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A comprehensive survey of game-theoretic approaches for networked systems

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ABSTRACT
Networked systems composed of heterogeneous and distributed agents – such as sensors, actuators, robots, and vehicles – play a critical role in modern infrastructures, including smart grids, industrial automation, and intelligent transportation systems. However, resource constraints, dynamic uncertainties, and cyber threats pose significant challenges to their scalability, resilience, and secure coordination. Game theory provides a rigorous framework for modelling strategic interactions among agents, capturing both competitive and cooperative behaviours under diverse constraints. This survey systematically reviews game-theoretic applications across five representative domains: resource allocation and scheduling, cybersecurity and adversarial defence, network topology and routeing optimization, coalition formation and cooperative strategies, and distributed multi-agent decision-making. Despite notable progress, open challenges remain in achieving scalability for large-scale heterogeneous systems, ensuring robustness under uncertainty, and integrating game-theoretic models with data-driven learning approaches. Collectively, game-theoretic methods demonstrate strong potential for enabling scalable, secure, and adaptive networked systems.

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1. Introduction

Over the past two decades, the rapid evolution of communication technologies, embedded computing, and distributed sensing has fundamentally reshaped traditional engineered infrastructures into networked systems. These systems consist of spatially distributed and heterogeneous agents, including sensors, actuators, controllers, mobile robots, smart metres, and vehicles, that interact through communication networks to achieve collective objectives (Mahmoud & Sabih, 2014). Research on networked systems has flourished due to their relevance in diverse applications such as smart grids (Saad et al., 2012), intelligent transportation systems, industrial automation, and the Internet of Things (IoT) (Z. Sun et al., 2021). Nevertheless, networked systems remain inherently complex and face pressing challenges, including limited resources, dynamic and uncertain operating conditions, and vulnerability to cyber threats (Tan et al., 2021). Coordinating the interactions among autonomous agents, optimizing global system performance, and ensuring resilience against adversarial behaviours remain central open issues.

Game theory provides a principled mathematical foundation for modelling and analyzing strategic decision-making among rational or bounded-rational agents. It not only captures competitive and cooperative behaviours but also offers systematic approaches to designing optimal or equilibrium strategies under diverse operational constraints. Classical game-theoretic models are commonly categorized along several axes, such as cooperative versus non-cooperative, static versus dynamic, and complete versus incomplete information (Jones, 2000). Representative approaches include Nash equilibrium analysis, Stackelberg games, evolutionary game theory, coalition and cooperative game models, and auction-based mechanism design (Başar & Olsder, 1999; Fudenberg & Tirole, 1991). These methodologies provide critical insights for guiding the development of distributed control and optimization algorithms.

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Over the years, game theory has become an indispensable tool for networked systems, enabling significant progress in key domains such as resource management, security, and distributed coordination. In resource-constrained environments, game-theoretic frameworks have been employed to address bandwidth allocation, power control, spectrum sharing, and computation offloading, thereby supporting both efficiency and fairness in competitive multi-agent settings (Chi et al., 2021). In security domains, game-theoretic defence models have been used to characterize the interactions between attackers and defenders, leading to the design of adaptive intrusion detection systems, dynamic defence mechanisms, and secure communication protocols (Huang et al., 2020). Beyond these, cooperative and evolutionary game models have been extensively applied to multi-agent coordination problems such as drone formation control, robotic swarm collaboration, and autonomous fleet management, where stability, resilience, and adaptability are essential (J. Zhang et al., 2020). More recently, research has expanded to emerging paradigms such as multi-access edge computing, software-defined vehicular networks, and blockchain-enabled infrastructures (Chi et al., 2021). These studies demonstrate how game-theoretic tools can be adapted to next-generation networking scenarios.

Despite extensive progress, several fundamental challenges persist. First, ensuring the scalability of game-theoretic frameworks in large-scale and heterogeneous networked systems remains a difficult problem (Wei et al., 2025). Second, dynamic and uncertain environments require adaptive mechanisms in which agents can revise their strategies online. This challenge has motivated hybrid approaches that integrate game-theoretic reasoning with machine learning and reinforcement learning (Nguyen & Reddi, 2023). A recent comprehensive review has further summarized computational game-theoretic models for adaptive urban energy systems, with particular emphasis on the integration of game theory and reinforcement learning for decision-making under uncertainty. This review also highlights the growing importance of learning-enabled game-theoretic frameworks in large-scale cyber–physical infrastructures (L. Cheng et al., 2025). Third, the increasing complexity of autonomous systems places new demands on game-theoretic models, particularly with respect to real-time decision-making, resilience against adversarial behaviour, and interoperability across heterogeneous platforms (R. Yu et al., 2024). Addressing these challenges requires advances in theory, closer integration with control and optimization methods, and validation in practical cyber-physical infrastructures.

To position this survey within the existing literature, it is worth noting that prior reviews often concentrate on particular domains, such as wireless communications, smart grids, or Quality of Service (QoS) optimization in IoT environments (Saad et al., 2012; Z. Sun et al., 2021). Other surveys primarily introduce game-theoretic fundamentals without sufficiently connecting them to the unique modelling and control challenges of networked systems (Başar & Olsder, 1999). In contrast, this paper provides a comprehensive and application-oriented overview that bridges theoretical game models with the practical demands of networked systems, aiming to deliver a unified discussion that both consolidates existing findings and identifies future research opportunities.

In line with this objective, this survey focuses on five representative domains in which game theory has had substantial impact: resource allocation and scheduling, cybersecurity and adversarial defence, network topology and routeing optimization, coalition formation and cooperative strategies, and distributed multi-agent decision-making. These areas are selected because they capture the core operational challenges of networked systems and exemplify the versatility of game-theoretic approaches. Other branches of game theory research, such as purely economic models or mechanism design without explicit networking contexts, are not included within the scope of this article. Figure 1 illustrates the correspondence between the five major application areas and the representative game-theoretic models that underpin their analysis.

We organize this paper as follows. Section 2 introduces the theoretical background of networked systems, including basic definitions and typical models. Section 3 reviews the fundamental concepts, historical development, and core models of game theory. Section 4 focuses on game-theoretic applications in networked systems and summarizes recent research advances across the five representative domains. Section 5 discusses the main theoretical and practical challenges and outlines future research directions. Finally, Section 6 concludes the paper.

2. Background of networked systems

Networked systems are composed of spatially distributed components that interact through communication infrastructures, enabling cooperative sensing, computation, and control. Typical subsystems include sensors,

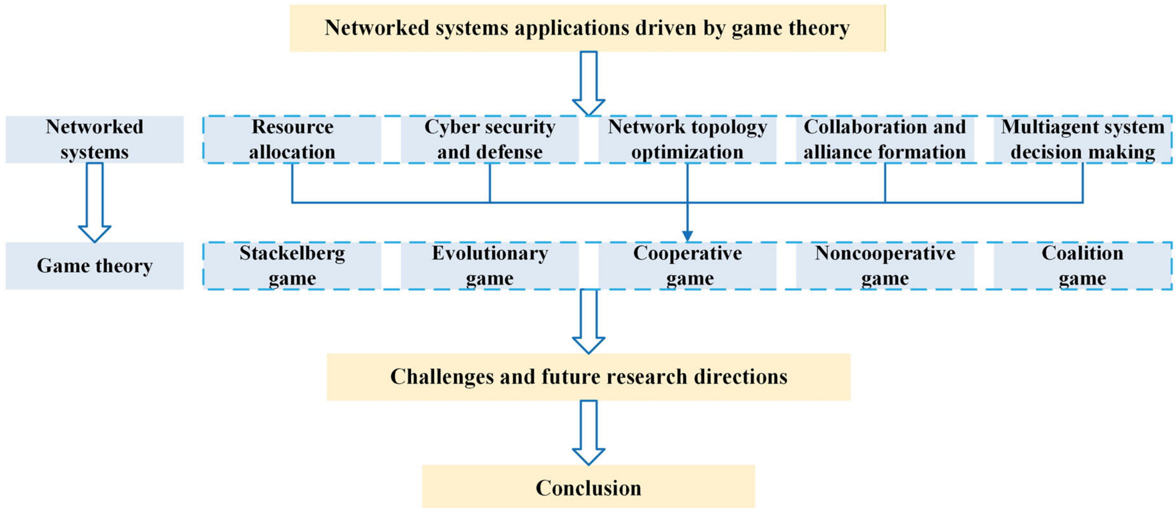


Figure 1. The structure of this work.

actuators, controllers, computing nodes, and communication devices. These systems are widely applied in smart grids, intelligent transportation systems (ITS), industrial Internet of Things (IIoT), and multi-robot networks. In contrast to traditional centralized architectures (Q. Liu & Wang, 2021), networked systems operate under dynamic topologies, constrained resources, and increased exposure to cyber threats, all of which fundamentally reshape the principles of control design and analysis. Within this domain, networked control systems (NCSs) and cyber-physical systems (CPSs) have emerged as representative paradigms. NCSs primarily address stability and performance issues arising from imperfect communication, where challenges include time delays, packet dropouts, and bandwidth limitations (X.-M. Zhang et al., 2020). CPSs extend this scope by integrating sensing, communication, computation, and control with additional emphasis on safety, security (Tan et al., 2021), and human–system interaction (Humayed et al., 2017). Both paradigms build upon control theory, communication theory, and distributed computing (Ding et al., 2018), thereby forming the theoretical foundation for scalable and resilient networked systems.

Among the imperfections introduced by communication networks, time delay remains one of the most critical and extensively studied factors. Unlike constant delays, which may be compensated through classical control techniques, time-varying delays arise from fluctuating traffic loads, dynamic routeing paths, and variable processing times at intermediate nodes (Guan et al., 2025). These delays may exhibit deterministic patterns or stochastic distributions, reflecting the inherent uncertainty of network communication. From a control perspective, delays alter the timing of feedback signals, reduce gain and phase margins, and may cause oscillations or instability even when their magnitudes are moderate. In large-scale distributed systems, multiple delays can accumulate and interact, producing complex temporal dynamics that are difficult to analyze and predict (H. Chen et al., 2025). Consequently, the study of delay-dependent stability criteria, Lyapunov–Krasovskii methods, and robust compensation strategies has become a central theme in the literature on NCSs.

Beyond delays, the reliance on open communication infrastructures exposes networked systems to malicious threats such as denial-of-service, replay, and false-data injection attacks. Security-oriented control seeks to integrate detection, estimation, and mitigation into feedback loops to defend against adversaries capable of manipulating communication channels or altering system dynamics (X.-M. Zhang et al., 2020). Historical incidents, including the Slammer worm at the Davis–Besse power plant, the Maroochy Shire sewage spill, and the Stuxnet attack, highlight the potentially severe consequences of such vulnerabilities. In response, a variety of countermeasures have been developed, ranging from resilient state observers, secure consensus protocols, and coding-based defences to game-theoretic approaches. More recently, adaptive schemes that incorporate data-driven methods have been proposed to counter evolving attack strategies. For instance, game-theoretic adversarial learning frameworks, such as dual-discriminator generative adversarial networks

(GANs), have been developed to significantly improve anomaly detection capabilities against complex threats (Ding et al., 2025), thereby enhancing system resilience (He et al., 2026).

Alongside time delays and cyberattacks, event-triggered control has received increasing attention over the past decade as a means of reducing bandwidth consumption and alleviating communication burdens. Unlike periodic sampling, event-triggered strategies update control signals only when predefined conditions are violated (G. Zhao et al., 2025). This mechanism conserves resources and mitigates congestion, particularly in large-scale or resource-constrained networks. However, careful design is required to prevent Zeno behaviour, where infinitely many events occur within finite time. Dynamic event-triggered mechanisms (DETMs) address this issue by allowing thresholds to adapt to system states, estimation errors, or network conditions. Compared with static rules, DETMs reduce redundant transmissions while maintaining stability and performance. Recent studies have established theoretical guarantees based on Lyapunov analysis, input-to-state stability, and stochastic frameworks, while extensions to multiagent systems demonstrate that adaptive thresholds can alleviate inter-agent communication overload (Xiao et al., 2022).

In addition to delays, attacks, and event-triggered strategies, networked control systems are further challenged by packet dropouts, quantization, and sampling effects (H. Li et al., 2025). Packet losses, which may occur sporadically or in bursts due to congestion, interference, or routeing errors, can degrade observability and threaten stability when persistent. Quantization restricts continuous signals to finite resolution, and although logarithmic and dynamic quantization schemes can reduce information loss, residual errors may propagate through feedback loops and compromise control performance (Doostmohammadian et al., 2025). The choice of sampling interval also has a direct impact on both accuracy and communication load. Shorter intervals improve precision but intensify network usage, whereas longer intervals alleviate network demands at the expense of transient performance (Hetel et al., 2017). Since these imperfections often interact with each other, their combined influence shapes the performance limits of distributed systems and highlights the need for integrated analysis and design methodologies.

3. Overview of game theory

This section introduces the fundamental principles of game theory. It begins by defining basic game models and equilibrium concepts, followed by a brief review of their historical development and key engineering applications. Finally, it discusses the main classifications of game theory and their roles in addressing theoretical challenges in networked systems.

3.1. Game theory concepts

For clarity and consistency, the key notation used throughout Sections 3 and 4 is summarized in Table 1.

Game theory is a branch of mathematics that studies strategic interactions among decision makers whose actions mutually affect outcomes. It provides a formal framework to represent and analyse decision problems in which agents select actions either simultaneously or sequentially. Objectives are expressed by payoff functions that assign real valued outcomes to strategy profiles.

A game in normal form is commonly represented by the triplet

$$G = \langle N, \{S_i\}_{i \in N}, \{u_i\}_{i \in N} \rangle \tag{1}$$

where $N = \{1, 2, \dots, n\}$ is the set of players, S_i denotes the set of strategies available to player i, and $u_i \colon S \to \mathbb{R}$ is the payoff function that maps a strategy profile $s = (s_1, \dots, s_n)$ to a real number for player i. The joint strategy space is $S = \prod_{i \in N} S_i$.

A strategy may be pure or mixed. When players employ mixed strategies $\sigma_i \in \Delta(S_i)$ for $i \in N$, the expected payoff of player i is

$$U_i(\sigma_1, \dots, \sigma_n) = \sum_{s \in S} \left(\prod_{j \in N} \sigma_j(s_j) \right) u_i(s) \tag{2}$$

The best response correspondence for player i is

$$\mathrm{BR}_i(\sigma_{-i}) = \arg \max_{\sigma_i \in \Delta(S_i)} U_i(\sigma_i, \sigma_{-i}) \tag{3}$$

Table 1. Summary of notation for game models and system parameters.

Symbol	Definition
N	Set of players, $N = \{1, \dots, n\}$
$\mathcal{S}_i$	Strategy (action) set of player i
s_i	Pure strategy of player i
S	Joint strategy space, $S = \prod_{i \in N} S_i$
$\Delta(S_i)$	Probability distributions over S_i
σ_i	Mixed strategy of player i
σ_{-i}	Mixed strategies of all other players
$u_i(\cdot)$	One-shot payoff function of player i
$U_i(\cdot)$	Expected payoff (utility) of player i
$\mathrm{BR}_i(\cdot)$	Best response correspondence
G	Normal-form game $\langle N, \{S_i\}, \{u_i\} \rangle$
T_i	Type set of player i (Bayesian game)
p	Common prior distribution over types
G^B	Bayesian game $\langle N, \{S_i\}, \{T_i\}, p, \{u_i\} \rangle$
$v(S)$	Value of coalition S
G^C	Coalition game $\langle N, v \rangle$
x_i	Payoff allocated to player i
$\phi_i(v)$	Shapley value of player i
Θ	Set of attacker types
Π	Set of admissible defence/control policies
p_i	Transmit power of user i
p_{-i}	Transmit powers of all users except i
R_i	Achievable data rate of user i
I_i	Interference experienced by user i
$C_i(\cdot)$	Cost of user i
α_i	Offloading ratio of user i
B_i	Allocated bandwidth for user i
λ	Price or reward parameter (leader)
U_{ES}	Utility of the edge server
s_L, s_F	Strategies of leader and follower
E_i	Residual energy of node i
$E_{\max}$	Maximum initial energy
$\mathcal{N}_i$	Neighbour set of node i
d_{ij}	Distance from node i to node j
$\mathbf{1}\{\cdot\}$	Indicator function
$H(S), L(S), B(S)$	Cache hit rate, latency, backhaul cost
L_i, Φ_i	Running and terminal cost
f_i	Dynamics of agent i
V_i	Value function of agent i
$\mathbf{u}_i[k : k + H]$	Control sequence over prediction horizon

A mixed strategy profile σ^* is a Nash equilibrium (NE) if

$$U_i(\sigma_i^*, \sigma_{-i}^*) \geq U_i(\sigma_i, \sigma_{-i}^*), \quad \forall\, \sigma_i \in \Delta(S_i), \quad \forall\, i \in N \tag{4}$$

The NE represents a stable state where no player can improve their utility by unilaterally deviating from their chosen strategy. However, Nash equilibrium is not always efficient or behaviourally plausible in non-cooperative networked systems, especially when multiple equilibria exist or agents are unable to coordinate. Alternative solution concepts have therefore been proposed. A correlated equilibrium (CE) allows players to condition their actions on common signals drawn from a joint distribution and requires that no player can gain by deviating from the recommended action. This concept naturally models coordination via broadcast messages or signalling devices in communication and control networks. In population-type models, evolutionarily stable strategies (ESS) formalize the idea that a strategy profile cannot be invaded by a small fraction of mutants under evolutionary dynamics, which is particularly relevant for large-scale IoT or vehicular systems where agent behaviour adapts through imitation, learning, or protocol updates. These generalized equilibrium concepts can be more appropriate than Nash equilibrium for analyzing efficiency, robustness, and long-run behaviour in networked systems with correlated decisions or bounded rationality.

3.2. Historical development and engineering applications

Since its inception, game theory has evolved from a purely mathematical discipline to a core analytical tool for solving complex engineering problems. Although its theoretical foundations were laid by von Neumann (1928) and Nash (1950), its modern impact is reflected in widespread engineering applications across communication networks, cyber–physical systems, energy systems, and intelligent multiagent platforms.

Early engineering adoption of game theory was mainly driven by problems of resource competition and conflict resolution in operations research and communication systems. As wireless and packet-switched networks began to scale in size and heterogeneity, centralized optimization became increasingly impractical, creating strong demand for distributed and incentive-compatible decision mechanisms. Game-theoretic models naturally filled this gap by enabling autonomous agents to optimize locally while implicitly coordinating through equilibrium constraints.

In wireless networks, game theory enables distributed resource allocation among users competing for spectrum, power and bandwidth (Jia et al., 2025; Qi et al., 2025). Typical applications include power control in interference-limited networks, spectrum sharing in cognitive radio, and pricing-based bandwidth allocation in access networks. By formulating these problems as non-cooperative or hierarchical games, network entities can adapt their strategies autonomously while the system converges toward an equilibrium with acceptable efficiency and fairness.

As systems become more interconnected and exposed to adversarial threats, game-theoretic analysis has been widely adopted in the domain of cyber security (H. Liu et al., 2025; Shao, Kai, et al., 2026). Attack–defence interactions are naturally modelled as zero-sum, Bayesian, or Stackelberg games, supporting the design of adaptive intrusion detection, moving target defence, and resilient control strategies. In such settings, defenders must allocate limited protection resources under uncertainty regarding attacker types, capabilities, and objectives.

Beyond communication and security, game theory has also been extensively applied in energy systems and smart grids, where distributed energy resources, prosumers, and system operators interact strategically under physical and economic constraints. Competitive electricity trading, demand response, and energy sharing among microgrids are commonly modelled as non-cooperative or cooperative games to balance grid stability and economic efficiency.

The scope of game-theoretic analysis further extends into the physical world of multiagent and cyber–physical systems, such as autonomous vehicle fleets and drone swarms (W. Hu et al., 2025; Y. Jiang & Li, 2024). In these systems, game theory is used to coordinate motion planning, task allocation, collision avoidance, and cooperative perception among multiple intelligent agents. Both cooperative and non-cooperative formulations are employed depending on whether agents pursue shared system-level objectives or individual performance goals.

With the rapid development of artificial intelligence and data-driven control, classical static game models have been increasingly integrated with learning mechanisms. The combination of game theory with multi-agent reinforcement learning (MARL) allows agents to learn equilibrium or near-equilibrium strategies through repeated interaction in non-stationary and partially observed environments (Yan et al., 2023). Beyond communication and computing systems, the integration of game theory with reinforcement learning has also been systematically investigated in large-scale urban energy systems. The review in L. Cheng et al. (2025) provides a comprehensive synthesis of computational game-theoretic models combined with advanced learning algorithms for adaptive energy management, demand response, and distributed resource coordination. These studies demonstrate how learning-enhanced game-theoretic frameworks enable real-time adaptation to stochastic renewable generation, time-varying loads, and incomplete information, which closely parallels the challenges encountered in networked systems considered in this paper. This integration is particularly important in highly dynamic networked systems where analytical equilibrium computation is infeasible. By integrating reinforcement learning with game-theoretic structures, agents can continuously update their strategies based on real-time observations without relying on accurate a priori models of the environment or opponents. This endows game-theoretic decision making with strong adaptability to dynamic conditions such as time-varying wireless channels, task arrivals in mobile edge computing, and evolving attack patterns in cyber–physical systems. From an efficiency perspective, learning-enabled game-theoretic frameworks avoid repeated centralized equilibrium computation and significantly reduce signalling overhead by relying on local observations and sampled rewards. Moreover, the centralized-training–decentralized-execution paradigm in MARL enables fast convergence while preserving scalability. As a result, the integration of game theory with machine learning and reinforcement learning improves both adaptability and overall system efficiency in dynamic networked environments.

For massive systems such as IoT and urban traffic networks, mean field game theory provides a population-level abstraction linking individual optimization with aggregate dynamics (B. Liu et al., 2025). By replacing high-dimensional multi-agent coupling with low-dimensional population statistics, mean field models offer a scalable analytical framework for characterizing the collective behaviour of a large number of interacting agents.

Overall, the engineering evolution of game theory reflects a clear transition from static, small-scale optimization toward data-driven, large-scale, and adaptive strategic decision frameworks. Modern applications increasingly emphasize scalability, robustness to uncertainty, and compatibility with learning-based control, which also motivates the growing integration of game-theoretic methods with reinforcement learning and distributed optimization techniques.

3.3. Game theory classifications

Game theory models are commonly classified along three principal axes: information structure, temporal sequence of moves, and degree of cooperation (Selim & Zhao, 2026). These axes are not mutually exclusive in practice and often coexist in networked systems, where agents face incomplete information, dynamic interactions, and decentralized decision making simultaneously.

In practical networked systems, players often operate under bounded rationality and incomplete information. Agents typically rely on noisy measurements, delayed feedback, and heuristic update rules. Such limitations may distort equilibrium outcomes, slow down convergence, or even lead to persistent performance oscillations in terms of throughput, latency, or energy efficiency. As a result, equilibrium predictions derived under perfect rationality and complete information assumptions may become biased or even unattainable in realistic networked environments.

3.3.1. Information structure

A primary distinction concerns complete and incomplete information. While complete information games assume transparent utilities, incomplete information games admit private types (e.g. unknown channel states or security levels). The Bayesian game framework formalizes this uncertainty (Barkatsa et al., 2024; Selim & Zhao, 2026):

$$G^B = \langle N, \{S_i\}_{i\in N}, \{T_i\}_{i\in N}, p, \{u_i\}_{i\in N}\rangle \tag{5}$$

Here, Bayesian Nash equilibrium is defined via belief-conditioned optimization, addressing the challenge of asymmetric information. In networked systems, mis-specified beliefs or delayed belief updates may lead to overly conservative or overly aggressive strategies, thereby degrading system-level efficiency and robustness.

3.3.2. Temporal sequence

Games may be static or dynamic. Dynamic games model sequential decisions and admit refinements such as subgame perfect equilibrium. In the context of network topology analysis, such sequential game structures have been successfully employed to detect significant communities by modelling node positioning as strategic moves (Y. Wang et al., 2024). Repeated games form a practically important subclass capturing long-term incentives, reputation, and sustainable cooperation, which are critical for stable network operation. Such temporal structures naturally arise in spectrum sharing, congestion control, and cybersecurity, where agents interact repeatedly over extended time horizons.

3.3.3. Cooperation

Non-cooperative games rely on Nash-type stability, whereas cooperative games permit enforceable agreements, represented by

$$G^C = \langle N, v\rangle \tag{6}$$

Solutions such as the Shapley value provide fair payoff allocation methods (Saad et al., 2009; Shapley, 1953), which underpin coalition formation in resource sharing scenarios such as cooperative caching, joint transmission, and collaborative sensing.

3.3.4. Adaptation and large populations

To address bounded rationality where exact best responses are intractable, Evolutionary Game Theory (EGT) describes decentralized adaptation via replicator dynamics (Weibull, 1997). Similarly, Mean Field Games (MFG) approximate interactions in systems with massive populations using statistical physics approaches (Lasry & Lions, 2007), offering scalability for large-scale IoT networks. These frameworks provide complementary mechanisms for capturing bounded rationality at the individual level and aggregate dynamics at the population level, thereby enabling scalable analysis of massive networked systems that are computationally intractable under classical N-player formulations.

4. Game theory in networked systems

Game theory has become a fundamental analytical framework for modelling decision-making in networked systems characterized by constrained resources, decentralized information, and strategic interactions among heterogeneous agents. By explicitly defining players, strategy spaces, and payoff functions, game-theoretic methods enable systematic analysis of equilibrium behaviour, stability properties, and efficiency trade-offs across a wide range of engineering scenarios.

As summarized in Table 2, choosing the appropriate game model requires balancing modelling fidelity with complexity. For instance, while Noncooperative Games offer the simplest implementation for resource competition, they often suffer from the 'Price of Anarchy.' In contrast, Stackelberg models provide higher efficiency for hierarchical systems but impose stricter requirements on information availability. This comparative analysis offers practical guidance for selecting formulations that balance theoretical fidelity with computational tractability.

With the methodological characteristics clarified, Table 3 further focuses on concrete applications across five major research directions: resource allocation, cyber security, topology optimization, coalition formation, and multiagent decision making. Beyond conceptual categorization, this table summarizes representative empirical studies that validate these models using large-scale simulations and hardware testbeds. Together, Tables 2 and 3 establish an integrated perspective linking theoretical models with practical implementations, providing a coherent foundation for the subsequent subsections.

4.1. Game theory for resource allocation and scheduling in networked systems

In vehicle-mounted edge computing and multi-layer offloading systems, game theory has become a widely used framework for coordinating resource interactions among vehicles, edge servers, and the cloud. Its applications can be broadly grouped into three domains: task offloading and bandwidth allocation, spectrum and energy management, and integration with intelligent optimization and learning. Across these domains, game-theoretic formulations provide flexible and economically interpretable mechanisms to address fairness, efficiency, and stability in dynamic network environments.

Game theory facilitates the coordination of resource allocation across the vehicle–edge–cloud hierarchy. A fundamental concept is the Nash equilibrium, where no participant can improve its utility by unilateral deviation. Formally, if the strategy profile is denoted as $\sigma^* = (\sigma_1^*, \ldots, \sigma_n^*)$, then for each player i,

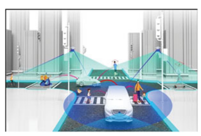
$$U_i(\sigma_i^*, \sigma_{-i}^*) \geq U_i(\sigma_i, \sigma_{-i}^*), \quad \forall\, \sigma_i \in \Sigma_i \tag{7}$$

where $U_i(\cdot)$ denotes the expected utility of player i under the mixed strategy profile and Σ_i is its feasible strategy set (typically $\Sigma_i = \Delta(S_i)$). Stackelberg and Cooperative game, in particular, have been employed to achieve hierarchical optimization and fair distribution of tasks and bandwidth. For example, J. Liu et al. (2022) proposed cooperative and noncooperative pricing games for multi-mode offloading, achieving fair allocation of tasks and bandwidth through Nash equilibrium and matching mechanisms under dynamic network conditions, while Xiong et al. (2019) extended such models to cross-organizational scenarios by introducing intermediary entities that coordinate incentives between users and operators.

Table 2. Comparative analysis of representative game-theoretic models in networked systems.

Game model	Refs.	Model description	Advantages	Limitations
Noncooperative game	Z. Sun et al. (2021) and N. Liu et al. (2024)	Models resource competition among agents (e.g. vehicles, edge nodes), where each player maximizes its individual utility under interference, bandwidth or QoS constraints.	Simple and widely applicable; directly captures selfish optimization; forms the basis of many distributed resource allocation schemes.	Equilibrium may be inefficient (price of anarchy); sensitive to incomplete information; joint strategy space grows quickly with the number of agents.
Stackelberg game	J. Liu et al. (2022), Xiong et al. (2019) and H. Zhao et al. (2024)	Hierarchical decision-making between leaders (e.g. edge servers, BSs) and followers (users, vehicles); leaders set prices or incentives and followers react optimally.	High efficiency in hierarchical systems; enables incentive alignment and flexible pricing; suitable for offloading, federated learning and network management.	Requires accurate leader–follower modelling and signalling; convergence may be slow in large-scale networks; performance degrades under model mismatch or delays.
Potential game	Rahman et al. (2022) and Glover et al. (2025)	Introduces a global potential function whose variation is aligned with each player's unilateral payoff change, enabling distributed learning to converge to an equilibrium.	Provides strong convergence guarantees for decentralized algorithms; scalable to large networks; robust to asynchronous and myopic updates.	Constructing an appropriate potential function can be non-trivial; may oversimplify complex inter-agent couplings in heterogeneous systems.
Bayesian game	N. Liu et al. (2024) and L. Zhang et al. (2022)	Models decision-making under incomplete information, where agents hold and update beliefs about unknown types (e.g. attacker capability, channel state).	Explicitly captures asymmetric information and uncertainty; supports belief-dependent strategies; well suited to security, intrusion detection and privacy-aware control.	Performance depends heavily on prior and belief accuracy; belief update and inference incur extra computation and communication overhead.
Zero-sum game	Huertas Celdrán et al. (2024) and Q. Yang et al. (2025)	Describes strictly competitive attacker–defender or two-player interactions, where one side's gain equals the other's loss; widely used for robust security design.	Provides strong robustness against worst-case attacks; yields clear min–max optimization criteria for defence.	Assumes perfect rationality and purely antagonistic objectives; may lead to overly conservative strategies and does not exploit potential cooperation.
Dynamic / differential game	J. Hu et al. (2025), Yuan et al. (2022) and M. Wang et al. (2021)	Captures time-coupled interactions among agents via system dynamics, often in continuous time; used for formation control, autonomous driving and cyber–physical coordination.	Can provide formal optimality and stability guarantees; naturally incorporates dynamics, constraints and multi-stage decision-making.	Solving coupled dynamic programs or HJB equations is computationally demanding; scalability is limited for large populations or long horizons.
Cooperative game	Fu et al. (2025), J. Chen et al. (2020) and K. Yu et al. (2025)	Agents form coalitions to share resources (e.g. caching, sensing, energy) and jointly optimize coalition utilities with specific payoff allocation rules.	Enhances social welfare and fairness; naturally models collaboration; effective for cooperative caching, energy trading and multi-UAV cooperation.	Requires negotiation and intra-coalition communication; coalition stability is difficult to guarantee; overhead grows quickly with network size.
Mean field game	B. Liu et al. (2025) and L. Cheng et al. (2025)	Approximates interactions in large populations using statistical effects; each agent optimizes its policy against the mean-field distribution of the others.	Excellent scalability; equilibrium complexity is essentially independent of agent number; averaging mitigates local randomness and stochastic fluctuations.	Accuracy depends on mean-field approximation; local pairwise interactions may be neglected; less suitable for small or highly structured networks.

Table 3. Representative empirical and numerical research examples of game-theoretic applications in networked systems.

Application Areas		Focuses	Refs.
Resource allocation and scheduling		• Efficient bandwidth allocation and task scheduling • Load balancing in cloud–edge–end systems • Energy-aware and game-theoretic distributed optimization	E. Wu and Peng (2024), Antonius (2024)
Cyber security and defence		• Attack–defence modelling and intrusion detection • Blockchain security: consensus, incentives, Sybil-resistance • Adaptive defence via evolutionary and Stackelberg game	Shao, Ji, et al. (2025), Zheng et al. (2025)
Network topology and routeing optimization		• Routeing and congestion control under multi-user competition • Self-organizing topology for energy efficiency and robustness • RL-enhanced routeing and QoS-aware optimization	Hausken and Zhuang (2018), Shen et al. (2021)
Collaboration and alliance formation		• Resource sharing and cooperative transmission • Stable coalition structures and incentive allocation • Collaborative sensing and distributed multi-task coordination	J. Chen et al. (2020), K. Yu et al. (2025)
Multiagent system decision making		• UAV formation and cooperative task allocation • Autonomous driving: interactive decision-making and safety • Multi-robot cooperation via evolutionary games and RL	M. Li et al. (2025), Z. Jiang et al. (2025)

A typical Stackelberg game formulation can be written as

$$s_F^*(s_L) = \arg\max_{s_F \in S_F} U_F(s_L, s_F) \tag{8}$$

$$\max_{s_L \in S_L} U_L(s_L, s_F^*(s_L)) \tag{9}$$

where $s_L \in S_L$ and $s_F \in S_F$ are the strategies of the leader and the follower, respectively, and $U_L(\cdot)$ and $U_F(\cdot)$ denote their utilities. The leader (e.g. an edge server) first sets s_L (such as a resource price), and the follower (e.g. vehicles) reacts with its optimal response $s_F^*(s_L)$. Game theory has been widely applied in vehicular networks to address resource competition, QoS, and security challenges in dynamic ITS environments (Z. Sun et al., 2021). Recent studies further show that coupling Stackelberg formulations with learning algorithms enhances scalability; for instance, J. Liu, Zhang et al. (2024) proposed a reinforcement learning based decentralized control framework for interconnected systems, combining game-theoretic resource allocation with learning-based adaptation to handle communication and control constraints.

Game-theoretic mechanisms have also been extended to federated learning and incentive design. In hierarchical federated learning frameworks, a two-layer Stackelberg game can be formulated in which the edge server or base station (BS) sets bandwidth prices or total rewards, while clients strategically decide their participation level and local iterations to maximize individual utilities. H. Zhao et al. (2024) investigated incentive mechanisms in federated wireless learning by modelling the interaction between a base station (BS) and mobile devices (MDs) as a Stackelberg game, where the BS determines the total reward allocation and each MD selects its local iterations to maximize its utility. They further incorporated evolutionary game theory into NOMA-based distributed federated learning, improving the robustness of the incentive mechanism under node heterogeneity and time-varying channel conditions. In this context, evolutionary stability is characterized by a strategy x^* satisfying

$$U(x^*, x^*) \geq U(x, x^*), \quad \forall\, x \neq x^* \tag{10}$$

indicating that x^* is resistant to unilateral deviations and remains stable against small perturbations. Compared with static Nash equilibria, evolutionarily stable strategies better capture the long-term outcomes of adaptation and learning in large-scale heterogeneous networks.

In terms of spectrum and energy management, the game model has demonstrated strong explanatory power and scalability. Naseer et al. (2021) proposed a cognitive radio spectrum game based on interference cost, where the payoff of user i can be formulated as

$$U_i(p_i) = R_i(p_i, p_{-i}) - C_i(I_i) \tag{11}$$

where p_i and p_{-i} denote the transmit power of user i and that of the other users, respectively, $R_i(\cdot)$ is the achievable data rate of user i, I_i is the experienced interference, and $C_i(\cdot)$ is the corresponding interference cost. Rahman et al. (2022) introduced potential games, which are characterized by the existence of a potential function Φ such that

$$U_i(s_i, s_{-i}) - U_i(s_i', s_{-i}) = \Phi(s_i, s_{-i}) - \Phi(s_i', s_{-i}) \tag{12}$$

for all players i and all strategy pairs $s_i, s_i' \in S_i$, where s_{-i} denotes the joint strategy of the other players. This structure enables convergence of distributed learning algorithms and balances fairness and throughput in WiFi–cellular coexistence. At the same time, cooperation and alliance games have also been explored for energy-aware clustering and routeing optimization (Alsheikh et al., 2017; Vivek Kumar & Saraniya, 2024). Overall, these methods effectively deal with the conflict between QoS, energy efficiency and fairness, but may lack robustness in highly dynamic environments or with irrational participants.

In terms of the integration of game theory and intelligent optimization methods, researchers have tried to combine game models with learning algorithms to improve adaptability and efficiency. Pricing-based Stackelberg offloading models often define the cost of a vehicle i as

$$C_i(\alpha_i, \lambda) = \alpha_i D_i T_i + (1 - \alpha_i)E_i + \lambda B_i \tag{13}$$

where $\alpha_i \in [0, 1]$ is the offloading ratio of user i, D_i and T_i denote the task size and delay, E_i is the local computation energy consumption, B_i is the bandwidth allocated to user i, and λ is the unit price announced by the edge server. The edge server, in turn, maximizes its profit by optimizing the pricing parameter λ:

$$U_{\mathrm{ES}}(\lambda, \alpha) = \sum_i \lambda B_i - C_{\mathrm{ES}}(\alpha) \tag{14}$$

where $U_{\mathrm{ES}}(\cdot)$ is the utility of the edge server, $\alpha = (\alpha_1, \ldots, \alpha_n)$ collects all users' offloading ratios, and $C_{\mathrm{ES}}(\alpha)$ denotes its operational cost associated with processing the offloaded tasks. Keshta et al. (2024) combined game-driven and particle swarm optimization to achieve low latency and fairness in task offloading in distributed IoT. Antonius (2024) proposed a CNN–game hybrid model to assist 5G/6G bandwidth allocation. Maldonado-Carrascosa et al. (2024) employed a game–PSO hybrid strategy to optimize virtual machine migration. Reported numerical simulations in these studies consistently demonstrate significant reductions in task latency and energy consumption compared with conventional non-game-theoretic baselines, confirming the effectiveness of the proposed frameworks in realistic edge computing environments. Overall, such hybrid approaches can alleviate convergence issues and improve performance, but they also introduce additional model complexity and parameter tuning challenges for large-scale deployments.

4.2. Game theory for cyber security and defence in networked systems

Existing literature has systematically examined the application of attacker–defender games in network security, highlighting extensions from single-agent to multi-attacker and multi-defender settings, and addressing strategy design under incomplete information. A canonical formulation of such attacker-defender interactions can be expressed as a zero-sum game:

$$\min_{d \in D} \max_{a \in A} U(a, d) \tag{15}$$

where $a \in A$ and $d \in D$ denote the strategies of the attacker and defender, respectively, and $U(a, d)$ represents the utility function. This model captures the strictly antagonistic nature of cyber conflicts. While zero-sum game formulations provide theoretical guidance for defence strategy design, practical implementation requires careful consideration of computational complexity and adaptability in dynamic environments. For example, Huertas Celdrán et al. (2024) proposed a Moving Target Defence (MTD) framework for heterogeneous zero-day attacks on single-board computers. By characterizing device states through behavioural fingerprinting and employing reinforcement learning to adaptively select among multiple MTD techniques, their method was validated on a Raspberry Pi platform infected with diverse malware samples. Results demonstrated effective mitigation of attacks while maintaining low resource consumption. However, the zero-sum assumption presumes fully rational participants, which may limit robustness in scenarios with incomplete information or dynamic attack behaviour. Similarly, J. Liu, Dong, et al. (2024) investigated reinforcement learning-based tracking control for networked control systems under denial-of-service attacks, illustrating the benefits of integrating learning-based approaches with game-theoretic defence strategies (J. Liu, Liu, et al., 2024).

For advanced persistent threats (APTs), L. Zhang et al. (2022) developed a multistage dynamic game framework modelling the interactions between attackers and defenders. The defender seeks to maximize the expected cumulative utility over the defence horizon, considering the system state s_t, attack action a_t, and defence action d_t at each stage:

$$\pi^* = \arg\max_{\pi \in \Pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t U(s_t, a_t, d_t)\right] \tag{16}$$

where π denotes the defender's policy, $\gamma \in (0, 1]$ is the discount factor, and $U(s_t, a_t, d_t)$ is the stage-wise utility function. Here Π denotes the set of admissible defence policies. This framework captures the concealment and diversity characteristics of APTs, allowing dynamic adjustment of defence strategies to enhance effectiveness. The study demonstrates that well-designed strategies can substantially reduce the probability of successful attacks, though the computational cost and information requirements remain significant practical constraints. In the context of network disruption and reachability analysis, Zheng et al. (2025) reformulated the destruction game as a reachability problem to evaluate attacker and defender strategies in dynamic networks. This approach facilitates security evaluation in large-scale networks but depends on accurate knowledge of network topology and node states. Additionally, J. Liu, Gong, et al. (2024) proposed an interval type-2 fuzzy-model-based filtering method under event-triggered weighted try-once-discard protocols and cyberattacks, complementing attacker-defender formulations by providing robust estimation under adversarial conditions (X. Sun et al., 2024).

Addressing botnet threats, researchers in Q. Yang et al. (2025) introduced a defence model based on sequential games, modelling the interaction as a multi-stage decision-making process. Results indicate that appropriate combinations of defence strategies can mitigate botnet impact while maintaining network functionality, although the complexity of the solution poses challenges for real-time defence in large-scale systems. Extending this approach, J. Liu et al. (2025) studied stabilization of uncertain parabolic PDE systems under weighted try-once-discard protocols with actuator failures, illustrating integration of security-oriented control design into game-theoretic frameworks.

In wireless sensor network intrusion detection, N. Liu et al. (2024) proposed a Bayesian game-based model combined with parallel particle swarm optimization to compute Nash equilibria. The posterior belief update of attacker types follows Bayes' rule:

$$\mu(\theta \mid h) = \frac{P(h \mid \theta)\mu(\theta)}{\sum_{\theta' \in \Theta} P(h \mid \theta')\mu(\theta')} \tag{17}$$

where θ denotes the attacker's type, h is the observed history, and $\mu(\theta)$ is the prior belief, while Θ denotes the set of possible attacker types. This approach improves detection efficiency and accuracy, although computational overhead may increase for large networks or frequently changing topologies.

The security challenges in the 6G network environment have attracted significant research attention. Several studies employ game-theoretic frameworks to analyze communication security issues in IoT environments and to design defence strategies that deter potential attackers while optimizing resource allocation. Nevertheless, in highly dynamic networks with massive numbers of nodes, achieving real-time performance and scalability remains a critical challenge. For intrusion detection in embedded systems, Shao, Kai, et al. (2026)

proposed an active defence model based on an attack-defence game, integrating defence strategies into system design to enhance attack detection and response capabilities. This model highlights the trade-off between strategy selection and system security; however, in complex scenarios, static strategies may be insufficient to address unforeseen threats. In the context of formation control under cyberattacks, Zha et al. (2025) developed a neural predictor-based approach for unmanned surface vehicles subject to aperiodic DoS attacks, formulating the problem as a noncooperative game and demonstrating improved resilience to communication disruptions.

A common pattern in these studies is the use of cooperative game models, noncooperative game models, Stackelberg games, and evolutionary games. Each framework provides distinct advantages for the design of security policies, ranging from promoting collaboration to ensuring long-term stability and fairness (W. Cheng et al., 2025). However, practical deployment is often limited by assumptions of rationality, the integrity of available information, computational complexity, and convergence or robustness issues in highly dynamic or large-scale networks. These observations underscore the continued need for low-overhead, adaptive, and intelligent game-theoretic mechanisms capable of supporting resilient network security in heterogeneous and rapidly evolving networked systems (Y. Wang, Zhang, et al., 2025).

4.3. Game theory for network topology and routeing optimization in networked systems

Game-theoretic approaches have been widely applied in diverse networked systems, including wireless sensor networks (WSNs), IoT networks, delay-tolerant networks, satellite systems, and connected and autonomous vehicles. These methods are primarily employed to address challenges in resource allocation, routeing, congestion control, and multiagent coordination. Noncooperative and cooperative games are commonly used to model competitive and collaborative interactions, while hierarchical and layered frameworks support multi-level coordination. The incorporation of learning and optimization mechanisms further enhances system adaptability in dynamic environments. Despite their effectiveness, game-theoretic methods face challenges such as high computational complexity, dependence on strong rationality and complete information assumptions, and limited convergence speed, which constrain their applicability in large-scale, real-time, and resource-constrained systems.

Several representative studies demonstrate the versatility of these methods across domains. In WSNs, Yao et al. (2022) proposed a multi-hop routeing protocol that integrates clustering games with coverage optimization. The network utility for a cluster-based routeing strategy can be expressed as

$$U_i = \alpha \frac{E_i}{E_{\max}} - \beta \sum_{j \in \mathcal{N}_i} d_{ij} \tag{18}$$

where E_i is the residual energy of node i, $E_{\max}$ is the maximum initial energy used for normalization, d_{ij} is the distance from node i to its neighbour $j \in \mathcal{N}_i$, and α, β are weighting coefficients balancing energy efficiency and coverage. By employing a penalty function to ensure uniform cluster-head distribution and using residual energy with node degree for path selection, their method significantly improved network lifetime, albeit at the expense of computational and communication overhead in dense or highly dynamic networks.

For IoT congestion control, Mishra et al. (2019) modelled the network as a congestion game, where the utility for node i selecting route r_i is

$$U_i(r_i, r_{-i}) = \frac{C_{r_i}}{1 + \sum_{j \neq i} \mathbf{1}\{r_j = r_i\}} - \gamma D_{r_i} \tag{19}$$

with C_{r_i} denoting available capacity, D_{r_i} the delay along route r_i, and γ a weighting factor. $\mathbf{1}\{r_j = r_i\}$ is the indicator function, which equals 1 if node j selects route r_i and 0 otherwise. This framework enforces strict delay constraints while improving throughput and latency. Hausken and Zhuang (2018) further extended this approach to multi-criteria traffic management, incorporating congestion, security, and flow dynamics into the payoff functions.

Game-theoretic models have also been adopted to optimize self-organizing coverage and routeing. As formalized in Equation (12), Glover et al. (2025) model the topology control as a stochastic potential game. Here, the potential function Φ represents the global network coverage metric, aligning individual node incentives with system-wide connectivity. where s_i and s_i' are alternative strategies of node i and s_{-i} denotes the strategy profile of all other nodes. This structure enables convergence to efficient network configurations. Similarly, Peng et al. (2023) applied a self-organizing game model to satellite-based spatial target tracking, allowing satellites to strategically coordinate sensing and communication, enhancing tracking accuracy while minimizing energy consumption. In vehicular networks, Shen et al. (2021) integrated machine learning with game-theoretic routeing, where vehicle utility functions are dynamically updated based on both local and neighbouring traffic conditions, improving overall performance under highly dynamic environments.

In summary, these works collectively illustrate that game-theoretic frameworks provide powerful tools for distributed, dynamic, and heterogeneous networked systems. The key research frontier lies in developing low-overhead, robust, and scalable game-theoretic mechanisms that can accommodate resource constraints, ensure privacy preservation, and support collaborative intelligent systems.

4.4. Game theory for collaboration and alliance formation in networked systems

Coalition game theory provides a natural framework for modelling collaboration, alliance formation, and cooperative resource sharing in networked systems. Typical application domains include cooperative caching, collaborative sensing, UAV cluster formation, vehicular cooperative perception, and energy trading, where agents dynamically form and dissolve coalitions to improve both individual and collective utilities.

Coalition game theory has been widely employed to model collaboration, alliance formation, and cooperative resource sharing in networked systems. Fu et al. (2025) developed a regional cooperative decision-making model based on coalition game theory for CAV coordination in mixed on-ramp merging traffic, where dynamically partitioned cooperative regions enable CAV coalitions to optimize efficiency and safety while modelling CAV–CMV interactions as non-cooperative games.

$$v(S) = \alpha H(S) - \beta L(S) - \gamma B(S). \tag{20}$$

For cooperative task allocation in multi-UAV systems, Qin et al. (2026) formulated an overlapping coalition formation game with energy-aware transmit power control, proving it to be an exact potential game and designing a JOCFTPO algorithm that enhances network utility over benchmark schemes. J. Chen et al. (2024) formulated joint optimization of UAV trajectories and CoMP cluster formation. J. Chen et al. (2020) further introduced graph-constrained coalition formation to maintain connectivity.

In vehicular networks and cooperative decision-making, Ji and Levinson (2020) proposed a game-theoretic lane-changing framework that integrates social welfare considerations into individual driver utility. Gong et al. (2024) investigated cooperative motion planning at unsignallized intersections for connected and automated vehicles (CAVs). The proposed decision-making architecture allows vehicles to implicitly form temporary coalitions to resolve conflicts under uncertainty, improving both intersection safety and throughput.

For communication reliability and resource management, Z. Lin et al. (2025) developed an edge-assisted collaborative perception framework to counter jamming and interference. X. Lin et al. (2020) proposed a blockchain-based incentive mechanism for energy-knowledge trading in IoT. K. Yu et al. (2025) developed a distributed hierarchical deep reinforcement learning framework with a two-layer control strategy to optimize semantic-aware QoE. While this formulation is not a coalition game in the strict sense, the hierarchical and distributed control structure induces implicit alliances among cells and users.

Studies show that coalition game models provide an effective framework for resource coordination and cooperative decision-making in networked systems. In wireless communication and edge computing, coalition formation improves caching efficiency and connectivity under bandwidth constraints; in vehicular networks, it enhances cooperative perception and safety through shared sensing; in cognitive radio and energy-limited systems, coalition strategies support spectrum sensing, access, and energy trading. Specifically in smart grids, multiagent-based coalition formation approaches have been introduced to detect prosumer-community groups, facilitating optimized energy management and distributed coordination (Cao et al., 2019). The formalization of coalition values and payoff allocation rules reveals how coalition size, communication overhead and fairness considerations jointly affect system performance. Larger coalitions may yield higher aggregate utility but increase signalling and computation costs, and heterogeneous devices with strict latency or privacy requirements make fair allocation more difficult. Dynamic coalition formation under time-varying topologies, heterogeneous QoS demands, and privacy constraints remains insufficiently understood, and the design of scalable, privacy-preserving coalition mechanisms is still an open research problem for large-scale networked systems.

4.5. Game theory for multiagent system decision making in networked systems

Game theory has been increasingly applied to multiagent systems (MASs), including drone formations, autonomous driving, and industrial multi-robot collaboration. Its strength lies in modelling both cooperative and non-cooperative interactions among agents, enabling the design of distributed control, strategy optimization, and decision-making mechanisms in dynamic and uncertain environments (Y. Wang, Wang, et al., 2025). In particular, cooperative games support alliance formation and collaboration, while non-cooperative and differential games capture competitive dynamics and robustness against disturbances. Hierarchical frameworks and the integration of learning methods, such as deep reinforcement learning and multiagent reinforcement learning (MARL), further enhance adaptability in complex scenarios (Y. Liu et al., 2025). Nevertheless, current game-theoretic approaches still face challenges including high computational complexity, dependence on rationality and complete information assumptions, and limited scalability for real-time applications (Z. Jiang et al., 2025).

A general multiagent decision problem can be formalized as a dynamic non-cooperative game:

$$\begin{aligned} \min_{u_i(t)} \quad & J_i = \int_0^T L_i(x_i(t), u_i(t), x_{-i}(t))\,\mathrm{d}t + \Phi_i(x_i(T)) \\ \text{s.t.} \quad & \dot{x}_i(t) = f_i(x_i(t), u_i(t), x_{-i}(t)), \quad i = 1, \ldots, N \end{aligned} \tag{21}$$

where $x_i(t)$ and $u_i(t)$ denote the state and control of agent i, $x_{-i}(t)$ represents the states of other agents, L_i is the running cost and Φ_i the terminal cost. The dynamics f_i encode agent interactions, including constraints from formation, collision avoidance, or resource sharing.

For differential games, the optimal control satisfies the Hamilton–Jacobi–Bellman equation:

$$0 = \min_{u_i}\{L_i(x_i, u_i, x_{-i}) + \frac{\partial V_i}{\partial x_i} f_i(x_i, u_i, x_{-i})\} \tag{22}$$

where $V_i(x_i, t)$ is the value function for agent i, encoding the optimal cost-to-go under competitive or cooperative interactions (Dey & Xu, 2025).

In distributed multiagent predictive control, agents solve local optimization problems considering neighbours' predicted trajectories:

$$\min_{\mathbf{u}_i[k:k+H]} \sum_{h=0}^{H} L_i\left(x_i[k+h], u_i[k+h], \hat{x}_{-i}[k+h]\right) \tag{23}$$

where H is the prediction horizon, $\hat{x}_{-i}[k+h]$ represents the predicted states of neighbouring agents, and $\mathbf{u}_i[k : k+H] = \{u_i[k], \ldots, u_i[k+H]\}$ denotes the sequence of planned control inputs for agent i over the horizon. Such formulations underpin formation control and collision avoidance in drone swarms (Yuan et al., 2022) and multi-robot task allocation (Qi et al., 2022).

Representative studies demonstrate the applicability of these models. In drone formations, J. Hu et al. (2025) combined non-cooperative and differential games with backstepping control to achieve fault-tolerant formation tracking. Yuan et al. (2022) integrated predictive MPC with distributed game strategies to navigate dynamic environments with interference and obstacles. In autonomous driving, L. Yang et al. (2026) combined game theory with deep reinforcement learning to construct an interactive decision-making framework for autonomous lane-changing, where an LSTM network incorporates temporal dependencies and adaptive preference adjustments ensure safe and efficient manoeuvring in diverse driving environments. Schwarting et al. (2021) formulated stochastic dynamic games in belief space to capture the interactive uncertainty among multiple vehicles, enabling trajectory prediction and planning that balances safety constraints with robust decision-making under partial observability.

In industrial and multi-robot systems, Qi et al. (2022) applied game models for task decomposition and collaboration, while M. Wang et al. (2021) proposed a receding horizon game-theoretic planner for self-driving cars in multivehicle competitive scenarios, where strategic interactions are explicitly modelled to optimize real-time trajectories, ensuring collision avoidance and efficient manoeuvre execution in dense traffic environments. From a broader perspective, recent reviews (Hady et al., 2025) summarize the integration of game theory with MARL, highlighting equilibrium concepts, distributed optimization, and strategic learning. Collectively, these studies illustrate that dynamic and hierarchical game-theoretic mechanisms can guide decision-making in MASs, balancing cooperation, competition, and robustness, while pointing to future challenges in scalability, real-time implementation, and learning-augmented control (Liang et al., 2025).

5. Challenges and future research directions

The integration of game-theoretic modelling into networked systems has established a rigorous framework for analyzing cooperation, competition, and coordination among distributed agents. Despite substantial theoretical progress, the practical deployment of such methods still faces fundamental obstacles. These challenges arise from both theoretical modelling limitations and implementation-level constraints, and they directly motivate the future research directions discussed in the following subsection.

5.1. Challenges

Model-Reality Mismatch in Hierarchical Games: While Stackelberg models effectively capture leader-follower dynamics, they typically assume the leader has perfect knowledge of the followers' utility functions to compute the Backward Induction solution. In practice, obtaining such private information from heterogeneous edge devices is often infeasible due to privacy concerns and signalling overhead, leading to significant performance degradation when the leader's model deviates from reality.

Complexity of Hybrid Learning Frameworks: Although integrating Game Theory with Deep Reinforcement Learning (GT-DRL) addresses dynamic adaptation, it introduces severe computational challenges. The training convergence of multi-agent algorithms (e.g. MADDPG) is often unstable in non-stationary environments, and the inference latency of deep networks may violate the real-time constraints of industrial control loops – a limitation rarely quantified in current simulation-based studies.

Coalition Stability in High-Mobility Networks: In cooperative games, verifying the stability of the core or calculating Shapley values involves combinatorial complexity that grows exponentially with the number of agents. For highly mobile networks like UAV swarms or V2X, the topology changes faster than the coalition structure can stabilize, rendering static coalition formation algorithms ineffective.

5.2. Future research directions

Despite the rapid progress of game-theoretic methods in networked intelligent systems, several fundamental challenges remain unresolved. This subsection discusses representative future research directions with an emphasis on mathematically tractable models, implementable algorithms, and realistic application scenarios.

5.2.1. Game-theoretic learning under incomplete information

Most existing game-theoretic frameworks rely on complete or quasi-complete information, which is difficult to guarantee in large-scale and highly dynamic environments such as massive IoT and UAV swarms (H. Wu et al., 2022). A viable direction is to integrate mean field games with online reinforcement learning, where the aggregate behaviour of the population is represented by an evolving state distribution. The original N-player dynamic game can then be approximated by a pair of coupled Hamilton–Jacobi–Bellman and Fokker–Planck–Kolmogorov equations, enabling scalable equilibrium computation with complexity independent of N. For instance, Hong et al. (2025) utilized this formulation to approximate large-scale interactions in ultra-dense access networks, reducing computational complexity from exponential to linear.

For continuous control and resource allocation problems, multi-agent deep deterministic policy gradient provides a practical learning mechanism. By employing a centralized critic and decentralized actors, the non-stationarity caused by simultaneous policy updates can be effectively mitigated. Future studies may further investigate its convergence properties under partial observability and stochastic channel dynamics (C. Li et al., 2024).

5.2.2. Cross-layer game modelling for 6G-oriented networks

Most existing studies optimize within a single protocol layer, failing to capture the intrinsic coupling among the physical, link, and application layers (Y. Li et al., 2025). Cross-layer game modelling offers a systematic framework for joint optimization in beyond-5G and 6G networks, where Stackelberg game is particularly suitable for hierarchical decision structures.

For instance, in semantic-aware communications, the application layer determines the semantic compression ratio, whereas the physical layer controls the transmit power and block length. This interaction can be formulated as a bi-level Stackelberg game, in which the upper-level leader minimizes the end-to-end semantic distortion subject to latency or Age-of-Information constraints, and the lower-level follower solves a constrained power allocation problem over fading channels. Such a formulation, as demonstrated by Cai et al. (2024) in blockchain-enabled scenarios, leads to tractable equilibrium analysis and admits closed-form solutions.

5.2.3. Data-driven payoff modelling and digital twin assistance

In practical networked systems, the construction of accurate payoff functions is often hindered by incomplete prior knowledge and human-in-the-loop behaviours. Inverse reinforcement learning provides a data-driven approach to infer latent reward structures from observed trajectories, enabling the identification of utility functions without strong a priori assumptions.

In addition, digital twin technology offers a high-fidelity virtual environment for validating game-theoretic strategies before physical deployment. By synchronizing real network states with a virtual replica, digital twin platforms facilitate large-scale evaluation of equilibrium dynamics, learning convergence, and robustness under controllable perturbations. This is particularly valuable for safety-critical systems such as smart grids and autonomous transportation networks.

5.2.4. Stability-aware integration of game theory and control

Classical game-theoretic formulations mainly focus on equilibrium rationality and efficiency, while long-term system stability is not explicitly guaranteed. A critical research direction is the integration of game-theoretic optimization with Lyapunov-based stability analysis. By embedding Lyapunov drift-plus-penalty techniques into dynamic games, both queue stability and strategic utility optimization can be addressed in a unified framework.

Furthermore, differential game models incorporating Lyapunov stability constraints allow the derivation of stabilizing Nash or Stackelberg strategies for networked control and cyber-physical systems. Such hybrid frameworks provide theoretical guarantees on boundedness, convergence, and safety under strategic interactions.

6. Conclusion

This survey has reviewed recent advances in the application of game-theoretic methods to networked systems. We presented the key characteristics of networked systems, summarized the main classes of game-theoretic frameworks, and systematically analyzed their applications in five domains: resource allocation, cyber security, topology optimization, cooperation, and distributed multiagent decision-making. Game theory provides a rigorous foundation for modelling cooperation, competition, and adaptation among heterogeneous agents, and offers effective mechanisms for distributed coordination. Cooperative and evolutionary games are particularly suitable for homogeneous systems with limited rationality, whereas Stackelberg, Bayesian, and auction-based models address the requirements of hierarchical and heterogeneous systems. Nevertheless, critical challenges remain, including scalability to large-scale networks, robustness under uncertainty and adversarial conditions, and practical limitations in communication, computation, and energy. Future research should focus on integrating game-theoretic frameworks with data-driven and learning-based approaches, developing scalable and robust solution concepts, and validating algorithms in realistic, resource-constrained scenarios. Game-theoretic methods are expected to continue playing a central role in the design and optimization of next-generation networked systems.

Author contributions

CRediT: **Meiyan Wang:** Writing – original draft; **Jinliang Liu:** Methodology; **Yan Li:** Writing – review & editing; **Engang Tian:** Writing – review & editing; **Chen Peng:** Visualization

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The authors confirm that no data are used in this paper.

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