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Constraint-Based Protocol for Efficient Automated Negotiation in Multi-issue Negotiation

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Abstract

This study investigates the impact of the number of fixed constraints on automated negotiation outcomes in a multi-issue negotiation scenario. Specifically, we analyze how the variation in the fixed constraints set by each negotiating agent influences social welfare, agreement frequency, and negotiation time. The negotiation protocol considers fixed constraints and evaluates their effects on the efficiency and feasibility of reaching agreements. Simulation results reveal that as the number of fixed constraints increases, social welfare and agreement frequency tend to decrease while negotiation time remains relatively unchanged. These findings highlight the importance of understanding the role of fixed constraints in optimizing negotiation outcomes and provide insights for designing more effective automated negotiation protocols.

Keywords: Agents, Negotiation protocol, Constraint.

1 Introduction

Automated negotiation systems have gained attention as a critical technology for efficiently forming agreements in negotiation scenarios characterized by multiple interests and conflicting concerns [1, 2, 3]. These systems are increasingly significant in business transactions, resource allocation, healthcare, and public policy, where swift and fair agreements are essential [4, 5]. Negotiation protocols define the interaction rules between agents, including mechanisms for proposing, evaluating, accepting, or rejecting offers [6, 7]. Among them, the Alternating Offers Protocol [8] is widely used. However, in multi-issue negotiation, prolonged negotiation time and deadlocks in reaching agreements remain key challenges [9, 10]. Furthermore, constraints imposed on negotiating agents significantly affect negotiation outcomes and efficiency [11, 12, 13]. Previous studies have proposed protocols focusing on the constraints set by negotiation agents. However, many of these studies are limited to evaluating the types of constraints and negotiation procedures [14, 15]. While some research has analyzed the effects of constraints on negotiation outcomes using mathematical models and simulations, these studies are often conducted under idealized conditions

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[16, 17]. There is a lack of research addressing how differences in the number of fixed constraints impact negotiation outcomes. This study focuses on the fixed number of constraints set by negotiation agents and evaluates their effects on social welfare, agreement frequency, and negotiation time. Specifically, we aim to examine how variations in the fixed number of constraints influence the quality of agreements and negotiation efficiency through simulations. Additionally, this study analyzes the impact of fixed constraints on the relationships between negotiation agents and agreement formation under realistic negotiation scenarios. This study aims to clarify the effects of variations in fixed constraint numbers on negotiation outcomes and to provide guidelines for the future design of automated negotiation protocols. This paper first provides an overview of existing research on automated negotiation and negotiation protocols, followed by an explanation of the experimental methods proposed in this study. Finally, the simulation results are analyzed to evaluate the impact of fixed constraints on negotiation outcomes.

2 Concepts and Mathematical Models of Automated Negotiation

In automated negotiation, mathematical formulas are essential for negotiation agents to calculate optimal proposals and responses. Here are some key elements of these formulas.

2.1 Multi-Issue Negotiation Problems with Constraints

In multi-issue negotiation problems [18], we consider the scenario where M agents $A = \{A_1, A_2, \ldots, A_M\}$ negotiate within a common negotiation domain. The negotiation domain defines the issues at stake and the options available for each issue, represented by a set of n issues $I = \{I_1, I_2, \ldots, I_n\}$ and a set of options for each issue I_i, containing k_i elements $V_i = \{v_{i1}, v_{i2}, \ldots, v_{ik_i}\}$. The proposed agreement candidates (Bids) during negotiation are determined by selecting options from each issue and can be expressed in the form (1):

$$\omega = (v_{1c_1}, v_{2c_2}, \ldots, v_{nc_n}) \tag{1}$$

where v_{ic_i} is the option chosen for issue I_i, and $c_i \in \{1, 2, \ldots, k_i\}$. The total set of agreement candidates Ω (2) is represented as:

$$\Omega = \{(v_{1c_1}, \ldots, v_{nc_n}) \mid c_i \in \{1, \ldots, k_i\}, i \in \{1, \ldots, n\}\} \tag{2}$$

The total number of agreement candidates in the negotiation domain is referred to as the domain size and is represented as $|\Omega|$.

Each negotiating agent has a utility associated with each option, reflecting their preferences. Generally, these utilities are private, meaning that other agents cannot access them. Agent a holds its own utility function $U_a(\cdot)$ to calculate the utility value for any Bid. The objective function for each agent is often assumed to be maximizing its utility value obtained from the negotiation, maintaining individual rationality.

When negotiations break down, each agent has a reservation value (Reservation Value) or a disagreement point $D = \{d_1, d_2, \ldots, d_M\}$, representing the minimum utility value obtainable. The interaction between agents follows a set of rules known as the negotiation protocol P.

Constraints C

In addition to the above structure, the negotiation is subject to a set of constraints $C = \{C_1, C_2, \ldots, C_l\}$. These constraints can represent a variety of conditions, including but not limited to:

- **Feasibility Constraints:** Certain combinations of options may be infeasible due to domain restrictions.
- **Resource Constraints:** Limited resources may prevent certain agreements from being achievable.
- **Fairness Constraints:** Agreements must meet fairness criteria, such as equal utility distribution.
- **Dependency Constraints:** The value of one issue may depend on the selection of options in another issue.

Formally, these constraints can be expressed as:

$$C(\omega) = \text{True}, \quad \forall \omega \in \Omega' \tag{3}$$

where $\Omega' \subseteq \Omega$ represents the subset of feasible agreements satisfying all constraints C.

Agents must negotiate within this constrained domain, ensuring that their bids and final agreements comply with the specified constraints. Constraints C add an additional layer of complexity to the negotiation problem, often requiring more sophisticated negotiation strategies and algorithms to find feasible and optimal solutions.

2.2 Utility Function with Constraints

The utility function $U(x)$ represents the satisfaction level of an agent with an offer x from the negotiating partner. The higher the utility, the more satisfied the agent is with the offer. Typically, the utility function is expressed as follows (4):

$$U(x) = \sum_{i=1}^{n} w_i \cdot u_i(x_i) \tag{4}$$

- x_i: Represents each attribute of the offer (such as price, quality, delivery time, etc.).
- $u_i(x_i)$: The partial utility function for attribute i.
- w_i: The weight of each attribute, adjusted so that the total equals 1.

Automated utility and mathematical negotiation models aim to mathematically formalize complex decision-making and interest adjustments to derive rational and efficient solutions. This focuses on defining utility functions and the interactions between agents in negotiations. Since this study involves two-party negotiation with $n = 2$ agents, they are represented as $i = 1, 2$. Here, equation (5) represents the utility maximization function, where the utility function $U(x)$ is maximized with respect to x, weighted by w_i.

$$\arg\max_x U(x) = \sum_{i=1}^{n} w_i U_i(x) \tag{5}$$

The utility maximization problem with constraints can now be formally expressed as:

$$\arg\max_x U(x) = \sum_{i=1}^{n} w_i U_i(x), \quad \text{subject to} \quad C(\omega) = \text{True} \tag{6}$$

Where:

- $C(\omega)$: Ensures that the selected solution ω satisfies all predefined constraints.
- ω: Represents the set of negotiation outcomes.

The introduction of constraints C ensures that the utility maximization process does not violate domain rules, resource availability, or any other predefined negotiation conditions. This adds a layer of realism and robustness to the negotiation model.

2.3 Issues and Constraints with C

In the proposed method, each user submits a fixed number of constraints to reach an agreement [16, 17]. The method then determines whether the submitted proposals can achieve a consensus by seeking a Nash equilibrium.

For example, consider a scenario where parents are purchasing toys. Their children discuss among themselves and decide that they want their parents to buy a LEGO block set. The children have mutually chosen the constraint of limiting their choice to a LEGO toy.

With the introduction of constraints C, the negotiation scenario can now include additional limiting factors:

- **Budget Constraint:** The toy must fall within a specific price range.
- **Availability Constraint:** The selected LEGO set must be available in stock.
- **Preference Constraint:** The set must meet specific design or feature preferences.

The negotiation process can thus be expressed as a constrained optimization problem, ensuring that both utility maximization and constraint satisfaction are achieved simultaneously:

$$\arg\max_x U(x) = \sum_{i=1}^{n} w_i U_i(x), \quad \text{subject to} \quad C(\omega) = \text{True} \tag{7}$$

This formulation ensures that while utility is maximized, all defined constraints C are respected, leading to feasible, efficient, and mutually agreeable outcomes.

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3 Experimental Setting and Result

3.1 Experimental Setting

This study's experimental setting is as follows: The method of fixing constraints is described. Constraints are set in equal numbers for each negotiating agent, assigned randomly. Two agents participate in each negotiation. Each negotiation session consists of 100 rounds, and the simulation is repeated 1,000 times. The agreement condition for the agents is determined by the value that maximizes the Nash bargaining solution. Each agent holds 100 constraints.

3.2 Experimental Result

The results of the experiment are presented below. In this study, the experimental results are evaluated based on the social welfare (sum of the utility values of the AI agents participating in the negotiation), and the negotiation time (in seconds).

First, we present the evaluation of social welfare. Figure (1) shows social welfare on the vertical axis and the number of fixed constraints on the horizontal axis.

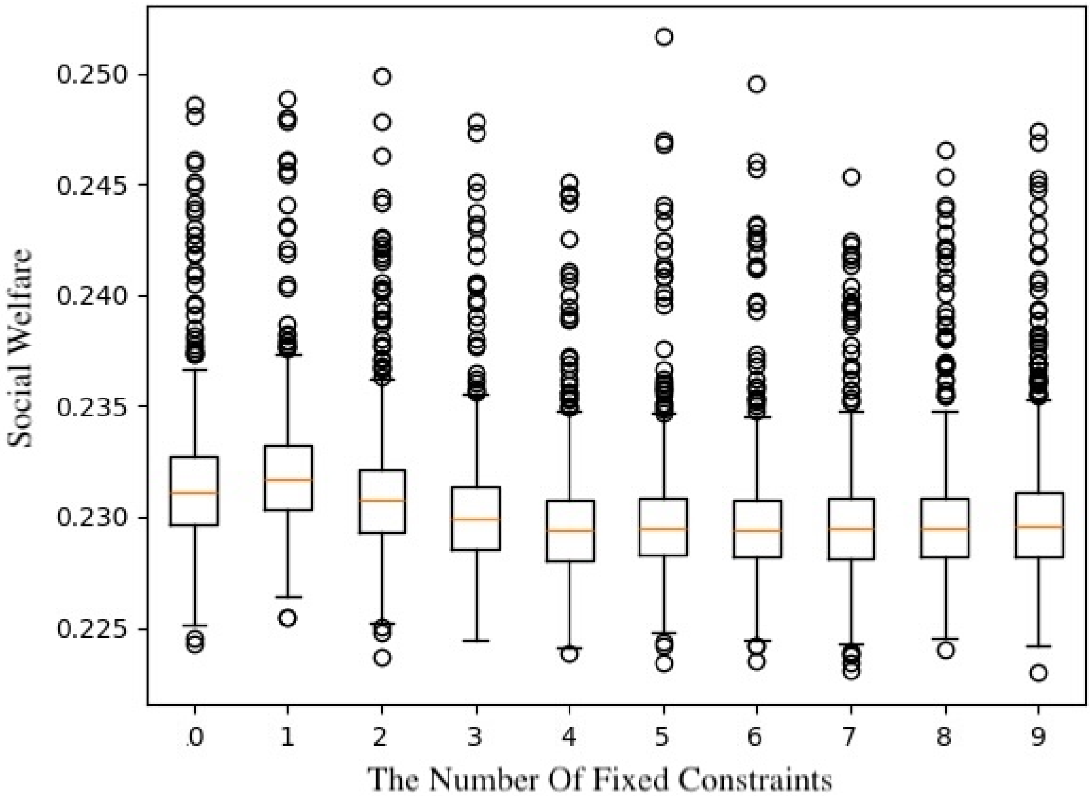

Figure 1: Social Welfare

It was observed that increasing the number of fixed constraints decreased social welfare.

This indicates that as the number of fixed constraints grows, it becomes more difficult to reach an agreement.

Finally, we evaluate negotiation time. Figure 2 suggests that there was not a significant difference in time, indicating that there may be little variation in negotiation time whether or not an agreement was reached.

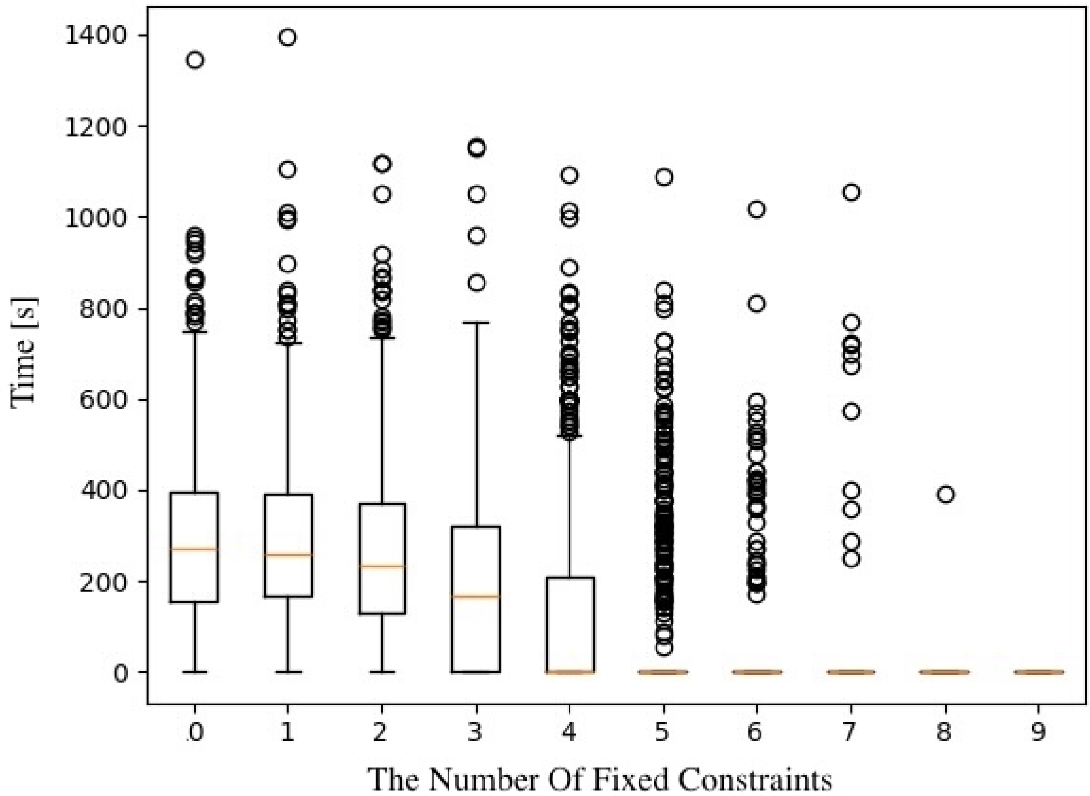

Figure 2: Negotiation Time

Considering these three results, we conclude that although changes in negotiation time were not substantial, both the number of agreements and social welfare decreased as the number of fixed constraints increased. In certain negotiations, it can be assumed that the importance of each constraint varies, and understanding the impact of fixed constraints is essential for examining real-world negotiations.

4 Conclusion

In certain negotiation scenarios, the relative importance of constraints may vary, making it essential to examine the impact of constraint fixation to assess negotiation dynamics effectively. This study investigates the outcomes of automated negotiation under fixed constraints, specifically focusing on social welfare (defined as the aggregate utility values of AI agents involved), the frequency of agreements reached, and the negotiation duration. Experimental results indicate that an increase in the number of fixed constraints correlates with a decrease in both social welfare and agreement frequency. Furthermore, the negotiation duration demonstrated minimal variation despite the increase in fixed constraints.

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References

[1] Sarit Kraus, Strategic Negotiation in Multiagent Environments. MIT Press, 2001.

[2] Tim Baarslag, Katsuhide Fujita, Enrico Gerding, Koen Hindriks, Takayuki Ito, Nick R. Jennings, Catholijn Jonker, Sarit Kraus, Raz Lin, Valentin Robu, Colin Williams, Evaluating Practical Negotiating Agents: Results and Analysis of the 2011 International Competition, Artificial Intelligence Journal (AIJ), Elsevier Science, Vol. 198, May 2013, pp. 73–103, 2013. (DOI:10.1016/j.artint.2012.09.004)

[3] Baarslag, Tim. What to bid and when to stop. Diss. Delft University of Technology, 2014.

[4] Peyman Faratin , Carles Sierra 1 , Nick R. Jennings, Negotiation Decision Functions for Autonomous Agents. Robotics and Autonomous Systems, 24(3-4), pp. 159–182, 1998.

[5] Shaheen S. Fatima, Michael Wooldridge, Nicholas R. Jennings, Multi-issue negotiation under time constraints, Proceedings of the first international joint conference on Autonomous agents and multiagent systems: part 1, pp. 143 - 150, 2002.

[6] Koen V. Hindriks, Catholijn M. Jonker, Creating human-machine synergy in negotiation support systems: Towards the pocket negotiator, Proceedings of the 1st International Working Conference on Human Factors and Computational Models in Negotiation, pp. 47-54, 2008.

[7] Tuomas Sandholm, Automated Negotiation: The Best for All Concerned. Communications of the ACM, 42(3), pp. 84–85, 1999.

[8] Ariel Rubinstein, Perfect Equilibrium in a Bargaining Model. Econometrica, 50(1), pp. 97–109, 1982.

[9] Akiyuki Mori, Takayuki Ito , An Automated Negotiating Agent Based on The Estimated Expected Utility, Transactions of the Information Processing Society of Japan (IPSJ Transactions), Vol. 56, No. 10, pp. 1968–1976, 2015 (In Japanese).

[10] Yuta Hosokawa, Ryohei Kawata, Katsuhide Fujita, Multi-Issue Negotiation Protocol with Pre-Domain Narrowing, Technical Committee on Artificial Intelligence and Knowledge-Based Processing, Vol. 119, No. 336, pp. 31–36, 2019 (In Japanese).

[11] Munenori Shioya, Hiroshige Inazumi, Mutual Agreement Mechanism for Multi-agent Systems by using Unified Negotiation Protocol, The 52th National Convention of IPSJ, pp. 261–262, 1996.

[12] Tatsuki Ikeda, Takayuki Ito, Automated negotiation simulation in the risk of not fulfilling agreements, The 37th Annual Conference of the Japanese Society for Artificial Intelligence, 1F4-GS-5-01, 2023 (In Japanese).

[13] Haolan Zhan, Yufei Wang, Tao Feng, et al., Let's Negotiate! A Survey of Negotiation Dialogue Systems, arXiv preprint arXiv:2402.01097, 2024.

[14] Ho-Chun Herbert Chang, Multi-Issue Bargaining With Deep Reinforcement Learning, arXiv preprint arXiv:2002.07788, 2020.

[15] Bram M. Renting, Holger H. Hoos, Catholijn M. Jonker, Automated Configuration of Negotiation Strategies, arXiv preprint arXiv:2004.00094, 2020.

[16] Hadfi, RafikUtility Hyper-graphs for Complex Decision Making, Doctoral thesis, Nagoya Institute of Technology, 2015.

[17] Shun Okuhara, Takayuki Ito, Compromising Strategies for Agents in Multiple Interdependent Issues Negotiation, IEICE Transactions on Information and Systems, vol. E103-D, no. 2, pp. 299-307, 2020.

[18] Takayuki Ito, Hiromitsu Hattori and Mark Klein, Multi-issue Negotiation Protocol for Agents: Exploring Nonlinear Utility Spaces, Proceedings of the 20th International Joint Conference on Artificial Intelligence (IJCAI), Hyderabad, India, 2007, pp. 1347-1352.