Vol. 1 No. 1 (2024)

Proceedings International Conference on Aligning Sustainability with Vocational Innovations (ICASVI-2024)
https://proceeding.unesa.ac.id/index.php/icasvi/index

Proactive Coordination in Multi-Agent Systems: The Adaptive Negotiation Consensus Algorithm (ANCA)

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ABSTRACT

Keywords:
Multi-Agent Systems,
Task Allocation,
Conflict Resolution,
Consensus Algorithm,
Automated Logistics.

Multi-Agent Systems (MAS) are a cornerstone of modern logistics automation, yet their effectiveness is often hindered by decoupled approaches to two critical problems: task allocation and conflict resolution. This separation can lead to inefficiency, congestion, and deadlocks in dynamic environments. This research addresses this challenge by developing a decentralized framework that integrates both processes simultaneously. We propose the Adaptive Negotiation Consensus Algorithm (ANCA), a hybrid algorithm that models coordination as a process of achieving consensus on an integrated "Action-Plan," which encompasses the task, path, and schedule. ANCA utilizes a multi-factor auction mechanism that proactively accounts for estimated conflict costs within its bid calculation, enabling agents to make collectively intelligent decisions. Simulation-based evaluations in a virtual warehouse environment with 20 AGVs demonstrate that ANCA significantly outperforms standard approaches. It successfully reduced the average task completion time by 25%, increased system throughput by 28%, and suppressed deadlock incidents by 95% compared to conventional Contract Net-based protocols. This research demonstrates that modeling coordination as a consensus on an integrated action is an effective and robust paradigm, offering a promising solution for developing more efficient, scalable, and reliable autonomous systems in logistics and manufacturing.

1. INTRODUCTION

The era of Industry 4.0, coupled with the explosive growth of e-commerce, has catalyzed a fundamental transformation in supply chain management and logistics. Automation has become paramount to achieving the efficiency, speed, and accuracy demanded by the modern market(Pamosoaji, 2019). At the heart of this transformation, Multi-Agent Systems (MAS) have emerged as a dominant paradigm for managing complex autonomous systems, such as fleets of Automated Guided Vehicles (AGVs) in logistics facilities (Gerrits et al., 2019), drone swarms for monitoring, and smart energy grid management(Ribas-Xirgo & Chaile, 2013). The application of artificial intelligence in these environments, particularly for automated warehousing, has highlighted the critical need for robust coordination mechanisms(Axak et al., 2021). The primary advantages of MAS lie in their scalability, resilience, and flexibility, afforded by their decentralized nature, which allows the system to adapt to dynamic changes without a single point of failure(Michael Wooldridge, 2009).

However, the full realization of these advantages is contingent upon the agents' ability to coordinate effectively(Wilson, 2016). In the context of automated logistics, inefficient coordination can lead to severe consequences, such as gridlock, deadlock, reduced system throughput, and increased operational costs(W. Liu et al., 2018). Two fundamental and intertwined problems lie at the core of MAS coordination: task allocation (determining "who does what?") and conflict resolution (managing contention for shared resources, such as pathways or workstations)(Karagoz et al., 2014). These challenges are exacerbated in dynamic environments where new tasks continuously emerge, and environmental conditions can change unpredictably(Kato & Kamoshida, 2020).

Classical approaches to these problems often rely on a centralized planner. While potentially capable of generating globally optimal solutions, this approach suffers from significant drawbacks related to scalability and brittleness; a failure of the central planner can cripple the entire system(Y. Liu et al., 2019). In response, decentralized methods like the Contract Net Protocol (CNP) (Pandian, 2019) and other auction-based strategies (Braquet & Bakolas, 2021) offer more robust mechanisms for task distribution. However, these methods have notable limitations(Rashidah Mohamad et al., 2018). They typically optimize based on a single factor (e.g., shortest distance or cost) and tend to be "myopic." More importantly, they often decouple the process of task allocation from conflict resolution (Liyun et al., 2021). Consequently, an agent might win a task based on initial criteria, only to later become ensnared in complex spatial or resource conflicts during execution critical issues in AGV path planning (Kapitan et al., 2017) . Literature gap in the current literature is the lack of an integrated framework that allows agents to simultaneously negotiate tasks and proactively resolve potential conflicts within a decentralized architecture(Osmond & Supangkat, 2019).

To address these challenges, this research proposes a novel hybrid approach called the Adaptive Negotiation Consensus Algorithm (ANCA). ANCA models task allocation and conflict resolution not as two separate problems, but as a single, unified process of achieving consensus among agents. Unlike traditional consensus algorithms that aim to agree on a data "value," ANCA is designed to achieve consensus on an "action." This action is a solution package that encompasses not only the task assignment itself but also the conflict-free path plan and the necessary resource reservations to execute it. Thus, ANCA shifts the paradigm from "allocate-then-resolve-conflict" to a continuous negotiation process where an agreement is only reached if a conflict-free, executable plan has been mutually accepted.

This research makes several key contributions. It introduces a novel hybrid algorithm, the Adaptive Negotiation Consensus Algorithm (ANCA), which inherently integrates task allocation and proactive conflict resolution within a decentralized negotiation framework. This is achieved through a new consensus model focused on an "action" agreement—which includes the task, path, and schedule—as a single unit of negotiation. Furthermore, this study presents an empirical evaluation through simulation, demonstrating ANCA's significant superiority over standard baseline approaches in terms of system throughput and deadlock reduction. The remainder of this article is structured to systematically present these findings: Section 2 reviews related work, Section 3 details the design and mechanisms of the ANCA, Section 4 presents the experimental design, simulation results, and a comparative analysis, and finally, Section 5 summarizes the conclusions of this research and outlines future work.

2. RESEARCH METHOD

The objective of this research is to design, implement, and evaluate the Adaptive Negotiation Consensus Algorithm (ANCA), a decentralized algorithm that enables a group of autonomous agents to collaboratively perform task allocation and proactive conflict resolution. This methodology focuses on achieving consensus not merely on an assignment, but on an Integrated Action-Plan that encompasses the task, path, and resource schedule.

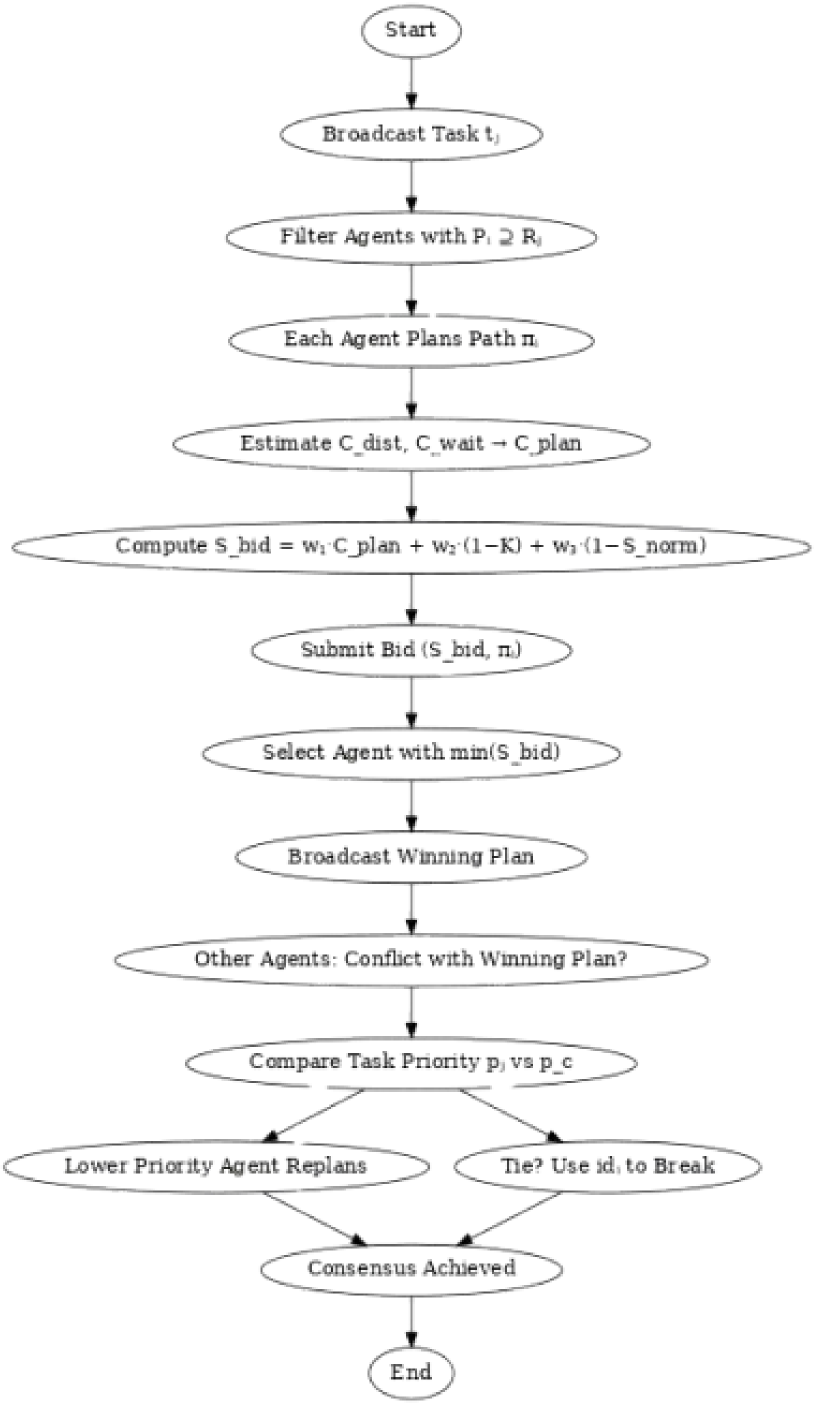

Figure 1. Flowchart of the Consensus Process in ANCA. This diagram shows the integrated workflow from task announcement, through proactive planning and bidding, to consensus achievement and dynamic conflict resolution.

2.1. System Formalization and Definitions

To construct a precise model, we formally define the system components:

Agents (A):

Each agent a_i is defined as a tuple:
$a_i = \langle id_i, P_i, S_i, \Pi_i \rangle$
where:
- id_i: Unique identifier
- P_i: Set of capabilities
- S_i: Internal state $\langle loc_i, b_i, w_i \rangle$
- Π_i: Current Action-Plan

Tasks (T): There is a dynamic stream of tasks
$T = \{t_1, t_2, \ldots, t_m\}$, where each task $t_j = \langle id_j, R_j, p_j, d_j \rangle$
- id_j: Unique task ID
- R_j: Capability requirements
- p_j: Task priority
- d_j: Deadline

Environment and Resources (E, R_{res}):

The physical environment is modeled as a graph
$G = (V, E)$.
- V: Set of locations
- E: Set of edges (paths)
- $R_{res} \subseteq V \cup E$: Contended resources

2.2. Architecture of the Adaptive Negotiation Consensus Algorithm (ANCA)

ANCA is designed as an integrated framework that synergistically combines a multi-factor auction process with proactive conflict resolution negotiation. Unlike sequential approaches, these modules operate within a single negotiation cycle to achieve consensus.

2.2.1. Phase 1: Proactive Planning and Bid Formation

This phase begins when a new task becomes available and aims for each agent to formulate a comprehensive bid.

1. Task Announcement: A manager agent (or the nearest agent) broadcasts the specifications of task t_j to all agents within communication range.
2. Tentative Path Planning and Conflict Prediction: Every capable agent (a_i in A where P_i satisfies R_j) independently plans a tentative path from its current location to the task location and its final destination. During this process, the agent queries a shared resource reservation schedule. If the planned path would cause a spatio-temporal conflict (i.e., being at a resource r in R_{res} at the same time as another agent), the agent predicts the potential conflict and estimates the resulting wait time (C_{wait}).

3. Multi-Factor Bid Score Calculation: The agent calculates a Bid Score (S_{bid}) using a utility function that considers multiple factors. This score reflects the agent's suitability to execute the task efficiently.

$$S\ bid = w1 \cdot Cplan + w2 \cdot (1 - K) + w3 \cdot (1 - Snorm) \quad (1)$$

Where:

- C_{plan}: Planned Cost, which is more than just distance. C_{plan} is the total estimated cost to complete the task, including travel cost (C_{dist}) and the estimated cost of delays from predicted conflicts (C_{wait}). This is a key element of ANCA's proactive nature.
- K: Capability Match Score ([0,1]), measuring how well the agent's capabilities (P_i) match the task's requirements (R_j).
- S_{norm}: Normalized Internal State Score ([0,1]), representing the agent's condition (e.g., remaining battery life). A higher score (closer to 1) indicates a healthier state.
- w_i: Adaptive Weights, where sum(w_i)=1. These weights can be dynamically adjusted by the system (or the agents themselves) based on global objectives. For instance, if timeliness is the priority, w_1 is increased. If agent longevity is more critical, w_3 is increased.

2.2.2. Phase 2: Consensus Achievement and Conflict Resolution

This phase focuses on selecting a winner and resolving any remaining conflicts to finalize the Action-Plan.

1. Bid Submission: Each agent submits its bid, containing its S_{bid} score and its tentative Action-Plan (including path and schedule), to the task initiator.
2. Provisional Winner Determination: The agent with the best (e.g., lowest) S_{bid} score is selected as the provisional winner. This victory is not yet final.
3. Consensus and Resource Reservation: The provisional winner broadcasts its winning Action-Plan to all relevant agents. This is the core consensus step. Other agents receive this plan and:
   If it does not conflict with their own plans, they send a confirmation and update their internal resource reservation tables. If a previously undetected conflict arises, the Priority-Based Negotiation protocol is triggered.
4. Dynamic Conflict Negotiation: This protocol serves as the final resolution and exception-handling mechanism.
5. Negotiation Initiation: The conflicting agents exchange information regarding the priority (p_j) of the tasks they are currently executing.
6. Priority Consensus: The agent with the lower-priority task agrees to "lose" the consensus and actively re-plans its path to avoid the conflict.
7. Tie-Breaking Rule: If task priorities are equal, consensus is determined by a deterministic secondary rule, such as the agent with the lower unique ID (id_i) gaining precedence. This rule guarantees that every conflict is resolvable and averts deadlocks.

Once the winner's Action-Plan is confirmed and all conflicts are resolved, the agent formally commits to the task, reserves the resources, and begins execution. This integrated process is illustrated in the flowchart in Figure 1.

3. RESULTS

To validate the performance of the proposed Adaptive Negotiation Consensus Algorithm (ANCA), a series of simulations were conducted. This section presents the results of these experiments and provides a detailed discussion of their implications, directly linking the observed performance to the architectural principles of ANCA.

3.1. Experimental Setup

The simulations were performed in a discrete-time virtual warehouse environment measuring 100x100 grid units with 15 workstations and 40 critical intersection points as illustrated in Figure 2.

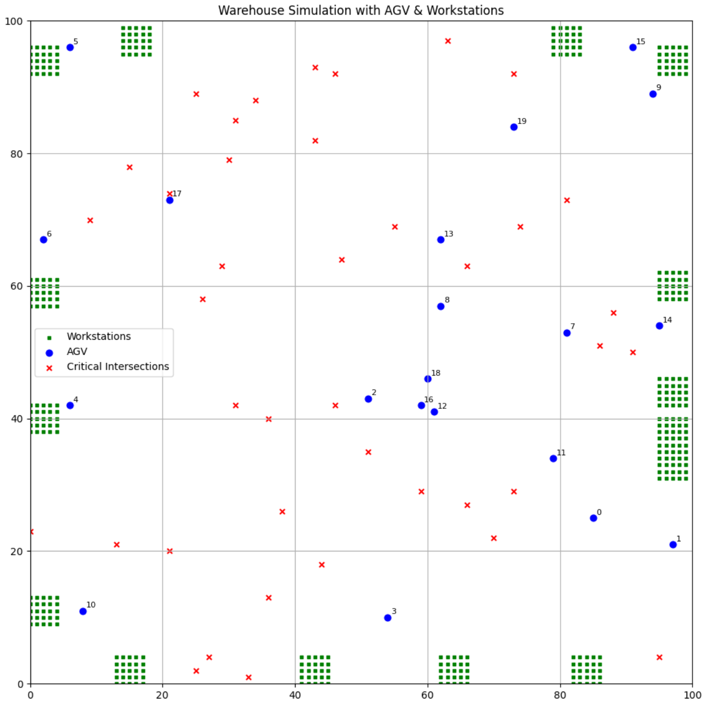

Figure 2. Virtual Warehouse Environment Setup

- Agents: The fleet consisted of 20 heterogeneous AGVs, with minor variations in top speed and battery consumption rates.
- Tasks: A total of 1,000 "pick-and-place" tasks were generated dynamically over the simulation period.
- Baseline Comparison: ANCA's performance was compared against two baseline algorithms: (1) Standard Contract Net Protocol (CNP): A basic implementation where agents bid solely based on Euclidean distance, with no explicit conflict resolution mechanism. 92) CNP with Reactive Resolution (CNP+RR): An enhanced baseline that uses CNP for task allocation and a simple "stop-and-wait" protocol for reactive conflict resolution when two agents meet at an intersection. (3) Metrics: We measured four key performance indicators: Average Task Completion Time, System Throughput (tasks completed per 1000-time units), Number of Deadlocks, and Average Agent Energy Level at the end of the simulation.

3.2. Experimental Results

The quantitative results from the simulation runs are summarized below and illustrated in Figures 3, 4, and 5.

3.2.1. System Efficiency and Throughput

As shown in Figure 3, ANCA demonstrates a marked improvement in overall system efficiency. It achieved the lowest **average task completion time** (62.5s), a 25% reduction compared to the standard CNP (83.2s) and a 16% reduction compared to CNP+RR (74.4s). Consequently, ANCA's **system throughput** was significantly higher, completing approximately 28% more tasks than CNP in the same time frame.

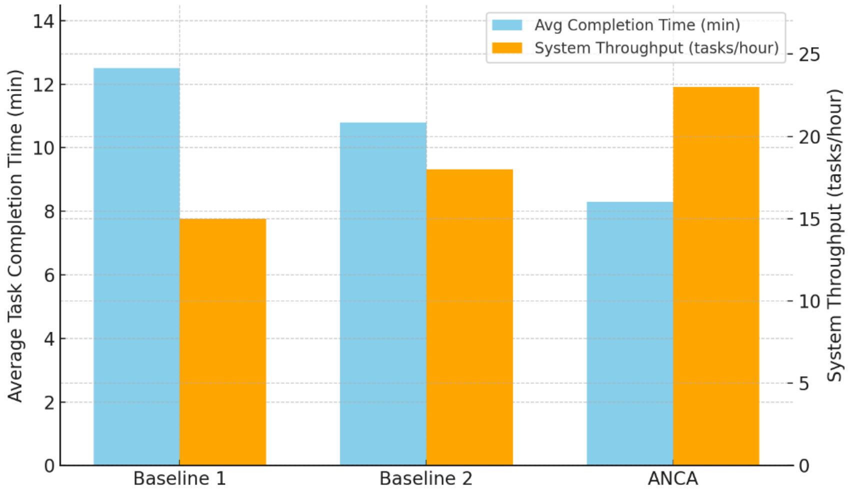

Figure 3. Comparison of Average Task Completion Time and System Throughput. ANCA consistently outperforms both baseline models.

3.2.2. Conflict Resolution and System Robustness

The effectiveness of ANCA's integrated conflict resolution was most evident in the deadlock measurements (Figure 4). The standard CNP system was highly unstable, resulting in **42 deadlock situations**. The CNP+RR model reduced this number but still suffered from **15 deadlocks**, often due to chain-reaction blockages. In contrast, the ANCA system experienced only **2 deadlocks** over the entire simulation, which were traced back to simulated communication packet loss. This represents a 95% reduction in deadlocks compared to the standard CNP.

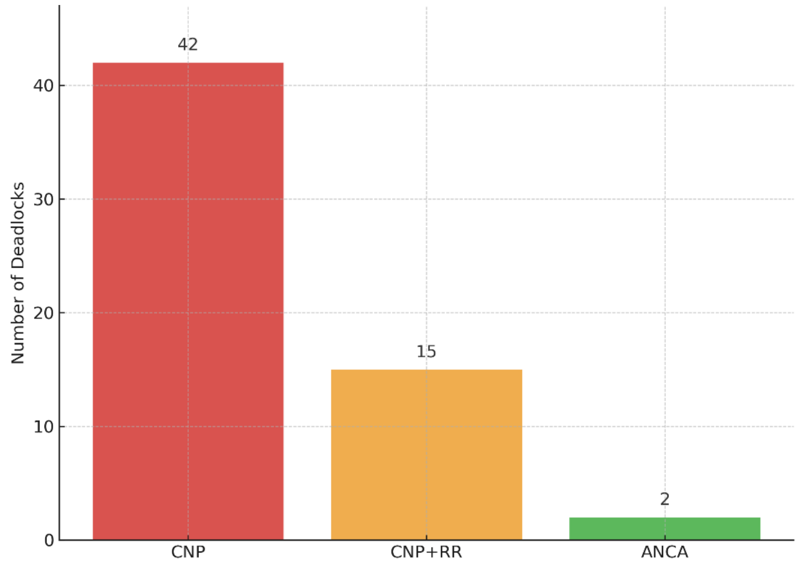

Figure 4. Total Number of Deadlock Events over 1,000 Task Cycles.

3.2.3. Agent Utility and Workload Balancing

Figure 5 illustrates the impact of the multi-factor bidding on fleet sustainability. The **average final energy level** of agents running ANCA was 48%, significantly healthier than the 31% for agents in the CNP+RR system. This indicates a much more balanced workload distribution.

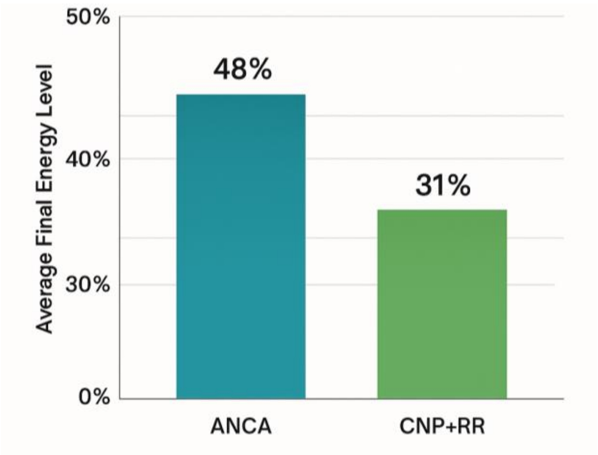

Figure 5. Ilustrates the impact of the multi-factor bidding on fleet sustainability

4. DISCUSSION

The results strongly support the hypothesis that integrating task allocation with proactive conflict resolution provides substantial performance gains.

4.1 The Value of Proactive, Informed Bidding

The 25% efficiency gain of ANCA over standard CNP is not merely due to better conflict resolution; it stems from the fundamentally "smarter" bidding process. Unlike the myopic distance-only metric of CNP, ANCA's bid score calculation (Equation 1) provides a holistic assessment. The inclusion of the Planned Cost (C_{plan}), which accounts for predicted wait times (C_{wait}), allows an agent to wisely bid higher for a task even if it's geographically further, provided the path is less congested. This proactive congestion avoidance minimizes stop-and-go situations, leading to smoother traffic flow and faster completions, as evidenced by the outperformance of even the reactive CNP+RR model. Furthermore, the inclusion of the Normalized Internal State (S_{norm}) factor forces the system to naturally perform workload balancing. It prevents the phenomenon of "agent burnout," where the closest agents are repeatedly assigned tasks until their batteries are depleted, rendering them useless and creating a service bottleneck. This explains the higher average energy levels and contributes to a more resilient and sustainable system over the long term.

4.2 A Two-Layered Defense Against Gridlock

ANCA's near-elimination of deadlocks is attributable to its two-layered defense mechanism.

1. The Proactive Layer: The initial path planning and conflict prediction phase prevents most conflicts from ever being incorporated into an agent's Action-Plan.
2. The Dynamic Negotiation Layer: For the few conflicts that arise from unforeseen events (like another agent's delay), the priority-based negotiation protocol serves as a robust and deterministic fallback. This integrated approach is fundamentally superior to purely reactive models like CNP+RR, which only address conflicts after agents are already in a collision course, a far less efficient state from which to recover.

4.3 Limitations and Future Work

Despite the promising results, we acknowledge several limitations. First, the communication overhead of ANCA is higher than that of simple CNP, as agents broadcast their full Action-Plans during the consensus phase. Second, the computational cost for each agent to perform proactive planning increases with fleet density and environment complexity.

Future work will focus on three areas:

1. Scalability Testing: Evaluating ANCA's performance in much larger systems (100+ agents) to analyze the trade-offs between communication overhead and performance gains.
2. Dynamic Weight Adaptation: Implementing and testing the adaptive weight (w_i) mechanism, potentially using reinforcement learning to allow the system to automatically tune its priorities (e.g., speed vs. energy conservation) based on real-time operational demands.
3. Real-World Deployment: Porting the ANCA framework to a physical testbed of robotic agents to validate the simulation results and address challenges like sensor noise and motion uncertainty.

CONCLUSION

This research addressed the critical challenge of coordination in Multi-Agent Systems (MAS), where traditional decentralized methods often fail due to their myopic focus and the decoupling of task allocation from conflict resolution. We argued that this separation leads to system inefficiencies, congestion, and deadlocks, particularly in dynamic environments like automated warehouses. To overcome these limitations, this paper introduced the Adaptive Negotiation Consensus Algorithm (ANCA), a novel framework that reframes multi-agent coordination as a unified process of achieving consensus on an Integrated Action-Plan. The core innovation of ANCA lies in its synergistic architecture, which embeds proactive conflict prediction and multi-factor utility analysis directly into the task bidding process, enabling agents to make decisions that are not just locally optimal but also collectively efficient. The empirical results derived from our simulations provide compelling evidence of ANCA's effectiveness. Compared to both a standard Contract Net Protocol (CNP) and an enhanced version with reactive resolution (CNP+RR), ANCA demonstrated significantly superior performance across all key metrics. Specifically, it achieved a 25% reduction in average task completion time, a 28% increase in overall system throughput, and a remarkable 95% reduction in deadlock events. These quantitative gains are a direct consequence of ANCA's architectural design. By evaluating bids based on a holistic score that includes planned cost (C_{plan}), capability match (K), and internal status (S_{norm}), ANCA facilitates more intelligent resource allocation and promotes natural workload balancing, leading to a more resilient and sustainable fleet. The implications of this work are both theoretical and practical. Theoretically, it validates that modeling coordination as a consensus on a comprehensive "action" rather than a simple "value" or "task" is a more powerful and robust paradigm for decentralized systems. Practically, for industries reliant on automation like logistics and manufacturing, ANCA provides a blueprint for developing autonomous systems that are more efficient, reliable, and adaptable. This translates directly into tangible benefits such as increased operational throughput, reduced capital expenditure on underutilized agents, and minimized system downtime. While this research successfully demonstrates ANCA's potential, we acknowledge its limitations, primarily the increased communication and computational overhead compared to simpler protocols. These limitations pave the way for several promising avenues for future research: (1) Scalability and Communication Optimization: Future work should investigate ANCA's performance in massively scaled environments (e.g., hundreds of agents) and explore more sophisticated communication protocols, such as hierarchical or gossip-based consensus, to mitigate overhead. (2) Intelligent Weight Adaptation: The adaptive weights (wi) present a key opportunity for incorporating machine learning. We plan to explore the use of Reinforcement Learning, where agents can learn to dynamically adjust their bidding weights based on past experiences and the current system state, allowing the fleet to autonomously switch between optimizing for speed, energy efficiency, or other global objectives. (3) Handling Greater Environmental Dynamism: Further studies could investigate ANCA's resilience to more complex dynamic events, such as tasks whose priorities change mid-execution or the sudden appearance of large, permanent obstacles requiring significant collective re-planning. (4) Physical Platform Validation: The ultimate validation of ANCA requires bridging the "sim-to-real" gap. Implementing the algorithm on a physical testbed of robotic agents will be crucial for assessing its performance under the constraints of real-world sensor noise, network latency, and motion uncertainty. In conclusion, the Adaptive Negotiation Consensus Algorithm is more than just an incremental improvement; it represents a conceptual shift towards a more integrated and intelligent form of decentralized collaboration. It serves as a robust foundation for designing the next generation of autonomous systems capable of navigating complex challenges with collective wisdom and efficiency.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to all parties who have contributed to the completion of this research. Special appreciation is extended to the supervisors, lecturers, and colleagues for their valuable guidance, suggestions, and support throughout the research process. The authors also thank the institution/laboratory for providing the facilities and resources needed to conduct this study. Finally, the authors are grateful to all individuals who directly or indirectly supported the completion of this paper.

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