International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 361-369

https://doi.org/10.70517/ijhsa46431

Research on Social Community Stability Analysis and Conflict Resolution Strategies Based on Dynamic Planning Models

Xiuli Yang[1] and Daixue Song[1,*]
[1] School of Public Administration and Law, Northeast Agricultural University, Harbin, Heilongjiang, 150030, China
Corresponding authors: (e-mail: 13114619037@163.com).

Abstract Based on the dynamic planning model and multi-player MZS game theory, this study constructs an adaptive optimization framework oriented to the stability of social community, and proposes a computable conflict reconciliation strategy by quantitatively analyzing the dynamic evolution law of social conflicts. First, the cooperative-competitive relationship among social members is mapped as a state-constrained tracking control problem in the game system, the control barrier function (CBF) is used to define the safe set boundary, and the Nash equilibrium strategy is solved by the dynamic planning recursive equation to realize the mathematical modeling of the conflict evolution. In order to verify the effectiveness of the model, simulation experiments were carried out in combination with the enterprise competition scenario, and the iterative dynamic programming (IDP) algorithm was used to solve the multi-stage optimal control problem, and the results showed that the optimal control performance index J=1.3470, and the error between the control strategy and the analytical solution was controlled in the order of 10−3, indicating that the model can accurately approximate the optimal solution and ensure the evolution of enterprise behavior within the compliance boundary. Further analyzing the initial value sensitivity of the system under the chaotic state, it is found that the initial value difference of only 0.01 (x0=3.50 vs. x0=3.51) can trigger the trajectory dispersion, arguing for the risk of social disorder when the security set constraints fail. In addition, delay strategy experiments show that a single firm's delay can raise its short-term profit by 4%, but the competitor's profit decreases by 3%-5%, which needs to optimize resource allocation through dynamic planning to balance the interests of multiple parties. The study proves that by integrating game rule design, real-time risk warning and diversified mediation mechanisms, conflicts can be effectively reconciled and the dynamic stability of the social community can be maintained.

Index Terms dynamic programming, social community, control barrier function, Nash equilibrium, chaos analysis

I. Introduction

Social community refers to the various communities in which people live or operate, which provide basic survival for people themselves [1]. As different from animals, human beings have unique spiritual needs such as identity and sense of belonging [2]. Therefore, in the context of modernity, “community” has gradually evolved into a social group or social association in which a group of people participate together and share common interests and cultural values [3], [4]. Unlike the traditional community, which emphasizes face-to-face interaction, common life and common territory, the community in the context of modernity pays more attention to spiritual factors, and territoriality is no longer a necessary element [5]. In the mobile modern society, due to the frequent changes in individual identity, the self-identification and belonging of individuals must be referred to and determined by a specific community [6].

Any individual in a real society possesses certain purposes, ideals and values, which constitute the self precisely as determined by the community, i.e., it defines the self and constitutes the individual's identification with the self [7]. At the same time, there is an evolutionary process of social community from autopoiesis to selfhood. Humans were once for a long time just as a part of the ecosystem, at least in the era of primitive populations, where autopoiesis dominated and self-activity was in the process of incubation [8]-[10]. By the emergence of clans the autopoietic nature was basically formed and dominated the social nature, and the autopoietic nature of the society was finally formed only marked by the entry of human beings into the civilized society. Therefore, self-reliance in the form of contradiction is the natural nature of the social community, and maintaining the stability of the social community and governing the contradictions that occur is the fundamental path to seek development [11], [12].

In this study, we introduce the dynamic programming model, combined with the state-constrained tracking control theory of game systems, to construct an adaptive optimization framework oriented to the stability of social community. Firstly, starting from the nature of self-activity of the social community, the inner driving force of its dynamic evolution is clarified. The generation and resolution of social conflicts essentially stem from members' interactive control of security boundaries (e.g., rules, resources) in a dynamic game. To quantify the stability of a social community, this section proposes a multi-player MZS game system model. By defining the system state, security set, and control barrier function (CBF), the social conflict is transformed into a tracking control problem under state constraints. In the model, the cooperative and competitive relationships of different players are mapped as a Nash equilibrium solution in a dynamic game, and its value function optimization process reflects the dynamic path of conflict reconciliation. Further, the complex interaction is simplified into a traceable error dynamic system through system transformation and augmented state design, which lays the foundation for the mathematical expression of the contradiction resolution strategy. Focusing again on the core equations of dynamic programming and its application in stability optimization. The Nash equilibrium problem of the game system is transformed into a recursive optimization problem by constructing a multi-stage value function with a set of strategies. Based on the optimization principle, the basic recursive formula of dynamic programming is derived and its implementation path in iterative solution is explained. The method can effectively balance the system performance and security, and provide a quantitative tool for the dynamic regulation of social community conflicts.

II. Game system modeling based on dynamic programming and optimization strategy for social community stability

II. A. General nature of the social community

The social community as a systemic entity has a distinctive intrinsic nature. While the natural nature of celestial systems lies in self-existence and that of ecosystems in autopoiesis, the natural nature of social communities lies in self-activity. The self-reliance of social community is not only because the ultimate entity constituting the social community is a self-reliant individual, but also because the social community is constructed by its members in order to realize their own nature of seeking a better existence, it is subordinate to the members of the society, and it is for the service of the members of the society. Therefore, in general, the social community is artificial, personal, and for human beings, and the self-made nature of the social community is reflected in the artificial, personal, and for human nature. This is the natural nature of social community, and with this nature, social community has entity, which is different from self-existing and self-generating system.

From the point of view of human history, the selfhood of the social community is not something that the social community possesses from the very beginning, but rather it is something that the social community has gradually acquired in the long process of human evolution. Human beings were once only a part of the ecosystem for a long time, at least in the era of the primitive people, autopoiesis dominated, and self-reliance was in the process of nurturing, to the emergence of the clan self-reliance is basically formed and dominated the social nature, and the self-reliance of the society marked by human beings' entry into the civilized society is the final formation of social self-reliance. Therefore, the social community has an evolutionary process from autopoiesis to autopoiesis. There is also a process of evolutionary development of the selfhood of the social community from one-sidedness to comprehensiveness, which has not yet been completed.

II. B. State-constrained tracking control of game systems based on adaptive dynamic programming

The nature of self-activity of social communities reveals the internal logic of their dynamic evolution, however, how to quantify such dynamics and realize stability control still needs to be supported by specific methods. To this end, this section introduces the theory of adaptive dynamic programming and constructs a multi-player game system model to map the evolution of social conflicts into a tracking control problem under state constraints.

II. B. 1) Description of the MZS gaming system

Consider a multi-player MZS gaming system:

$$\dot{x} = f(x) + \sum_{s=1}^{k} g_s(x)u_s(t) + p(x)\psi \tag{1}$$

where $x(t) \in \square \in \square^n$ is the state of the system; $u_s(t) \in \square^m$ represents the player $1 \sim k$ respectively; $\psi \in \square^d$ represents the $k+1$th player; $f(x) \in \square^n$ is the system dynamics matrix; $g_s(x) \in \square^{n \times m}$ and $P(x) \in \square^z$ are the control dynamics matrices. The set $\square$ is referred to as a safety set, such as a safe region of exploration for a spacecraft, and the system state is represented as being in a safe state when it evolves within the set. The safe set consists of system constraints, defined in mathematics as:

$$\begin{cases} \square = \left\{ x \in \square^{n} \mid q(x) \geq 0 \right\} \\ \text{int}(\square) = \left\{ x \in \square^{n} \mid q(x) > 0 \right\} \\ \partial\square = \left\{ x \in \square^{n} \mid q(x) = 0 \right\} \end{cases} \tag{2}$$

where $q(x)$ is a continuous function on x; $q(x) > 0$ means within the safety range; $\text{int}(\square)$ denotes the interior of the safety set; and $\partial\square$ denotes the boundary of the safety set.

In mathematically constrained optimization, the CBF is a continuous function whose value increases to infinity as the state reaches the boundary of the feasible region of the optimization problem. The goal of the control is to make the derivative of the CBF near the boundary negative. As the system state approaches the boundary, the negative derivative condition pushes the system state back to the safe set. In addition, the CBF can replace the inequality constraint with a penalty that is easier to handle in the objective function.

Assumption 1: The following assumptions are made in order to define the relationship between different players in the MZS game:

(1) System (1) is admissible in the sets $\Omega \in \square^{n}$ and $\square \subset \Omega$;

(2) For any tolerable control strategy $\{u_1, \ldots, u_k, \psi\}$ in the set Ω, the state of the system is always within the safe set $\square$;

(3) In the case where player k and player $1 \sim k-1$ form a cooperative relationship and a competitive relationship with player $k+1$, there exists an equilibrium state in the system (1) that allows the value function defined in Eq. (6) and Eq. (7) to be optimized.

Besides in control systems, the MZS game situation can also be found in firm competition. In the context of a real project, one can understand the $k+1$ players constituting the MZS game as $k+1$ firms, and the state constraints as market regulations that cannot be violated, and the firms k cooperating with Eq. $1 \sim k-1$ and competing with the firms 1, a game situation that can also be found in the animal world and the immune systems.

II. B. 2) System conversion

Under Assumption 1, it is obtained that player k and player $1 \sim k-1$ form an NZS game and player k and player $k+1$ form a ZS game. Define $\varsigma(t)$ as the target trajectory and $\dot{\varsigma}(t) = f_S\left(\zeta(t)\right)$, where $f_S\left(\zeta(t)\right)$ on the set Ω is Lipschitz Continuous. Define the tracking error e_ς as:

$$e_\varsigma = x(t) - \varsigma(t) \tag{3}$$

Can be obtained from system (1):

$$\dot{e}_\varsigma = f(\varsigma(t) + e_\varsigma) + \sum_{s=1}^{k} g_s(\varsigma(t) + e_\varsigma)u_s(t) + p(\varsigma(t) + e_\varsigma)\psi - f_\varsigma(\varsigma(t)) \tag{4}$$

Define the augmentation state to be $z = [e_\varsigma^T, \dot{\sigma}(t)^T]^T \in \square^{2n}$, and then the augmentation system can be obtained as:

$$\dot{z}(t) = \mathrm{F}(z(t)) + \sum_{s=1}^{k} \mathrm{G}_s(z(t))u_s(t) + \mathrm{P}(z(t))\psi \tag{5}$$

where $\mathrm{F}(z(t)) = [f(\varsigma + e_\varsigma) - f_\varsigma(\varsigma), f_\varsigma(\varsigma)]^T$; $\mathrm{G}_s(z(t)) = [g_s(\varsigma + e_\varsigma), 0]^T$; $s \in K$ is a constant; K ranges from $K = \{1, 2, \ldots, k\}$ and the control dynamics is $\mathrm{P}(z(t)) = [p(\varsigma + e_\varsigma), 0]^T$. The value function of player $1 \sim k-1$ is:

$$V_j(z(t)) = \int_t^\infty e^{-\ell(\tau - t)}[z^T Q_j z + \sum_{s=1}^{k} u_s^T R_{js} u_s + B(z)]d\tau \tag{6}$$

The value functions of players k and $k+1$ are:

$$V_k(z(t)) = \int_t^\infty e^{-\ell(\tau - t)}[z^T Q_k z + \sum_{s=1}^{k} u_s^T R_{ks} u_s + B(z) - \beta^2 \left\|\psi\right\|^2]d\tau \tag{7}$$

where $j \in \mathrm{K}$, $\mathrm{K} = \{1, 2, \ldots k-1\}$, $Q_j = diag\{Q_j, 0_{2\times 2}\}$, and β is a constant greater than zero; $Q_i \in \square^{n\times n}$ and $R_{is} \in \square^{m\times m}$ are symmetric positive definite matrices, where $i \in K$ and $s \in K$. $\tilde{n} > 0$ is a discount factor which is a constant with an upper limit $\vartheta_{\tilde{n}}$. $B(z)$ is a CBF candidate function, and the following assumptions are needed to introduce the properties of $B(z)$ more clearly.

Assumption 2: The CBF candidate function $B(z)$ is a monotonically decreasing function and has the following properties.

$$\begin{cases} B(z) \geq 0 \ \forall(\varsigma(t)+e_{\varsigma}) \in \square, \\ B(z) \to \infty, (\varsigma(t)+e_{\varsigma}) \to \partial\square \end{cases} \tag{8}$$

Under the condition of satisfying Assumption 2, the CBF candidate function is selected as:

$$B(z) = -\log\left(\frac{\gamma q(z)}{\gamma q(z)+0.1}\right) \tag{9}$$

where $\gamma > 0$ is a constant that regulates the decay rate, which moderates the relationship between system performance and security. When Assumptions 1 and 2 hold, there exists $B(x) \geq 0$ for any control strategy $\{u_1, \ldots, u_k, \psi\}$. By optimizing functions (6) and (7), player $1 \sim k-1$, player k, and player $k+1$ will all reach a Nash equilibrium $\{u_1^*, \ldots, u_k^*, \psi^*\}$.

Definition 1 In the MZS gaming system, player $1 \sim k+1$ will both reach the Nash equilibrium $\{u_1^*, \ldots, u_k^*, \psi^*\}$ when the control strategy $\{u_1^*, \ldots, u_k^*, \psi^*\}$ satisfies inequalities (10) and (11). The inequality is:

$$V_i^*(u_1^*, \ldots, u_i^*, \ldots, u_k^*) \leq V_i(u_1^*, \ldots, u_i^*, \ldots, u_k^*), i \in \mathrm{K} \tag{10}$$

$$V_k(u_1^*, \ldots, u_k^*, \psi) \leq V_k^*(u_1^*, \ldots, u_k^*, \psi^*) \leq V_k(u_1^*, \ldots, u_{k-1}^*, u_k, \psi^*) \tag{11}$$

where $\{u_1^*, \ldots, u_k^*, \psi^*\}$ can be referred to as the optimal control policy for system (5); and $V_j^*, j \in K$ is the optimal value function.

II. C.Common equations for dynamic programming

After the modeling and state transitions of the game system are completed, the ultimate goal of conflict resolution needs to be achieved by computable optimization strategies. The core equations of dynamic programming provide theoretical tools for this purpose. In this section, we will elaborate the value function construction, recursive optimization process and its specific application in Nash equilibrium solving, so as to bridge the complete link from model to algorithm.

Solving a K-stage optimization problem with dynamic programming, the set of strategies U obtained from the search can be expressed as:

$$\{u(x_1), u(x_2), \cdots, u(x_N)\} \in U \tag{12}$$

where $u(x_n)$ denotes the policy for the n th state:

$$u(x_n) = \{u_1(x_n), u_2(x_n), \cdots, u_K(x_n)\} \tag{13}$$

where $u_k(x_n)$ denotes the set of decisions for the n th state at the k th stage.

Dynamic programming relies on the value function to evaluate the merits of a strategy and thus search and select the optimal solution to the entire problem. The value function $I_k(x_n; u_1, u_2, \cdots, u_k)$ of the strategy for the n th state at the k th stage can be expressed as:

$$I_k(x_n; u_1, u_2, \cdots, u_k) = \sum_{i=1}^{k} w_i(x_{nk}, y_{nk}) \tag{14}$$

where (x_{nk}, y_{nk}) denotes the coordinates of the decision made in this state at the k th stage, and $w_i(x_{nk}, y_{nk})$ denotes the evaluated value of (x_{nk}, y_{nk}) at the coordinates of the i th stage, with different ways of constructing the value function influencing the magnitude of the evaluated value.

When solving a specific problem, dynamic programming optimizes the solution by finding the strategy that maximizes the value function:

$$f_k(x_n) = \max_{\{u_1,u_2,\cdots,u_{k-1}\}} I(x_n; u_1, u_2, \cdots, u_k) \tag{15}$$

where $f_k(x_n)$ denotes the maximum value function of the n th state at the k th stage, and according to the principle of optimization, the above equation is deformed as:

$$\begin{aligned} f_k(x_n) &= \max_{\{u_1,u_2,\cdots,u_{k-1}\}} [I_k(x_n)] = \max_{\{u_1,u_2,\cdots,u_{k-1}\}} \left[\sum_{i=1}^{k} w_i(x_{nk}, y_{nk})\right] \\ &= \max_{\{u_1,u_2,\cdots,u_{k-1}\}} \left[w_k(x_{nk}, y_{nk}) + \max_{\{u_1,u_2,\cdots,u_{k-1}\}} \sum_{i=1}^{k-1} w_i(x_{n(k-1)}, y_{n(k-1)})\right] \\ &= \max_{\{u_1,u_2,\cdots,u_{k-1}\}} \left[w_k(x_{nk}, y_{nk}) + \max_{\{u_1,u_2,\cdots,u_{k-1}\}} [I_{k-1}(x_n)]\right] \\ &= \max_{\{u_1,u_2,\cdots,u_{k-1}\}} \left[w_k(x_n, y_n) + f_{k-1}(x_n)\right] \end{aligned} \tag{16}$$

From the above equation for the n th state of K stages there are:

$$\begin{cases} I_1(x_n) = f_1(x_n) = w_1(x_n, y_n) \\ I_{k,k=1,2,\cdots,K} = w_k(x_n, y_n) + \max_{\{u_1,u_2,\cdots,u_{k-1}\}} [I_{k-1}(x_n)] \end{cases} \tag{17}$$

The above equation is the basic recursive solution formula for the dynamic programming algorithm.

III. Dynamic Programming-based Competitive Simulation of Firms and Community Stability Verification of Society

After completing the theoretical construction of game system modeling and stability optimization strategy based on dynamic programming, this chapter verifies the practical efficacy of the model through simulation experiments and complexity analysis of enterprise competition scenarios. Combined with specific cases, it explores the quantitative application of dynamic programming in reconciling social conflicts, and reveals the potential threat of chaotic state to the stability of the community, providing empirical support for the optimization of conflict resolution strategies.

III. A. Example of Iterative Dynamic Programming for Solving Optimal Control Problems

In order to verify the effectiveness of the stability analysis method of social community based on dynamic programming, this section takes the enterprise competition scenario as an example and uses iterative dynamic programming (IDP) to solve the multi-stage optimal control problem. The specific parameters are set as follows: the number of time segments p=100, the number of iterations 20, the initial control policy u=0, the initial reward coefficient rin=10, the discount factor r=0.95, the end-state penalty coefficient R=12, and the number of state grids 1. The optimal control performance index obtained by optimization of the algorithm is J=1.3470, and the control curves obtained by the iterative dynamic programming algorithm are shown in Fig. 1 in comparison with the state curves and analytical solutions. The control curve obtained by the iterative dynamic programming algorithm is compared with the state curve and the analytical solution as shown in Fig. 1 below, and the IDP optimal state and analytical solution errors are shown in Fig. 2.

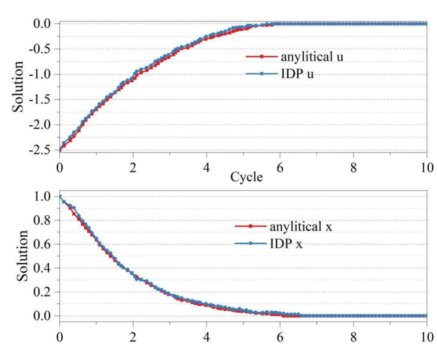

Figure 1: Comparison of the analytical solution to IDP

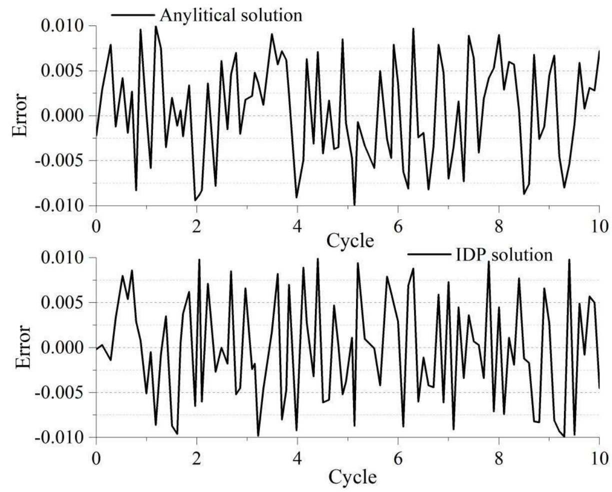

Figure 2: State error of the analytical solution and IDP

In the dynamic game, the behavior of firms can be regarded as state evolution in a multi-player MZS game system. With the IDP algorithm, the stability problem of the social community is mapped to a tracking control problem, in which the security set realizes boundary protection through the control barrier function (CBF). In Fig. 1, the control policies generated by the IDP algorithm (blue line segments) highly match the analytic solutions (red line segments), indicating that the algorithm is able to effectively approximate the optimal solution. This approximation capability implies that the dynamic planning model can quantify the decision paths of enterprises in competition and ensure that their behaviors are always within the safety set (i.e., compliant operation), thus avoiding social conflicts caused by excessive competition or irregular operation. In addition, the convergence of the state curves indicates that the system can quickly converge to a stable state through the recursive optimization of dynamic programming, verifying the feasibility of the model in regulating the dynamic equilibrium of the social community.

III. B. Analysis of complexity under dynamic games in social communities

Through the control strategy validation of the IDP algorithm in the ideal state, Section 3.1 demonstrates the effectiveness of the dynamic programming model in compliance management. However, the community dynamic game in real society is often accompanied by chaotic characteristics. This section further explores the subversive impact of initial value sensitivity on system stability, reveals the risk evolution path when the security set constraints fail, and provides a theoretical basis for the design of the conflict warning mechanism.

The dynamic game of social community has a high degree of complexity, especially in the chaotic state, the initial value sensitivity of the system may lead to the collapse of stability. In order to better study the characteristics of the chaotic state, a certain enterprise is taken to simulate the time series graph of the enterprise in the stable and chaotic state of the social community, comparing the difference of the system behavior between the stable state and the chaotic state. Where Fig. 3 depicts the time domain diagram in the stable state and Fig. 4 depicts the time domain diagram in the chaotic state.

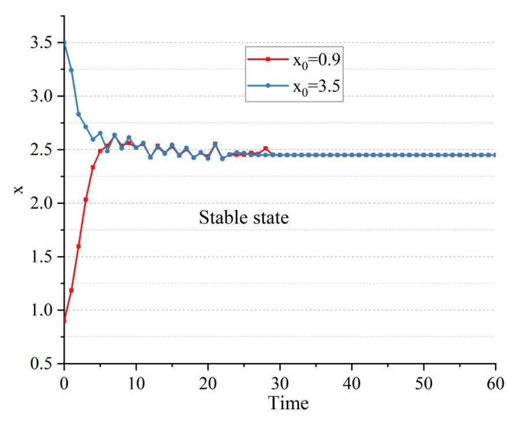

Figure 3: Time domain of stable state

According to Fig. 3, it can be observed that when the system is in a steady state, even though the initial service levels are significantly different (e.g., x0=0.9 vs. x0=3.5), the system converges to the same stable value after about 15 cycles. This phenomenon suggests that when the rules of the game (i.e., the state constraints in the dynamic programming model) are strictly followed, the self-organizing ability of the social community can effectively reconcile conflicts and maintain long-term stability.

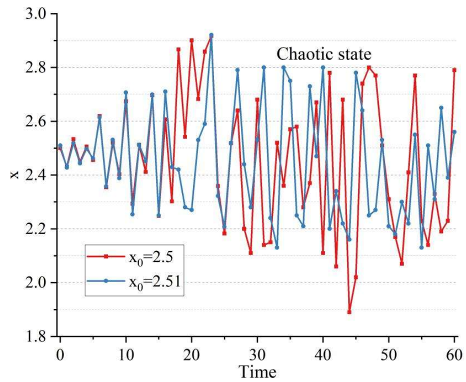

Figure 4: Time domain of steady chaotic state

However, in the chaotic state shown in Fig. 4, the small difference in the initial values (x0=3.50 vs. x0=3.51) leads to a rapid dispersion of the system trajectory, which exhibits strong unpredictability. When the game system is in a chaotic state, even if the difference in initial values is 0.1, the difference in values becomes larger and larger as the number of cycles increases, showing strong instability, and this phenomenon demonstrates that the system in a chaotic state has a strong sensitivity to initial values. This chaotic property is directly related to the failure of the safety set boundary in the dynamic programming model - when the control strategy cannot satisfy the derivative constraint of the CBF, the system state will break through the safety set (e.g., the enterprise violates the market regulations), which in turn triggers the disorganization of the social community.

The results show that chaos can cause the dynamic game of the social community to fall into disorder and confusion, so enterprises should slow down the adjustment speed and control the internal parameters during the dynamic game to avoid the emergence of chaos and the potential harm.

III. C. Profit analysis of the game under the delay-based strategy

The analysis of chaotic state shows the limitation of purely relying on static rules, for this reason, this section introduces the optimization of delay strategy, and explores the regulation role of active intervention on profit distribution and system equilibrium by combining with the dynamic planning model. Through simulation experiments, we quantify the impact of delay strategy on the profits of competing enterprises, verify its key role in avoiding chaos and maintaining the stability of the community, and provide practical references for the contradiction reconciliation strategy under the dynamic game.

Take three competing enterprises as an example, set the initial parameters: delay time $\tau \in [0,5]$, stability weight λ=0.8, discount factor γ=0.9. Solve iteratively through dynamic planning to get the system evolution results under delay strategy.
delayed), the simulation results are shown in Figs. 5 and 6, and the profit of enterprise 1 is significantly increased in the short term, while the profits of enterprises 2 and 3 are decreased.

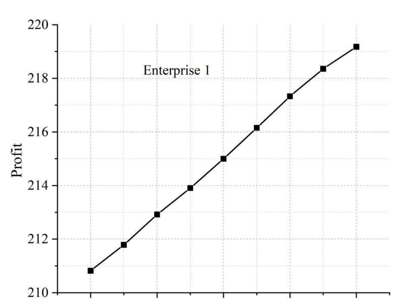

Figure 5: The impact of w1 on its own profits

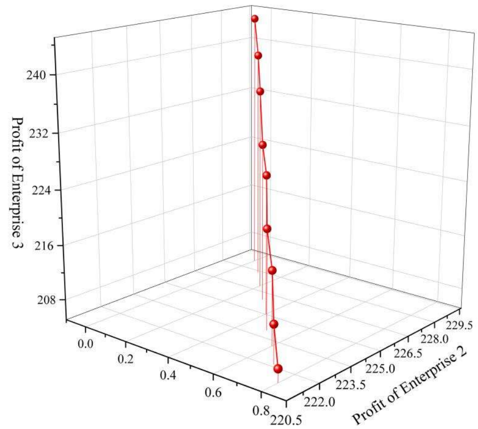

Figure 6: The influence of w1 on the profits of enterprises 2 and 3

It can be seen that firm 1's profit improves by about 4% under the delayed strategy, while firm 2's and firm 3's profits fall by 3.6% and 5% respectively.

IV. Countermeasures to improve the mechanism for the diversified settlement of conflicts

According to the previous analysis of the stability of the social community based on adaptive dynamic planning, in order to better improve the diversified conflict resolution mechanism, the article proposes corresponding countermeasures from three aspects. Through the practical transformation of the dynamic planning model and game theory, the conflict resolution mechanism can realize the precise regulation of the complex social system, and ultimately promote the community of society to continue to evolve on the track of security, stability and efficiency.

IV. A. Constructing smooth channels for the expression of interests and demands and opening the social safety valve

Based on the state feedback mechanism in the dynamic planning model, it is necessary to build a multi-level, digitalized platform for the expression of demands, mapping the individual interests of social members into real-time inputs to the gaming system. Through the establishment of online and offline integrated feedback channels, such as smart government systems and community consultation platforms, individual or group demands can be efficiently transformed into quantifiable “state variables” to avoid the accumulation of conflicts due to information blockage. Combined with the control barrier function (CBF) theory, a safety threshold should be set for the expression of demands: when the density of demands exceeds the boundary, the system automatically triggers the mediation process to prevent the spread of localized conflicts.

IV. B. Strengthening the search and investigation of conflicts and improving early warning of social risks

Drawing on the theory of state-constrained tracking control in dynamic planning, it is necessary to construct a mechanism of “active monitoring -- dynamic early warning -- closed-loop disposal”. Utilizing big data and artificial intelligence technology, we can conduct real-time scanning of the operating state of the social community and identify potential conflicts that deviate from the security set, such as economic inequality and policy resistance. By defining the “risk CBF function”, we can quantify the trend of conflict evolution: when the monitoring indicators are close to the critical value, the system automatically generates warning signals and pushes them to the decision-making level. The system is further combined with a multi-player game model to design a hierarchical response strategy: grassroots organizations are responsible for quickly intervening in micro-contradictions, while the macro-policy department adjusts the rules of the game in response to systemic risks, ensuring that contradictions can be effectively contained in the nascent stage.

IV. C. Integrating the resources of conflict resolution organizations and applying diversified conflict resolution measures

Based on the cooperative competition model of multi-player MZS game, it is necessary to integrate the resources of government, enterprises, social organizations and other multiple subjects to form a collaborative governance network. Through the dynamic planning recursive optimization strategy, a “phased-differentiated” mediation scheme is formulated: at the early stage of conflict, low-cost negotiation mechanism is the main focus; after entering the complex stage, judicial, arbitration and other coercive means are activated. At the same time, combined with the theory of adaptive dynamic planning, we have established an inter-agency information sharing and strategy coordination platform to avoid duplication of resources or strategy conflicts. For example, in the enterprise competition scenario, market regulators and industry associations can jointly formulate dynamic compliance standards to guide enterprises to compete within the scope of compliance, so as to reduce the social loss caused by vicious games.

V. Conclusion

This study quantitatively analyzes the stability evolution mechanism and contradiction reconciliation path of social community through the combination of dynamic programming model and multi-player MZS game theory. Simulation experiments based on the iterative dynamic programming (IDP) algorithm show that the optimal control performance index of the system reaches J = 1.3470, and the error between the control strategy and the analytical solution is stable on the order of 10-3, which verifies the model's high-precision approximation ability in ensuring the compliant operation of the enterprise (i.e., evolution within state constraints).

Further analysis of the chaotic state reveals that a small difference in the initial value can trigger a significant dispersion of the system trajectory, indicating that the social community will face the risk of disorder when the boundary of the security set fails, and the constraint protection needs to be strengthened by the control barrier function (CBF) in dynamic planning.

In the delay strategy experiment, set the delay time $\tau \in [0,5]$, stability weight $\lambda = 0.8$, the results show that the delay of a single enterprise can make its short-term profits improve, but the profits of competing enterprises decline, which highlights the ambivalence of individual interests and system stability in the game.

References

[1] Khan, U., Wang, H., & Ali, I. (2021). A sustainable community of shared future for mankind: Origin, evolution and Philosophical foundation. Sustainability, 13(16), 9352.

[2] Liu, C. (2019, September). The Logical Starting Point and Value of the Conception of a Community of Shared Future for Mankind. In The 4th International Conference on Economy, Judicature, Administration and Humanitarian Projects (JAHP 2019) (pp. 677-680). Atlantis Press.

[3] Folke, C., Polasky, S., Rockström, J., Galaz, V., Westley, F., Lamont, M., ... & Walker, B. H. (2021). Our future in the Anthropocene biosphere. Ambio, 50, 834-869.

[4] Zhang, W. (2017). The Human Rights Dimension in Building a Community with a Shared Future for Mankind. J. Hum. Rts., 16, 423.

[5] Liu, S. (2019). The philosophic interpretation of a community of shared future for mankind from the perspective of the Marxist philosophy. Open Access Library Journal, 6(07), 1.

[6] Sagiv, L., Roccas, S., Cieciuch, J., & Schwartz, S. H. (2017). Personal values in human life. Nature human behaviour, 1(9), 630-639.

[7] Kaasa, A. (2019). Determinants of individual-level social capital: Culture and personal values. Journal of International Studies, 12(1), 9-32.

[8] Fougère, M., & Solitander, N. (2020). Dissent in consensusland: An agonistic problematization of multi-stakeholder governance. Journal of Business Ethics, 164(4), 683-699.

[9] Putnam, L. L., Fairhurst, G. T., & Banghart, S. (2016). Contradictions, dialectics, and paradoxes in organizations: A constitutive approach. Academy of Management Annals, 10(1), 65-171.

[10] Peng, B. (2022). Digital leadership: State governance in the era of digital technology. Cultures of Science, 5(4), 210-225.

[11] Massey, A., & Johnston-Miller, K. (2016). Governance: public governance to social innovation?. Policy & Politics, 44(4), 663-675.

[12] Shamsoldini, A., Jamini, D., & Jamshidi, A. R. (2016). Measurement and analysis of social stability in rural areas (Case study: Javanrood Township). Journal of Rural Research, 7(3), 486-503.