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QoS-Aware Tripartite Evolutionary Game Strategy: A Task-Driven Performance Optimization Based on ISCC for IoV

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***Abstract*—In the development of Intelligent Transportation Systems (ITS) and the Internet of Vehicles (IoV), traditional management strategies that separate communication, sensing, and computation resources, as well as the uneven scheduling of resources, are increasingly unable to meet the needs of complex scenarios such as higher-level autonomous driving and integrated vehicle-road-cloud systems. This paper proposes a Quality of Service (QoS) tripartite evolutionary game model based on task-driven Integrated sensing, communication, and computation (ISCC). The dynamic evolution of resource allocation is analyzed by constructing a resource game platform centered on task requirements. Additionally, a joint utility function involving multi-node competition, dependency, and cooperation as QoS indicators has also been developed to achieve a unified representation of performance metrics. Subsequently, task-driven analysis effectively guides resource allocation strategies, ensuring optimization of resource utilization and precise alignment with task requirements. This paper offers new methodological support for designing and optimizing future intelligent transportation systems.**

***Index Terms*—ISCC, Task-Driven, Tripartite Evolutionary Game, Quality of Service aware, IoV**

I. Introduction

The widespread commercial deployment of 5G is driving economic, societal, and industrial transformations towards digitalization and intelligence, further deepening the exploration of integrated sensing and communication (ISAC). With the advancement of complex application scenarios in 6G, the future will see a high degree of coupling between sensing and communication, making ISAC a key technology in 6G. Concurrently, the development of Intelligent Transportation Systems (ITS) and smart Internet of Vehicles (IoV) demands faster information sensing, processing, and computation, necessitating more robust and ubiquitous computing capabilities for both communication and sensing. Therefore, the integration of sensing, communication, and computation (ISCC) emerges as a significant evolutionary direction for 6G [1].

The rapid growth of smart IoV highlights the importance of efficiently managing the integration of communication, sensing, and computation resources. Existing research has detailed resource allocation schemes based on ISAC [2], which lay the foundation for integrating these capabilities. In IoV, communication, sensing, and computation resources must be dynamically allocated to meet varying service demands. The challenge lies in the heterogeneity of these resources and the need for a unified framework that can seamlessly manage their interaction. For instance, the vehicular environment is characterized by high mobility and varying network conditions, complicating the resource allocation process [3]. Moreover, the diverse applications, ranging from safety-critical services to infotainment, require different levels of resource prioritization and quality of service (QoS) guarantees.

The traditional and standalone performance metrics for communication, sensing, and computing can no longer meet the diverse and complex service demands of smart IoV. Therefore, a unified performance metric for ISCC is crucial for optimizing multi-domain resource allocation and enhancing overall system performance [4]. This integrated technological framework paves the way for the continuous development and performance improvement of smart IoV.

Several studies have proposed various frameworks and algorithms to address these challenges. Feng et al. [5] developed a framework that integrates communication, sensing, and computing capabilities through unified hardware, resources, and protocol designs, enhancing collaboration and mutual benefits. Addressing the requirements of 6G networks, Jin et al. [6] proposed a multi-granularity resource allocation algorithm, modeling the joint optimization of these resources as a utility maximization problem across different time scales. Zhao et al. [7] investigated the trade-offs within an integrated framework, using matching theory to describe resource competition among mobile devices with multifunctional requirements, and introduced a novel resource scheduler. Yang et al. [8] introduced a wireless scheduling architecture to enhance the coordinated gains of ISCC, designing heuristic algorithms to maximize the adjusted utility functions in IoV. In the above studies, a unified performance metric for ISCC remains to be researched. Furthermore, the use of evolutionary game theory in IoV has not been fully explored, despite its potential to address the natural competition among communication, sensing, and computation resources under constraints.

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In this paper, we present an innovative QoS tripartite evolutionary game model that allocates ISCC resources based on task requirements. This model offers a dynamic framework for analyzing and optimizing resource allocation through natural competition and cooperation among these resources. We establish a joint utility function that captures the competition and dependency among multiple nodes as a QoS indicator. This function provides a unified representation of performance metrics, enabling a comprehensive evaluation of the integrated system's performance. Finally, we conduct simulations to analyze the dynamic evolution of resource allocation within the proposed platform. We guide resource allocation strategies through task-driven analysis to ensure optimal resource utilization and precise alignment with task requirements. This approach demonstrates the proposed model's feasibility and effectiveness in enhancing the system's overall performance and efficiency.

The remainder of this paper is organized as follows. Section II presents the system model and problem formulation. Section III details the tripartite evolutionary game strategy used for resource allocation. Section IV discusses the experimental results and analysis. Finally, Section V concludes the paper.

II. System Model and Problem Formulation

In this section, we introduce the system model and formulate the problem we aim to solve. Using a tripartite evolutionary game framework, our proposed system integrated communication, sensing, and computation resources in IoV. We detail the components and interactions within the system model and define the optimization objective to enhance the ISCC quality of service (ISCC-QoS).

A. System Model

We propose a tripartite evolutionary game platform integrated with communication, sensing, and computation resources in IoV. The model, illustrated in Fig. 1, is divided into three main layers: the Decision Space Layer, the Task-Driven Layer, and the Resource Layer.

1) Decision Space Layer: **Participants of the Game.** Participants include vehicles, roadside units, and cloud servers, each competing and collaborating for resources; **Game Dynamics.** Each participant's strategy involves allocating resources for communication, sensing, and computation to maximize their utility functions. The interactions can be competitive or collaborative, depending on the task requirements and available resources.

2) Task-Driven Layer: **Task Requirements.** Tasks define specific requirements for communication (Com), sensing (Sen), and computation (Cpu). Tasks are dynamic and vary over time, influencing the demand for resources; **Resource Transfer.** Based on the outcomes of the game dynamics, resources are transferred to meet the evolving task requirements.

3) Resource Layer: **Resource Mapping and Integration.** Resources are mapped from participants to a multi-domain resource pool. This pool integrates communication, sensing, and computation resources, allowing for dynamic allocation based on task-driven demands.

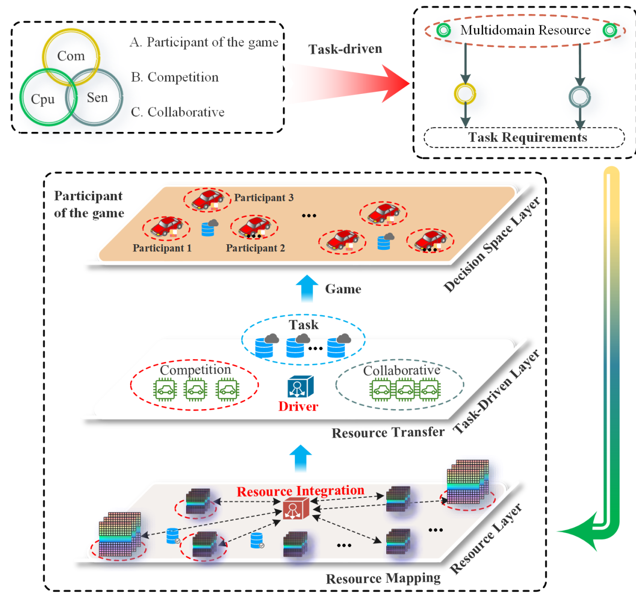

Fig. 1. ISCC Game Platform for IoV.

B. Problem Formulation

The optimization objective is to maximize the ISCC-QoS. The problem can be formulated as follows:

$$\begin{aligned} &\max \ \text{ISCC-QoS} \\ &\text{s.t.} \quad \left\{ \begin{array}{l} \text{utility\_com} \\ \text{utility\_sen} \\ \text{utility\_cpu} \end{array} \right\} \\ &\text{Where} \quad \begin{array}{l} \text{utility\_com} \in \{\Delta R, G, L_1, I_1\}, \\ \text{utility\_sen} \in \{\Delta S, G, L_2, I_2\}, \\ \text{utility\_cpu} \in \{\Delta F, G, L_3, I_3\} \end{array} \end{aligned} \tag{1}$$

where ΔR represents the benefit of improved communication performance upon task completion, G indicates the balance of resource allocation, L_1 represents the proportion of communication resources not effectively utilized within the system, and I_1 denotes the operational cost of the communication system. Similarly, ΔS, L_2, and I_2 are the corresponding parameters for the sensing side. ΔF, L_3, and I_3 are the parameters for the computation side.

III. Tripartite Evolutionary Game Strategy

A. Analysis of the Interests of the Game Participants

1) Analysis of Communication Side Interests: In order to process and transmit large volumes of data in real-time, the communication side needs to provide high bandwidth and low latency communication services. This facilitates the effective delivery and sharing of sensing information, thereby expanding its depth and breadth. In the IoV environment, the continuity and stability of communication are crucial. Moreover, maintaining service quality under resource-limited conditions is essential to sustain system operations. Overall, the efficiency of the communication side directly affects the real-time transmission of sensing data and the response time

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of the computation side, thus determining the overall system's reaction speed and accuracy.

2) Analysis of Sensing Side Interests: **High-Quality Data (Accuracy and Completeness)**. Collect high-quality sensing data to ensure accuracy and completeness, providing reliable input for the communication and computation sides. **Real-Time Capability**. Rapidly collect and transmit data to meet the needs for real-time data processing and decision-making. **Energy Efficiency**. Achieve minimal energy consumption without sacrificing data quality. Overall, the data quality and transmission speed on the sensing side directly determine the data processing quality on the computation side and the overall performance of the system.

3) Analysis of Computation Side Interests: **Efficient Data Processing Capability**. Strong computational power is needed to process and analyze large volumes of data from the sensing side while also managing operational costs and energy consumption. Similarly, the processing capability and efficiency of the computation side directly impact the decision-making quality and operational efficiency of the entire system, making them key determinants of system performance.

The interests of each game participant are shown in Fig. 2.

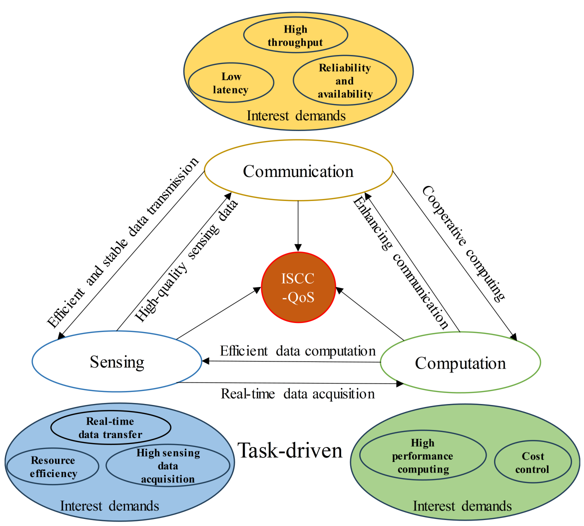

Fig. 2. The interests of the main players in the game.

B. Model Assumption

To establish a unified performance metric driven by task-driven ISCC, we conducted performance optimization and evolution experiments. For ease of research, the following assumptions are made. We completed the benefit analysis in Section III-A by referencing [9], [10], and [11], and set the relevant parameters as shown in Section II-B.

- Assumption 1: Based on the common tasks performed by intelligent vehicles in vehicular networks, these tasks are categorized into data transmission (communication side), environmental sensing (sensing side), and data processing (computation side). Eight specific tasks are identified: participation in real-time traffic management, automatic emergency braking, onboard entertainment and information, remote vehicle diagnostics, environmental monitoring and data analysis, static traffic sign recognition, cloud computing data processing, and routine vehicle maintenance updates.
- Assumption 2: For communication, sensing, and computation, each side has two strategic options. Firstly, the communication side can adopt a strong coupling strategy, where task requirements are highly related to communication, with a probability of $x(0 \leq x \leq 1)$. Alternatively, it can adopt a weak coupling strategy, where task requirements are less related to communication, with another probability of $1-x$. Similarly, the sensing aspect can choose a strong coupling strategy with a probability of $y(0 \leq y \leq 1)$ or a weak coupling strategy with a probability of $1-y$. Likewise, the computation aspect can have a strong coupling strategy with a probability of $z(0 \leq z \leq 1)$ or a weak coupling strategy with a probability of $1-z$.
- Assumption 3: Based on the strategic choices of the game participants, each participant's additional gain is denoted as $\beta C(0 < \beta < 1)$. Additionally, the basic benefits for completing tasks on the communication, sensing, and computation sides are denoted as B_1, B_2, and B_3 respectively.

C. Model Analysis, Building and Solving

Based on the assumptions and parameters, we derived the evolutionary game payoff matrices for the communication side under strong task coupling, weak task coupling, sensing side under strong task coupling, weak task coupling, and computation side under strong task coupling, weak task coupling strategy sets. These matrices are shown in Table I. The evolutionary game payoff tree is shown in Fig. 3.

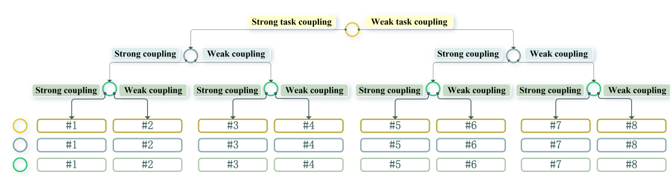

Fig. 3. The evolutionary game payoff tree.

According to the evolutionary game matrix and game tree, the expected and average profits for the communication, sensing, and computation sides are calculated, constructing the replicator dynamic equations for each party.

1) Replicator Dynamic Equations and Equilibrium Points for the Three Parties: Assume E_{x1} is the expected profit for the communication side choosing 'strong task coupling', E_{x2} is the expected profit for choosing 'weak task coupling', and E_x is the average expected profit for the communication

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TABLE I

EVOLUTIONARY GAME PAYOFF MATRIX BETWEEN COMMUNICATION, SENSING, AND COMPUTATION SIDES.

Number	Task-Driven Strategy Chain	Payoff Matrix		
		Communication Side	*Sensing Side*	*Computation Side*
#1	{Strong coupling, Strong coupling, Strong coupling}	$B_1 + \Delta R - L_1 - I_1 + \beta C$	$B_2 + \Delta S - L_2 - I_2 + \beta C$	$B_3 + \Delta F - L_3 - I_3 + \beta C$
#2	{Strong coupling, Strong coupling, Weak coupling}	$B_1 + \Delta R - L_1 - I_1 + \beta C - G$	$B_2 + \Delta S - L_2 - I_2 + \beta C - G$	$B_3 - L_3 - I_3 + \beta C - G$
#3	{Strong coupling, Weak coupling, Strong coupling}	$B_1 + \Delta R - L_1 - I_1 + \beta C - G$	$B_2 - L_2 - I_2 + \beta C - G$	$B_3 + \Delta F - L_3 - I_3 + \beta C - G$
#4	{Strong coupling, Weak coupling, Weak coupling}	$B_1 + \Delta R - L_1 - I_1 - G$	$B_2 - L_2 - I_2 + \beta C - G$	$B_3 - L_3 - I_3 + \beta C - G$
#5	{Weak coupling, Strong coupling, Strong coupling}	$B_1 - L_1 - I_1 + \beta C - G$	$B_2 + \Delta S - L_2 - I_2 + \beta C - G$	$B_3 + \Delta F - L_3 - I_3 + \beta C - G$
#6	{Weak coupling, Strong coupling, Weak coupling}	$B_1 - L_1 - I_1 + \beta C - G$	$B_2 + \Delta S - L_2 - I_2 + \beta C - G$	$B_3 - L_3 - I_3 + \beta C - G$
#7	{Weak coupling, Weak coupling, Strong coupling}	$B_1 - L_1 - I_1 + \beta C - G$	$B_2 - L_2 - I_2 + \beta C - G$	$B_3 + \Delta F - L_3 - I_3 - G$
#8	{Weak coupling, Weak coupling, Weak coupling}	$B_1 - L_1 - I_1$	$B_2 - L_2 - I_2$	$B_3 - L_3 - I_3$

side's decision-making. The replicator dynamic equation for the strategy selection on the communication side is as follows:

$$\begin{aligned} E_{x1} &= yz(B_1 + R - L_1 - I_1 + \beta C) \\ &+y(1-z)(B_1 + R - L_1 - I_1 + \beta - G) \\ &+(1-y)z(B_1 + R - L_1 - I_1 + \beta - G) \\ &+(1-y)(1-z)(B_1 + R - L_1 - I_1 - G) \end{aligned} \tag{2}$$

$$\begin{aligned} E_{x2} &= yz(B_1 - L_1 - I_1 - G) \\ &+y(1-z)(B_1 - L_1 - I_1 - G) \\ &+(1-y)z(B_1 - L_1 - I_1 - G) \\ &+(1-y)(1-z)(B_1 - L_1 - I_1) \end{aligned} \tag{3}$$

$$E_x = xE_{x1} + (1-x)E_{x2} \tag{4}$$

Similarly, the expected profit for the sensing and computation sides adopting 'strong task coupling' and the average profit.

According to evolutionary game theory [12], the replicator dynamic equation for the communication side adopting 'strong task coupling' behavior is F_x:

$$\begin{aligned} F_x = \frac{dx}{dt} &= x(E_{x1} - E_x) \\ &= x(1-x)\big(R - G + Gy + Gz \\ &\quad + \beta Cy + \beta Cz - \beta Cyz\big) \end{aligned} \tag{5}$$

Similarly, we can derive the replicator dynamic equations F_y and F_z considering the strategy behaviors of the sensing and computation sides.

According to the stability theorem of replicator dynamics, the probability of the communication side undergoing 'strong task coupling' and in a stable state must be satisfied: $F_x = \frac{dx}{dt} = 0$ and $\frac{dF_x}{dx} < 0$. When $y = y^* = (R - G + Gz + \beta Cz)/(\beta Cz - G - \beta C)$, $\frac{dF_x}{dx} = (1 - 2x)\left[(R - G + Gz + \beta Cz) - (\beta Cz - G - \beta C)y\right] = 0$, at this point, all points on the X-axis are in an evolutionary stable state; when $y < y^*$, $\frac{dF_x}{dx} \mid x = 1 < 0$, meaning $x = 1$ is the evolutionarily stable strategy (ESS) for the communication side, meaning it tends to choose the 'strong task coupling' strategy; whereas when $y > y^*$, $\frac{dF_x}{dx} \mid x = 0 < 0$, meaning $x = 0$ is the ESS for the communication side, meaning it tends to choose the 'weak task coupling' strategy.

Similarly, the probability of the sensing side undergoing 'strong task coupling' and in a stable state must be satisfied: $F_y = \frac{dy}{dt} = 0$ and $\frac{dF_y}{dy} < 0$. When $z = z^* = (S - G + \beta C + Gx - \beta Cx)/(\beta C - G - \beta Cx)$, $\frac{dF_y}{dy} = (1 - 2y)[(S - G + \beta C + Gx - \beta Cx) - (\beta C - G - \beta Cx)z] = 0$, at this point, all points on the Y-axis are in an evolutionary stable state; when $z < z^*$, $\frac{dF_y}{dy} \mid y = 1 < 0$, meaning $y = 1$ is the ESS for the sensing side, meaning it tends to choose the 'strong task coupling' strategy; whereas when $z > z^*$, $\frac{dF_y}{dy} \mid y = 0 < 0$, meaning $y = 0$ is the ESS for the sensing side, meaning it tends to choose the 'weak task coupling' strategy.

Similarly, the probability of the computation side undergoing 'strong task coupling' and in a stable state must be satisfied: $F_z = \frac{dz}{dt} = 0$ and $\frac{dF_z}{dz} < 0$. When $x = x^* = (G - Gy - F)/G$, $\frac{dF_z}{dz} = (1 - 2z)[Gx - (G - Gy - F)] = 0$. At this point, all points on the Z-axis are in an evolutionarily stable state; when $x < x^*$, $\frac{dF_z}{dz} \mid z = 0 < 0$, meaning $z = 0$ is the ESS for the computation side, meaning the computation side tends to choose the 'strong task coupling' strategy; whereas when $x > x^*$, $\frac{dF_z}{dz} \mid z = 0 < 0$, meaning $z = 1$ is the ESS for the computation side, meaning it tends to choose the 'weak task coupling' strategy.

2) Analysis of three-party equilibrium strategies in evolutionary game models: Based on the analysis above, we derived a three-dimensional dynamical system for the evolutionary game, as can be seen in (6).

From $F_x(x, y, z) = 0$, $F_y(x, y, z) = 0$, and $F_z(x, y, z) = 0$, the system has eight pure strategy equilibrium points: $E_1(0, 0, 0)$, $E_2(1, 0, 0)$, $E_3(0, 1, 0)$, $E_4(0, 0, 1)$, $E_5(1, 1, 0)$,

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$E_6(1,0,1)$, $E_7(0,1,1)$, $E_8(1,1,1)$.

$$\begin{cases} F_x(x,y,z) = x(1-x)(R-G+Gy+Gz \\ \qquad\qquad +\beta Cy+\beta Cz-\beta Cyz) \\ F_y(x,y,z) = y(1-y)(S-G+\beta C+Gx+Gz \\ \qquad\qquad -\beta Cx-\beta Cz+\beta Cxz) \\ F_z(x,y,z) = z(1-z)(F-G+Gx+Gy) \end{cases} \tag{6}$$

According to Friedman's method, the stability of the system's equilibrium points is determined by analyzing the eigenvalues of the system's Jacobian matrix. Using the eigenvalue analysis method of the Jacobian matrix, the stability of the eight pure strategy equilibrium points existing in the evolutionary system is analyzed. (1) If all eigenvalues at an equilibrium point are less than 0, then the equilibrium point is an ESS; (2) If at least one eigenvalue is greater than 0, then the equilibrium point is unstable. Therefore, the stability analysis of the pure strategy equilibrium points is shown in Fig. 4.

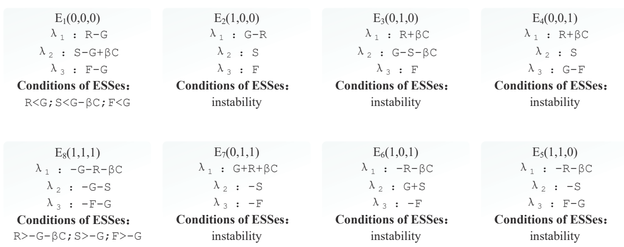

Fig. 4. Stability analysis chart.

Based on the stability conditions of the aforementioned eight equilibrium points, the performance improvement and the balance of resource allocation determine the strategy choices of the tripartite game participants. As proposed by Jiang et al. [10], during the technological development of ISAC in 6G, communication and sensing will evolve in phases and levels. In ISCC, the tripartite game also evolves in stages: the initial stage (coexistence phase), the development stage (mutual aid phase), and the maturity stage (integrated benefit phase). In the following, we will analyze the stability of the equilibrium points at different stages.

Initial Stage (Coexistence Phase): In this phase, the functionalities of communication, sensing, and computation operate independently with minimal interaction. Each entity focuses on its core tasks and objectives without significant collaboration or resource sharing. Therefore, this phase corresponds to equilibrium point $E_1\,(0,0,0)$, and according to the stability conditions shown in Fig. 3, three conditions must be met for this point to be stable: $R < G$; $S < G - \beta C$; $F < G$. At this time, all parties tend to choose the 'weak coupling' strategy because they focus more on self-optimization rather than overall performance, indicating that independent operation is more stable when individual gains are lower than collaborative gains.

Development Stage (Mutual Aid Phase): In this phase, as the system operates and demands evolve, the three sides begin to recognize the potential and necessity of collaboration. The communication, sensing, and computation sides start assisting each other through resource sharing and strategy adjustment to enhance their performance. However, in this stage, the unilateral strong coupling shown in equilibrium points $E_2\,(1,0,0)$, $E_3\,(0,1,0)$, $E_4\,(0,0,1)$ is not enough to stabilize the system temporarily and does not form effective performance enhancement; or any two sides' strong coupling with the third side's weak coupling, as in equilibrium points $E_5\,(1,1,0)$, $E_6\,(1,0,1)$, $E_7\,(0,1,1)$, where two sides attempt to enhance collaboration through strong coupling, but with the third side's low participation, thus not fully integrating all sides' capabilities and not achieving optimal resource sharing.

Mature Stage (Integrated Benefit Phase): In this phase, not only do the three functional entities coexist but they also collaborate highly. Through evolution, they perform efficient resource scheduling, and the game outcome points to a cooperative win-win, with all entities adopting the 'strong coupling' strategy to achieve optimal system performance. Therefore, this phase corresponds to equilibrium point $E_8\,(1,1,1)$, and similarly, according to the stability conditions shown in Fig. 4, to make this point stable, three conditions need to be met: $R > -G - \beta C$; $S > -G$; $F > -G$, indicating that when the benefits of collaboration (performance improvement) far outweigh working alone (uneven resource allocation), the strong coupling strategy choice of all sides provides the best performance.

IV. Experimental Results

To achieve the optimal state $E_8(1,1,1)$ for the system, the ESS of the system must satisfy three conditions: $R > -G - \beta C$, $S > -G$, and $F > -G$. We simulated the system evolution diagram for the maturity stage, as shown in Fig. 5(a). The different colored dashed lines represent the evolutionary processes of the tripartite evolutionary game with 125 randomly generated non-fixed strategies. The parameter settings are listed in Table II. After iterations, all strategies converge to $E_8(1,1,1)$. It can be observed that regardless of the initial strategy, $E_8(1,1,1)$ is the ESS in the system under the given constraints, thus validating our analysis.

During this stage, we analyzed the changes in the behavior probabilities of each participant over time. As shown in Fig. 5(b), as the system evolves with $G = 0.2$, all participants tend to adopt the 'strong task coupling' strategy, with the communication and computation sides converging more rapidly. Under this configuration, the demand on the sensing side is relatively low.

Additionally, we performed task decoupling analysis driven by tasks and constructed joint utility functions involving multi-node competition, dependency, and collaboration as QoS indicators. We simulated the changes in each participant's joint utility function with varying degrees of resource imbalance G, as shown in Fig. 5(c). The lower the resource imbalance, the higher the joint utility for each participant, consistent with the analysis of the mature stage described above. The multi-node joint utility function integrates the individual utilities of

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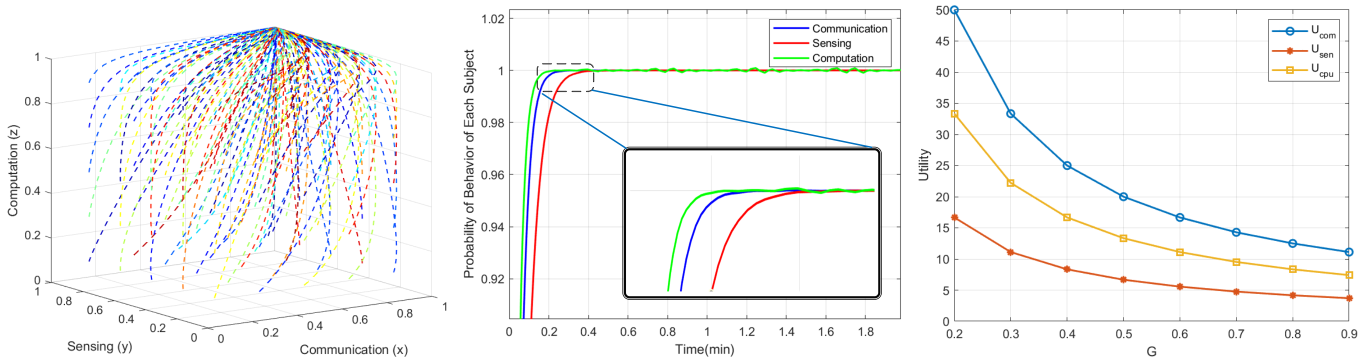
TABLE II
THE PARAMETER VALUES FOR EACH STAGE IN THE EVOLUTIONARY GAME MODEL.

Parameters	R	S	F	βC	G	B_1	B_2	B_3	L_1	L_2	L_3	I_1	I_2	I_3
Initial value of the mature stage	30	20	40	0.9	0.2	15	14	16	0.1	0.15	0.12	3	4	5



(a) (b) (c)

Fig. 5. Numerical analysis results (a) Evolution process of the system in the mature stage; (b) Probability of Behavior of Each Subject with G=0.2; (c) Utility varies with G

communication, sensing, and computation sides, capturing the interdependencies and competitive nature of these resources.

V. CONCLUSIONS

In the context of intelligent IoV, vehicles exhibit game-like behavior in resource scheduling. In this paper, we innovatively propose and implement a task-driven tripartite evolutionary game model, successfully optimizing the integrated use of communication, sensing, and computation resources in intelligent IoV. We constructed a joint utility function encompassing multi-node competition, dependency, and cooperation as QoS indicators, which unified the standard of performance evaluation under the ISCC. Additionally, the resource game platform dynamically adapts to various task demands through precise resource mapping and optimization strategies, significantly enhancing the overall performance and intelligence level of vehicular network systems. Overall, our work not only provides a practical perspective for resource management in vehicular networks but also lays a solid foundation for the development of future intelligent transportation systems.

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