific countermeasures will be proposed for multiple parties. Although the research focuses on the core subject and simplifies parameters, in the future, it is necessary to combine generative artificial intelligence with distributed cloud computing SDN intelligent architecture optimization, expand the influence of auxiliary subjects and complex parameter scenarios, in order to improve the efficiency and adaptability of technological collaborative innovation.

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