

AdaptiveBathNegotiator: An Adaptive Preference-Concealing Negotiation Agent for ANL 2026

Abstract

This report describes AdaptiveBathNegotiator, a bilateral negotiation agent for the ANL 2026 competition. Combining MiCRO-inspired descending aspiration with adaptive concession and dual frequency-based opponent modeling, the agent aims to maximize both negotiation advantage and preference concealment on the NegMAS platform.

1. Introduction

The ANL 2026 competition challenges participants to build agents that both secure favorable outcomes and conceal preferences from opponents. The scoring function is: $score_A = adv_A + tau_A / (tau_A + tau_B)$, where adv is normalized advantage and tau measures Kendall rank correlation between estimated and actual utility functions. Our agent addresses this through integrated bidding, opponent modeling, and acceptance components.

2. Concealing Bidding Strategy

2.1 MiCRO-Style Descending Aspiration

The bidding strategy uses a MiCRO-style function: $target(t) = u_{max} - (u_{max} - u_{floor}) * t^{e(t)}$. The target is strictly non-increasing, with u_{floor} = reserved + 0.50 x utility range. This avoids bathtub late-rise breakdown risks.

2.2 Adaptive Concession Speed

$e(t)$ adapts via opponent trajectory classification using linear regression on offered utilities. **Hardliner** (negative slope): e +2.5 to stand firm. **Conceder** (slope > 0.08): e -1.5 to exploit. **Erratic** (variance > 0.25): e +0.3 for safety. **Regular**: base e = 3.0 (boulware). A stalemate detector (utility variance < 0.02 over 6 rounds) adds +0.8 to freeze concessions.

2.3 Bid Selection

Candidates in a utility band around target are scored by multi-factor weighting: self-utility (0.55 to 0.37), opponent model (0.20 to 0.60), closeness to target, novelty, diversity, opponent-offer bonus, and repeat penalty. Novelty/diversity bonuses obscure preference patterns from the opponent model, providing implicit preference concealment. Random noise adds further unpredictability.

3. Opponent Modeling

SFM: Per-issue frequency counts with stability scores. Effective in early negotiation. **DFM:** Chi-square tests on distribution shifts between sliding windows. Detects concessions and weights unchanged issues. **Combined:** Fused as $w_{dfm} = \min(0.85, 0.35 + 0.50 \times \text{confidence})$, transitioning from SFM to DFM dominance as data accumulates.

4. Acceptance Strategy

Early ($t < 0.30$): All offers rejected. **Mid-Early ($t < 0.75$):** Requires opponent concession evidence before relaxing. **MiCRO Baseline:** Accept if offer $\geq$ target. **Late ($t > 0.65$):** Tolerance gap gradually widens. **Endgame ($t > 0.90$):** Accept best historical within margin; $t > 0.95$ accepts any offer above reservation.

5. Experimental Results

Rank	Agent	Mean Score
1	AdaptiveBathNegotiator	1.637
2	MAPNeg	1.617
3	BoulwareTBNegotiator	0.788
4	AspirationNegotiator	0.782

Table 1. Tournament results (3 scenarios, 108 negotiations).

The agent achieves strong scores against Conceder-style opponents (1.95 vs ConcederTB) while remaining competitive against MAPNeg (1.30 vs 1.33). All negotiations follow AOP protocol with no state preserved between negotiations per competition rules.

6. Conclusion

AdaptiveBathNegotiator combines MiCRO aspiration, adaptive concession, dual frequency opponent modeling, and multi-phase acceptance into a competitive agent. Future work could add explicit bluff bidding and Bayesian opponent modeling for improved concealment.

References

- [1] de Jonge & Zhang (2024). MiCRO is Near-Optimal for Bilateral Negotiations.
- [2] Tunali et al. (2017). Rethinking Frequency Opponent Modeling.
- [3] ANAC 2026. <https://anac.cs.brown.edu>