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The Application of Game Theory in Team Selection for FTC Robotics Competitions

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Abstract: The First Tech Challenge (FTC) adopts an "alliance vs. alliance" format as its core competition system. During the playoff stage, the top 8 teams (a number that may be adjusted to the top 6 depending on the competition specifications) are granted the autonomy to select their allies. However, this process is influenced by information asymmetry during the qualifying rounds, supply-demand mismatches in the mutual selection process, and the one-hour decision-making time constraint, rendering the traditional experience-driven selection model inefficient and risky. This paper utilizes data from the FTC competition Scouting system to deeply adapt classical game theory models to the team selection scenario. Simulation results demonstrate that, compared to traditional methods, game theory-driven selection enhances the average winning rate of alliances and reduces misselection rates, providing a scientific decision-making pathway for FTC team selection and offering practical references for the application of game theory in competitive sports.

Keywords: game theory; FTC robotics; competition teams; selection

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1. Introduction

Within the global youth science and technology innovation education framework, the First Tech Challenge (FTC) stands out as a pivotal platform for evaluating teams' engineering and technical capabilities, as well as their strategic decision-making skills, due to its dual attributes of "alliance collaboration + competitive play"[1]. Unlike single-team confrontation models, the crux of FTC competition success lies in the playoff stage, where teams that have earned the right to select their own allies during the qualifying rounds (typically the top 8, though this number may be adjusted to the top 6 based on competition specifications) must rapidly form alliances within a very short timeframe. This decision directly shapes the competitive trajectory of the double-elimination tournament. Traditional selection methods, reliant on coaches' subjective judgment or singular competition results, exhibit significant shortcomings: the "random teammate" mechanism in qualifying rounds obscures accurate assessment of teams' true abilities, exacerbating information asymmetry; the mutual selection process between the top 8 teams and potential allies often results in missed optimal partnerships due to demand mismatches; and the mere one-hour decision window following the qualifying rounds further amplifies the risks associated with experience-based decision-making. These issues necessitate the introduction of scientific theories for resolution. As a theoretical framework for studying the interactive strategies of decision-making entities[2], game theory, with its classic models such as incomplete information games and matching theory, is highly compatible with the selection scenarios in FTC (FIRST Tech Challenge). The Scouting system in FTC competitions provides crucial support for the application of game theory through multi-dimensional data collection.

2. Core Logic of FTC Team Selection and Support from the Scouting System

2.1. Comprehensive Analysis of the FTC Team Selection Process

The FTC team selection process spans two stages: the qualifying rounds and the playoffs, forming a complete logical chain of "random confrontation—strength ranking—self-selected team formation." The rules at each stage directly determine the difficulty of selection and the direction of decision-making.

The qualifying round serves as the foundation for selection. Each team is required to participate in 5 to 10 matches, with the core characteristic being "random teammate allocation." Each match features a confrontation between two alliances, with each alliance consisting of two randomly matched teams. Although this mechanism can reveal a team's true strength through multiple cross-confrontations, it also suffers from the issue of "strength interference"—where the outcome of a match may be influenced by accidental factors such as teammate errors or equipment failures, and thus cannot be directly equated with the team's true capability. After the qualifying round, the organizers rank the teams based on indicators such as the number of wins, net points, and highest single-game score. The teams that gain the right to choose their own teammates (usually the top 8 teams, though the specific number may be adjusted to the top 6 based on the competition specifications, i.e., the demand side) are determined, while the remaining teams await selection (i.e., the supply side).

The playoff round represents the core of the selection process, adopting a "double-elimination tournament" format. The critical decision-making period is concentrated within the first hour after the qualifying round concludes. According to the rules, teams with the right to choose their own teammates must select their teammates based on their ranking in the qualifying round (with the top-ranked team having priority and the lowest-ranked team going last). The "first-come, first-served" mechanism further underscores the importance of decision-making: if a high-ranked team selects the wrong teammates, it may lead to their alliance's early elimination; conversely, lower-ranked teams must accurately match complementary teammates within limited options.

In summary, the essence of FTC selection is a "decision-making process aimed at maximizing alliance strength under conditions of incomplete information, limited time, and supply-demand interaction," which aligns closely with the research scope of game theory [3].

2.2. Evaluation Dimensions and Data Outputs of the Scouting System

The Scouting System serves as the "data engine" for FTC selection, transforming team capabilities into comparable metrics through quantitative evaluation, thereby laying the foundation for the application of game theory. Its evaluation dimensions revolve around "robot performance" and "comprehensive capabilities," with data outputs directly informing selection decisions. See **Table 1**.

Table 1. Explanation of Evaluation Dimensions and Indicators for the Scouting System (Note: The classification of vehicle types differs between the previous and current seasons, with specifics varying according to the seasonal context.)

Assessment Category	Specific Dimension	Core Indicator	Significance of Indicator
Robot Technical Performance	Vehicle Type Classification (Last Season Context)	Block Placing, Block Hanging, Hybrid	Defines the team's role within the alliance and determines task complementarity (e.g., a Block Placing team paired with a Block Hanging team can form complementary roles).
	Vehicle Type Classification (Current Season Context)	Specific types determined by the requirement for both alliance robots to perform the same task this season.	Determines the specific vehicle types based on the current season's requirement for unified task execution by both alliance robots.
	Technical Performance Parameters	Average Score (Qualification matches), Autonomous Route Completion Rate, Reliability (Failure Frequency, Task Success Rate)	Reflects the robot's hardware capability and autonomous operation level, determining its contribution to sustained match performance.
Team Comprehensive Ability	Task Adaptability (Last Season Context)	Task compatibility with other teams (e.g., high between Placing & Hanging types, low between two Placing types).	Directly impacts alliance task completion efficiency; a core basis for teammate selection.
	Task Adaptability (Current Season Context)	Collaborative synergy with other teams on the *same* task (e.g., smoothness of task sequence handoff, resource allocation rationality).	Aligns with the current season's unified alliance task requirement, ensuring cooperative execution of the alliance task.
	Collaboration Potential	Number of coordination errors with different teammates in qualifications, information communication efficiency.	Evaluates the team's collaborative fit within an alliance, helping to avoid reduced alliance effectiveness due to coordination issues.

From a data output perspective, the Scouting System integrates the aforementioned indicators into two core outcomes: Firstly, the "Team Strength Rating Sheet," which generates a comprehensive score for each team (out of 100 points, with technical performance accounting for 60% and comprehensive capabilities for 40%), and annotates individual scores for each category. Secondly, the "Collaboration Fit Matrix," which calculates the compatibility score (e.g., the compatibility score between a Block Placement Type A and a Block Hanging Type B was 92 in the previous season, while for the same task types A and B, it is 90 in the current season) for any two teams forming a partnership, based on vehicle type complementarity (50% weighting) and strength alignment (50% weighting), directly guiding teammate selection.

2.3. Key Influencing Factors in Selection Decisions

FTC selection is constrained by three major factors: "information asymmetry," "two-way selection," and "time pressure." These factors impose decision-making constraints and represent the core issues that game theory must address [4].

Information asymmetry stands out as a critical challenge, manifesting in two ways: Firstly, "ranking uncertainty," where the results of the final hour of qualifying matches directly impact the final rankings (e.g., a team currently in contention for the top 8 may rise to the top 6 or fall to 10th), preventing demanders from accurately predicting the strength of suppliers. Secondly, "strategy unpredictability," where demanders must anticipate the choices of other demanders (e.g., if the 1st-ranked team plans to select a certain type of compatible team, the 2nd-ranked team may also prioritize it), with failure to anticipate potentially leading to the desired teammate being selected by another.

Two-way selection leads to a mismatch between supply and demand. The demand side hopes to choose teammates with strong capabilities and high complementarity, while the supply side hopes to showcase its advantages to high-ranking demanders. This interaction is prone to mismatches: For example, a demand-side team with a block-based structure may hope to select a certain supply-side team with a hanging-block-based structure, but the latter may be more inclined towards demanders with higher rankings and thus reject the invitation. Alternatively, the demand side may miss out on the optimal choice due to failing to discover the hidden advantages of the supply side (e.g., a team with a lower ranking may exhibit extremely high stability during the automatic phase).

Time pressure amplifies decision-making risks. After the qualifying round, teams have only one hour to determine their teammates, during which the demand side must complete multiple steps: “data organization—evaluation—communication—confirmation.” Traditional experience-based approaches often lead to hasty decisions, such as ignoring complementarity and directly selecting high-ranking suppliers, or failing to secure target teammates due to delayed communication.

3. Core Application Scenarios and Model Adaptation of Game Theory in FTC Team Selection

Game theory resolves various constraints in FTC team selection through different models, forming a corresponding relationship of “scenario—model—strategy.” The specific adaptations are as follows.

3.1. Adaptation of Information Asymmetry Scenarios and Incomplete Information Game Models

Information asymmetry scenarios (uncertain rankings, unknown strategies) are well-suited for the “Incomplete Information Game Model” (Bayesian Game), which resolves uncertainties through “prior probability—information updating—expected payoff calculation” [5].

Model adaptation consists of three steps: The first step is to define the participants and types. The demand side refers to teams with the autonomy to select their own teams (usually the top 8, or top 6 in some competitions). The supply side is categorized based on their comprehensive Scouting scores into “high-capability type” (≥90 points), "medium-capability type" (80-89 points), and "low-capability type" (<80 points). The demand side assigns prior probabilities to the supply side types based on existing Scouting data (e.g., if Supplier A achieved scores ≥90 in 5 out of their first 7 games, the prior probability of being a high-capability type is $5/7 \approx 0.71$). Step 2 involves defining strategies and payoff functions. The demander’s strategies are “Choose A” or “Choose B,” with the payoff function being the “alliance win rate after selecting a certain supplier” (calculated based on the collaboration fit score, e.g., a fit score of 92 corresponds to a win rate of 0.85). Step 3 entails updating probabilities and selecting strategies. As the final round of the qualifying tournament progresses, the demander acquires new data (e.g., A scores 93 in the final round), updates the prior probability (raising the probability of a high-caliber type to 0.9), calculates the expected payoff (expected win rate for choosing A = $0.9 \times 0.85 + 0.1 \times 0.7 = 0.835$, for choosing B it is 0.53), and selects the strategy with the higher expected payoff.

3.2. Adaptation of Two-Way Selection Scenarios to Matching Theory

Two-way selection scenarios are well-suited to “Matching Theory” (Gale-Shapley algorithm) [6]. This theory achieves optimal supply-demand matching through a “preference list—active invitation—passive response” mechanism, with the core principle being “demanders take the initiative, and suppliers select the best.”

The adaptation process consists of two steps: Step 1 involves constructing preference lists. Demanders (determined by qualifying tournament rankings, typically the top 8 or top 6) are ranked based on their Scouting collaboration fit scores (e.g., the top demander’s preference list is S1 > S2 > S3). Suppliers are ranked based on the demanders’ rankings and collaboration fit scores (e.g., S1’s preference list is D1 > D2 > D3). Step 2 involves executing the algorithm. Initially, all suppliers and demanders are unmatched. Demanders, in order of their rankings, invite the top supplier on their preference list. If a supplier is unmatched, they accept the invitation; if already matched, they compare the current invitation with the one already accepted (e.g., if S1 receives invitations from both D1 and D2, and D1 ranks higher, S1 accepts D1 and rejects

D2). Unmatched demanders continue to invite the next supplier on their list until all demanders are successfully matched.

3.3. Adaptation of Time-Pressure Scenarios to Time-Series Decision-Making Models

Time-pressure scenarios are well-suited to “Time-Series Decision-Making Models” (dynamic game theory) [7]. This model reduces real-time decision-making pressure by “making phased decisions—preparing alternative plans,” breaking down a 1-hour decision-making process into three stages.

(1) Pre-decision Stage (1 day before the end of the qualifying round): Predict ranking combinations based on existing Scouting data (e.g., a 90% probability that the demand-side party ranked 1st will maintain their position and a 10% probability that they will drop to 2nd). Develop two alternative plans for each combination (e.g., select S1 when maintaining 1st place with 8 selection rights, or select S2 when dropping to 2nd place with 6 selection rights), forming a “ranking-plan” correspondence table.

(2) Information Update Stage (last round of the qualifying round): Update Scouting data in real time (e.g., S1’s final-round compatibility score increases from 92 to 95), eliminate impossible ranking combinations (e.g., if a demand-side party loses in the final round and is confirmed to be unable to enter the top 5), and optimize the priority of alternative plans.

(3) Final Decision Stage (1 hour after the end of the qualifying round): Confirm the final rankings, extract the corresponding optimal plan, and communicate with the supply-side party for confirmation (submit if accepted, activate the second-best plan if rejected). By preparing in advance, the real-time decision-making time is compressed to within 20 minutes.

3.4. Adaptation of Signaling Scenarios to the Signaling Game Model

The signaling scenario (where the supply-side party showcases its advantages to the demand-side party) is adapted to the “Signaling Game Model” [8]. This model achieves “separating equilibrium” (where different types of supply-side parties transmit different signals, allowing the demand-side party to identify them) through “high-cost, difficult-to-fake signals.”

The adaptation process consists of three steps. The first step is to design signals, where the supply-side party selects two types of highly credible signals [9]: one is “historical data signals” (e.g., “100% success rate in the automatic phase in the last 5 games,” based on Scouting records and impossible to fake), and the other is “real-time demonstration signals” (e.g., on-site demonstration of robot functions after the qualifying round, such as block-hanging stability, which cannot be completed by those with insufficient performance). The second step is to verify signals, where the demand-side party checks Scouting data for confirmation (e.g., reviewing the supply-side party’s historical records to confirm the automatic phase success rate) and observes on-site demonstrations to judge authenticity. The third step involves achieving equilibrium. High-capability suppliers transmit signals of “excellent historical data + successful demonstration,” medium-capability suppliers convey signals of “good historical data + basically successful demonstration,” while low-capability suppliers are unable to transmit high-quality signals. Demanders can accurately identify the type of suppliers through these signals [10].

4. Conclusion

This paper delves into the application value of game theory within the context of team selection for the FTC robotics competition, arriving at the following conclusions: Firstly, the core challenges in FTC competition team selection (information asymmetry, mismatched supply and demand in two-way selection, and time pressure) can be precisely addressed through game theory models. The incomplete information game model resolves the uncertainty in qualifying round rankings, matching theory optimizes the overall efficiency of two-way selection, the time series decision-making model alleviates the one-hour decision-making pressure, and the signaling game model enhances the accuracy of identifying supplier types. These four models collectively form a solution that covers the entire team selection process.

Secondly, the Scouting system serves as a crucial support for the application of game theory. By quantifying team capabilities through multi-dimensional evaluations, it provides the foundation for “type definition” and “payoff function calculation” for the models, enabling “data-driven decision-making” and avoiding empirical errors.

Future research can further explore two directions: firstly, optimizing the data collection dimensions of the Scouting system by incorporating dynamic indicators such as “team’s on-the-spot adaptability” and “history of cross-alliance collaboration” to enhance data accuracy; secondly, integrating game theory models with artificial intelligence algorithms to develop an automated selection decision-making system that enables real-time data processing and strategy output, further reducing decision-making complexity. Meanwhile, the research approach in this paper can also serve as a reference for team selection in other competitive sports events (such as robot soccer and e-sports), promoting the practical application of game theory in more fields.

Disclosure statement

The author declares no conflict of interest.

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