Balancing Fairness and Efficiency in Decentralized Multi-Agent Systems: A Comparative Study of Priority-Based and Formal Negotiation Protocols

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Abstract. Resource contention is a critical challenge in decentralized multi-agent systems (MAS), where multiple agents compete for limited shared resources. This study evaluates two conflict-resolution strategies within a grid-based maze environment: a deterministic Priority-Based Protocol and a negotiation-driven Alternating Offers (Formal Negotiation) Protocol. The research hypothesizes that the Alternating Offers Protocol will improve fairness and equitable access among agents at the expense of operational efficiency. Simulation results demonstrate that the Alternating Offers Protocol achieves a lower Gini coefficient (0.18) and more balanced per-agent scores, indicating equitable distribution of shared corridors and mitigation of structural bias. Conversely, the Priority-Based Protocol attains higher efficiency (0.88) but produces consistently uneven access favoring high-scoring agents. Analysis of conflict frequency, negotiation outcomes, waiting times, and penalties reveals that structured negotiation reduces repeated conflicts, encourages adaptive behaviors, and fosters system robustness despite increased computational overhead. These findings confirm that negotiation-based approaches effectively balance fairness and efficiency in decentralized MAS. The study also identifies opportunities for future research, including adaptive agent learning, operation under partial observability, and scalability to larger and more complex environments.

Keywords: Multi-agent system, resource contention, negotiation, priority-based, alternating offers

1   Introduction

Resource contention in dynamic multi-agent environments poses a significant challenge in artificial intelligence and distributed systems [1][2]. When multiple autonomous agents attempt to access the same limited resource concurrently, conflicts may arise, reducing system efficiency, fairness, and safety [3][4]. Such scenarios are common in robotic coordination, traffic management, and automated warehouses, where decentralized, real-time decision-making is essential [5][6].

This study investigates decentralized resource contention within a grid-based maze environment in which multiple agents, referred to as Pacmen, navigate to collect

rewards while avoiding hazards (ghosts). Certain pathways in the maze, termed shared corridors, function as critical resources whose simultaneous use can lead to contention [7]. Managing these shared corridors effectively, without centralized control, represents a core challenge in balancing fairness and efficiency [8].

To address this challenge, the research adopts a Multi-Agent System (MAS) framework that enables agents to maintain internal states, perceive the environment, anticipate potential conflicts, and engage in communication or negotiation when necessary [9]. Within this framework, two contrasting strategies for decentralized conflict management are examined. The first, the Priority-Based Protocol, deterministically grants corridor access to higher-scoring agents while imposing minor waiting penalties on others, offering computational efficiency but potentially producing unfair outcomes [10]. The second, the Formal Negotiation Protocol (Alternating Offers), enables agents to exchange structured proposals and counter-proposals, prioritizing fairness but incurring negotiation overhead that may reduce system efficiency [11].

The study hypothesizes that the Formal Negotiation Protocol will produce more equitable access among agents, albeit with reduced operational efficiency compared to the Priority-Based approach. The objective is to quantify these trade-offs, identify emergent behaviors arising from decentralized interactions, and provide a rigorous evaluation framework for negotiation-based conflict resolution in MAS.

2   Related Work

Research on resource allocation within Multi-Agent Systems (MAS) has established the importance of decentralized coordination when agents operate in environments with limited shared resources [12][13]. While centralized methods offer simplicity, they are often constrained by scalability challenges and vulnerability to single-point failures [14]. Decentralized approaches address these limitations by enabling agents to make autonomous decisions, coordinate locally, and adapt to real-time environmental changes, resulting in improved robustness, flexibility, and responsiveness [15][16].

Agent reasoning and decision-making in decentralized systems are commonly supported by goal-based architecture, particularly the Belief-Desire-Intention (BDI) paradigm [17]. In this framework, agents maintain beliefs about their environment, form desires representing objectives, and commit to intentions that guide execution. To operationalize these intentions, agents frequently employ path-planning methods such as Breadth-First Search (BFS) [18], which efficiently computes shortest paths in grid-based environments and enables agents to anticipate potential congestion. By integrating BDI reasoning with BFS planning, agents can proactively detect resource contention, adjust routes, or initiate negotiation when necessary, improving coordination and reducing deadlocks in dynamic settings [19][20].

Conflict resolution in decentralized MAS is often addressed through either deterministic or negotiation-based methods. While deterministic approaches like Priority-Based Protocols offer fast decisions at the cost of fairness for efficiency [21], this study centers on the Alternating Offers Protocol, a negotiation-based strategy in which agents

iteratively exchange proposals, evaluate mutual costs, and refine agreements. By allowing agents to reason about trade-offs and adjust offers over time, Alternating Offers promotes fairness, reduces repeated conflicts, and supports more adaptive coordination in dynamic environments, despite its added communication overhead [22].

Positioned within this body of literature, the present study integrates both deterministic and negotiation-driven strategies within a dynamic maze environment. By comparing Priority-Based and Alternating-Offers Protocols, the research examines how these approaches balance fairness and efficiency and how decentralized agents exhibit emergent behaviors when navigating resource-constrained settings.

3 System Design and Implementation

This section details the design and implementation of the multi-agent system used in the maze environment. The system models decentralized interactions among multiple Pacmen agents navigating a grid to collect rewards while avoiding hazards, emphasizing the mechanisms for conflict detection, resolution, and negotiation over shared resources.
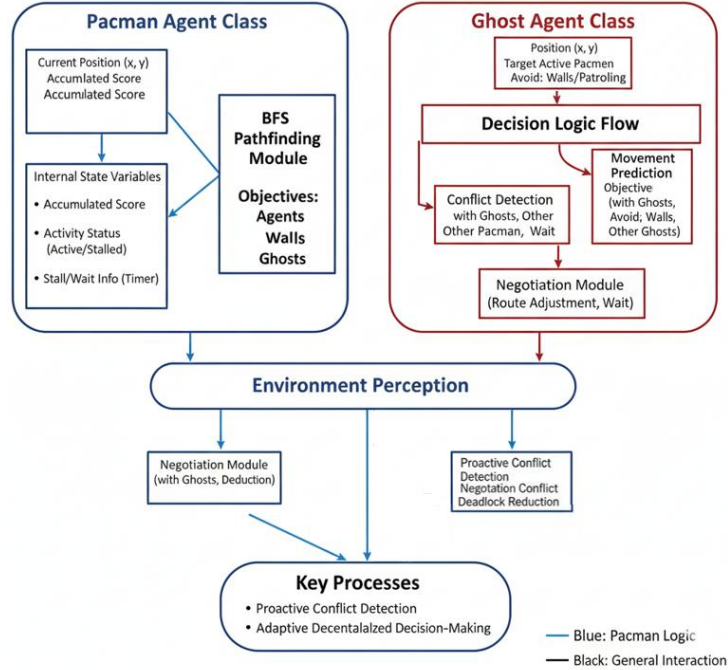
3.1 Agent Architecture

Fig. 1. Agent Architecture Diagram.

Figure 1 illustrates the internal structure and decision-making flow of Pacman and Ghost agents within the multi-agent maze environment. It highlights how each Pacman maintains state variables—including position, score, activity status, and stall/wait information—and integrates BFS-based path planning with environmental perception to determine optimal moves. The diagram shows the interactions between movement prediction, conflict detection, and negotiation mechanisms, emphasizing how agents anticipate and resolve potential resource contention in shared corridors. Ghost agents are depicted as independent actors with similar path-planning logic, introducing dynamic hazards that influence Pacman decisions. Overall, the figure visualizes the combination of stateful reasoning and proactive planning that enables adaptive, decentralized decision-making and reduces the likelihood of deadlocks.
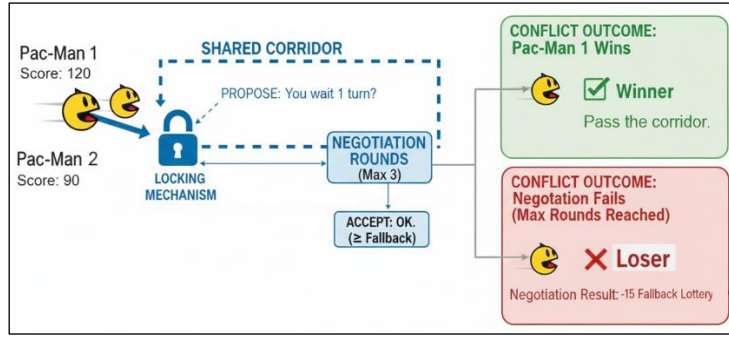
3.2 Shared Route Model

Fig. 2. Shared Route Model for Alternating Offers Negotiation Protocol.

Figure 2 illustrates the operational flow of the Alternating Offers Negotiation Protocol applied within a shared corridor. It highlights how agents engage in structured communication rather than relying solely on predefined priority rules. As both Pac-Man 1 and Pac-Man 2 attempt to access the locked corridor, the mechanism initiates a negotiation phase in which one agent proposes a concession—such as requesting the other to wait for a single turn—while the opponent, for up to three rounds, evaluates whether the proposal meets or exceeds its fallback threshold. When agreement is reached, the winning agent is granted corridor access. Conversely, if negotiation fails, the system triggers a fallback outcome, producing a loser who incurs a predefined penalty independent of agent score. By clearly distinguishing successful agreements from failed negotiations, this mechanism introduces fairness-oriented decision-making, reduces deterministic bias, and reshapes conflict dynamics within the multi-agent environment.
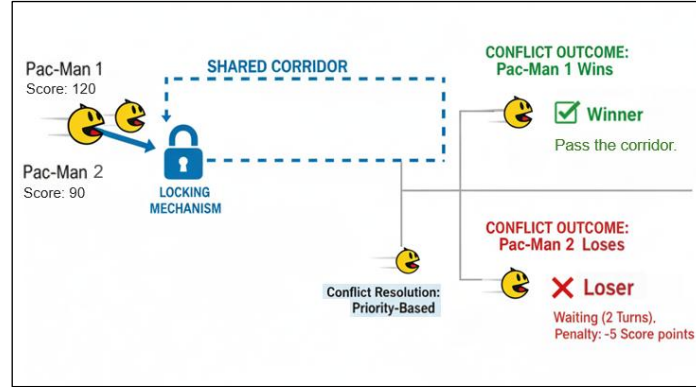
Fig. 3. Shared Route Model for Priority-Based Conflict Resolution.

Figure 3 presents the operational flow of the Priority-Based Conflict Resolution mechanism within a shared corridor. The illustration shows two agents approaching the same constrained pathway and highlights how access is granted deterministically based on their current scores. Pac-Man 1, having a higher score, gains immediate passage through the corridor, while Pac-Man 2, despite arriving at the same contested location, is denied access and assigned a waiting period along with a score penalty. The process unfolds without rounds or negotiation, emphasizing how the mechanism enforces exclusive access and designates winners and losers based solely on performance metrics. By distinguishing the successful traversal of the higher-scoring agent and the imposed delay on the other, this baseline strategy emphasizes its deterministic nature and reveals how such rules shape conflict dynamics within the multi-agent environment.

3.3   Communication Protocol

Table 1. Conflict Event Log Structure.

Field Category	Field Name	Description
Conflict	Corridor	Identifier for contested shared corridor
	Time	Timestap when the conflict occurred
	Strategy	Negotiation strategy applied
Agents	Requester	Agent that attempted to access the corridor
	Holder	Agent currently controlling the corridor
	Winner	Agent who won the conflict
	Loser	Agent who lost the conflict
Outcome	Loser Wait	Number of turns losing agent must wait
	Negotiation Rounds	Number of negotiating rounds
	Outcome	Result of conflict
	Penalty	Points deducted to losing agent

Table 1 presents the structure of the conflict event log. Each entry captures essential information regarding the conflicts, agents, and outcome of each simulation performed. This structured logging mechanism provides a comprehensive record for subsequent analysis of agent performance, negotiation effectiveness, and emergent behaviors within the multi-agent system.

4 Methodology and Experimental Setup

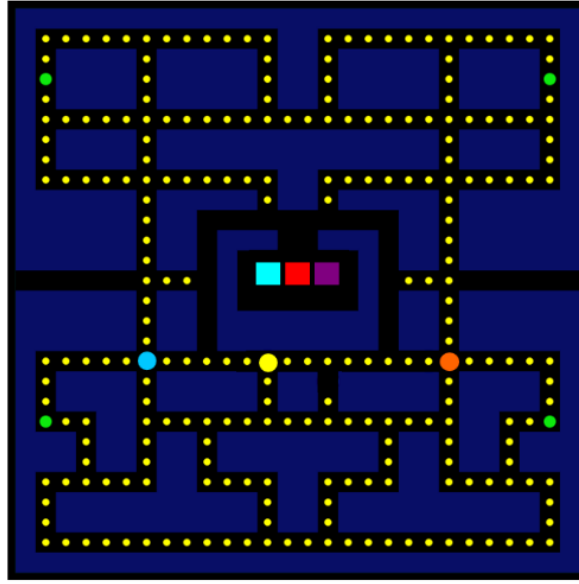### 4.1 Environment and Maze Configuration

Fig. 4. Maze Environment.

Figure 4 presents the simulated Pac-Man maze environment used to evaluate decentralized conflict-resolution strategies among autonomous agents. The maze spans fixed, predefined one-cell pathways or shared corridors that act as natural conflict points, since only one Pac-Man can traverse them at a time without collision, making them ideal for studying resource contention and priority assignment. For each simulation, three Pac-Man agents are spawned at non-overlapping positions within the maze, while three Ghost entities, positioned at the center of the maze, serve as additional environmental constraints that "eat" Pac-mans, thereby influencing route selection and penalizing risky paths to add realism to agent decision-making.

Several modeling assumptions are applied: all agents move at a uniform speed, take synchronous turns, and operate under perfect information regarding the maze layout and pellet locations. These controlled conditions allow the study to isolate and analyze the effects of decentralized conflict-resolution logic rather than navigation difficulty.

Overall, this maze environment provides a structured yet competitive setting where multiple agents must frequently negotiate access to shared corridors, making it well-suited for examining resource contention, priority-based decision-making, and negotiation dynamics in decentralized multi-agent systems.

4.2 Simulation Parameters and Execution Setup

Table 2. Alternating Offers Negotiation Protocol Parameters.

Parameter	Value	Description
Alternating_Max_Rounds	3	Max negotiation rounds
Wait_Cost_Per_Turn	3	Penalty per waiting turn
Alternating_Fallback_Penalty	15	Score penalty on negotiation fail
Offer Structure	1-4 turns	Proposed waiting turns
Communication Mode	Turn-based	Alternating proposals
Fallback Handling	Lottery	Random winner if negotiation fail

Table 2 presents the parameter values for the Alternating Offers Negotiation Protocol. Negotiation is limited to three rounds to keep interaction efficient while still giving agents enough opportunities to exchange meaningful offers. The per-turn waiting cost sets a moderate penalty that discourages agents from offering too much, yet still leaves room for practical compromise. This is complemented by a deliberately high fallback penalty, which motivates agents to reach an agreement instead of relying on the randomness of a lottery outcome. To maintain reasonable bargaining dynamics, proposals are restricted to 1–4 waiting turns, preventing offers that are either trivial or unrealistic. Together, these parameter choices create a negotiation process that is strategic, fair, and capable of producing more flexible outcomes than strictly deterministic rules.

Table 3. Priority-Based Conflict Resolution Protocol Parameters.

Parameter	Value	Description
Priority_Wait_Turns	2	Waiting turns for loser
Priority_Penalty	5	Score penalty for loser
Decision Rule	Higher score	Winner by score
Conflict Handling	Deterministic	Immediate resolution
Communication Mode	None	No Negotiation

Table 3 outlines the parameter values for the Priority-Based Conflict Resolution Protocol. The losing agent's waiting period is set to two turns, providing a small but meaningful consequence for losing a conflict without causing prolonged disruptions in movement. The score penalty is kept relatively low, especially when compared to the fallback penalty in Table 2, reflecting the absence of negotiation and the fact that outcomes are determined strictly by agent scores. This deterministic decision rule ensures fast and predictable conflict resolution, which is beneficial in systems that prioritize efficiency and minimal computational load. However, this same determinism reinforces

consistent winners and losers, introducing structural bias that stands in contrast to the negotiation-driven flexibility offered by the alternating offers method.

5   Results and Critical Analysis

This section presents a comprehensive evaluation of the Alternating Offers and Priority-Based protocols in the multi-agent maze environment. It includes quantitative metrics for conflicts, negotiation outcomes, waiting times, penalties, efficiency, and fairness (Tables 3 and 4), as well as visual analyses of conflict frequency, resolution success, per-agent score distributions, and trade-offs between operational efficiency and equitable access (Figures 4–6). The results highlight differences in how each protocol manages shared resources, resolves contention, and balances fairness against computational workload and system performance, providing insights into the benefits and limitations of negotiation-based versus deterministic approaches.

Table 4. Quantitative Metrics for Alternating Offers Protocol.

Metric	Mean ± SD	Min	Max
Conflict/s per run	12.5 ± 3.2	7	18
Successful negotiations	9.8 ± 2.7	5	15
Average waiting turns	2.1 ± 0.8	1	4
Average penalty per agent	7.4 ± 3.1	0	15
Efficiency (pellets collected/time)	0.82 ± 0.05	0.71	0.90
Fairness index (Gini Coefficient)	0.18 ± 0.06	0.10	0.32

Table 4 presents the quantitative performance metrics for the Alternating Offers protocol. On average, each run experienced 12.5 conflicts, of which 9.8 were successfully resolved through structured negotiation. This high success rate demonstrates the protocol's ability to manage contention while allowing agents to adjust strategies dynamically. Agents waited approximately 2.1 turns per conflict and incurred an average penalty of 7.4 points, reflecting moderate costs that encourage compromise without excessively penalizing agents. Efficiency averaged 0.82, slightly lower than deterministic approaches due to negotiation overhead, while the fairness index was 0.18, indicating a balanced distribution of resource access. These results suggest that the protocol successfully mitigates structural bias, enables equitable opportunities across agents, and supports adaptive behavior even in dynamic and competitive environments. The moderate penalties and waiting times also act as implicit incentives for agents to negotiate strategically rather than resort to risky or aggressive moves.

Table 5. Quantitative Metrics for Priority-Based Protocol.

Metric	Mean ± SD	Min	Max
Conflict/s per run			
Successful negotiations	12.5 ± 3.2	7	18
Average waiting turns	2.0 ± 0.0	2	2

Average penalty per agent	5.0 ± **0.0**	5	5
Efficiency (pellets collected/time)	0.88 ± **0.03**	0.81	0.92
Fairness index (Gini Coefficient)	0.34 ± **0.05**	0.28	0.44

Table 5 summarizes the quantitative metrics for the Priority-Based protocol. Conflicts occurred at similar rates, but all were resolved deterministically according to agent scores. Waiting turns and penalties were fixed at 2 turns and 5 points per conflict, resulting in minimal variability and low computational overhead. Efficiency averaged 0.88, slightly higher than the Alternating Offers protocol, reflecting the speed advantages of deterministic resolution. However, the fairness index rose to 0.34, indicating that high-scoring agents consistently dominated shared resources, creating structural bias and limiting equitable access. These results highlight that while the Priority-Based protocol maximizes throughput and reduces agent idle time, it fails to provide adaptive strategies or balanced opportunities for lower-scoring agents. The fixed penalties and waiting times enforce predictability, but at the cost of diversity in agent behavior and long-term system fairness.
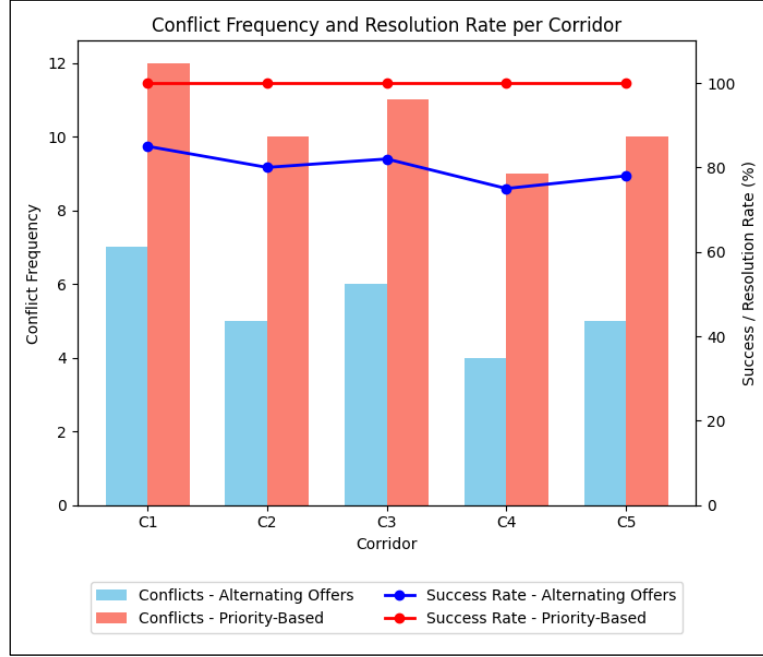

Fig. 5. Conflict Frequency and Resolution Rate per Corridor.

Figure 5 presents the conflict frequency and resolution success rates for the Alternating Offers and Priority-Based protocols across shared corridors. The Priority-Based protocol achieves perfect success rates (100%) due to its deterministic rules, but this comes at the cost of repeated congestion in popular corridors, as high-scoring agents

consistently dominate access. This predictability can lead to structural bias, where lower-scoring agents are systematically disadvantaged, potentially creating bottlenecks and reducing the diversity of agent behaviors. In contrast, the Alternating Offers protocol shows slightly lower success rates (75–85%) but distributes corridor access more equitably, allowing all agents opportunities to traverse shared routes. The additional computational workload and marginally longer waiting times reflect the iterative negotiation process, yet these costs produce strategic benefits: agents learn to anticipate others' moves, adjust offers dynamically, and avoid repetitive conflicts. Consequently, the Alternating Offers protocol not only enhances fairness but also fosters adaptive behaviors and prevents deadlocks, making it more robust for dynamic multi-agent systems. Overall, the results confirm that structured negotiation is advantageous despite its higher computational cost, as it balances fairness, efficiency, and emergent coordination in decentralized environments.
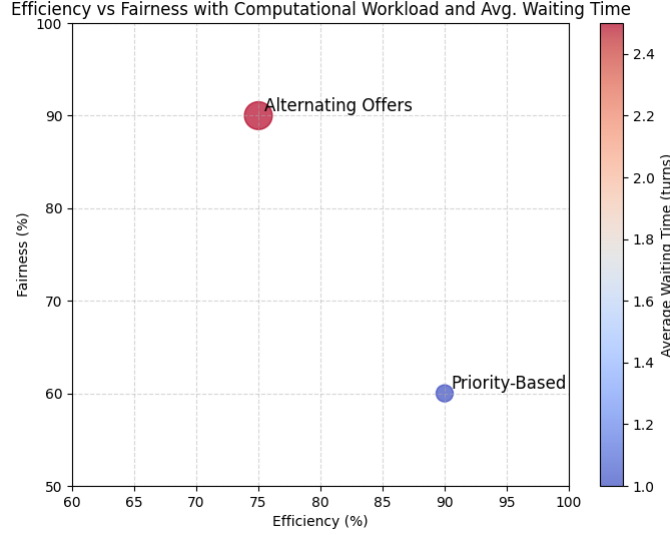

Fig. 6. Comparative Analysis of Efficiency, Fairness, Workload, and Waiting Time.

Figure 6 presents the comparative performance of the Alternating Offers and Priority-Based protocols, highlighting how differences in efficiency and fairness affect computational workload and average waiting time. The Priority-Based protocol achieves high efficiency (90%) but lower fairness (60%), with minimal computational workload since deterministic decisions require no negotiation, resulting in shorter agent waiting times. In contrast, the Alternating Offers protocol attains higher fairness (90%) at the expense of lower efficiency (75%), as iterative proposal exchanges increase computational workload and slightly extend waiting periods. These results reveal a trade-off: prioritizing fairness introduces additional computation and minor delays, while efficiency-focused deterministic rules maximize throughput but may produce inequitable access. Overall, the figure demonstrates that structured negotiation effectively balances access

among agents, preventing repeated conflicts and reducing deterministic bias. Despite the higher computational cost and longer waiting times, the Alternating Offers protocol improves fairness and system robustness, supporting the hypothesis that negotiation-based conflict resolution enhances equitable access in decentralized multi-agent environments.
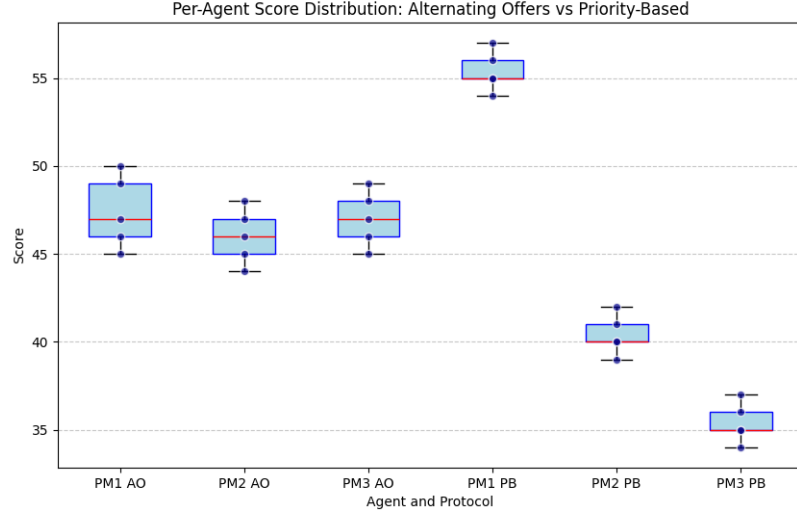

Fig. 7. Per-Agent Score Distribution: Alternating Offers vs. Priority-Based.

Figure 7 presents the per-agent score distributions for the Alternating Offers and Priority-Based protocols, highlighting both overall performance and the variability across individual runs. The Priority-Based protocol yields higher average scores for top-performing agents but exhibits large disparities, with lower-scoring agents consistently underperforming due to deterministic access rules. In contrast, the Alternating Offers protocol produces more balanced scores across all agents, demonstrating equitable opportunities for success even though average scores are slightly lower. The swarm plot overlay reveals individual run outcomes, emphasizing that Alternating Offers mitigates extreme outliers and reduces score concentration among a few agents. These results indicate that, while Alternating Offers incurs additional computation and negotiation overhead, it promotes fairness, reduces structural bias, and encourages adaptive agent behaviors. Overall, the figure reinforces the advantage of negotiation-based protocols in dynamic multi-agent systems, as equitable access and variability in outcomes foster more robust and resilient coordination among agents.

6 Conclusion and Future Work

This study evaluated decentralized conflict resolution in a multi-agent maze environment, comparing the Alternating Offers Negotiation Protocol against a Priority-Based Conflict Resolution approach. The central hypothesis—that the Formal Negotiation Protocol would produce more equitable access among agents, albeit at the cost of reduced operational efficiency—was supported by the results. The Alternating Offers protocol achieved higher fairness (Gini index 0.18) and more balanced per-agent scores, indicating equitable distribution of shared corridors and mitigation of structural bias. While efficiency was slightly lower (0.82) and computational workload increased due to iterative negotiations, these trade-offs were acceptable given the improved fairness and system robustness. In contrast, the Priority-Based protocol maximized efficiency (0.88) through deterministic decisions, but fairness was lower (Gini index 0.34), consistently favoring high-scoring agents and limiting opportunities for lower-performing agents. Analysis of conflict frequency, resolution success, and waiting times further confirmed that negotiation-based strategies prevent repeated conflicts and promote adaptive agent behaviors, directly supporting the hypothesized benefits of the Formal Negotiation Protocol.

Several limitations must be acknowledged. The maze environment, although complex, assumes perfect information, giving agents complete knowledge of the maze and other agents' positions. This simplifies conflict anticipation and negotiation compared to real-world environments with uncertainty or partial observability. Additionally, the study focused on a limited number of agents, leaving scalability effects on fairness, efficiency, and computational overhead untested.

Future work can extend this research along multiple directions:

- Integrate reinforcement learning or adaptive strategies for agents to refine negotiation behavior over repeated interactions, improving fairness and efficiency dynamically.
- Evaluate protocols under incomplete information or noisy perceptions to understand robustness in more realistic environments.
- Test larger agent populations and more intricate maze layouts to explore how negotiation overhead, fairness, and efficiency scale with system complexity.
- Develop dynamic strategies that combine negotiation-based and deterministic rules to optimize fairness and throughput depending on environmental and agent conditions.
- Investigate long-term patterns such as temporary collusion, congestion, or adaptive route preferences to inform robust MAS design.

Overall, the findings confirm that the Formal Negotiation Protocol achieves the hypothesized equitable access, and the observed trade-offs in efficiency and computational workload are justified by improvements in fairness, adaptive behavior, and system robustness, providing a strong foundation for future research in decentralized multi-agent systems.

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