



**Vilnius
University**

A Multi-Agent System for Facility Location Problems

Sathuta Sellapperuma

PhD supervisor - Assoc. Prof. Dr. Algirdas Lančinskas, PhD)

Year of start & end of the PhD (2023 - 2027)

Content

- **Study Progress**
- **Motivation, Objectives of the study**
- **Previous Work**
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- **Conclusion and Future**

Courses of Study Plan

Study Year	Examinations	
	Plan	Completed
1 st Year – 2023/2024	1	1
2 nd Year – 2024/2025	3	2
3 rd Year – 2025/2026	0	1
4 th Year – 2026/2027	0	-
Total	4	4

Publication Plan

Year of Study	Attending Conference				Publications					
	International		National		With impact factor			Without Impact factor		
	Plan	Implemented	Plan	Implemented	Plan	Implemented	Condition	Plan	Implemented	Condition
1st (2023/2024)				1 (doctoral consortium – DBIS-2024)						
2nd (2024/2025)				1 DAMSS						
3rd (2025/2026)	1	NUMTA - Abstract Accepted			1 (A paper plan to submit soon)			1		
4th (2026/2027)	1				1					
Total	2		1	2	2			1		

	agency's of the multi-agent system.		
2.3.	Empirical study:		
2.3.1.	Data Collection for Agent Model Training and Analysis	2025 y. III quarter	2026 y. III quarter
2.3.2.	Application of the developed methods to solve facility location problems.	2025 y. III quarter	2026 y. III quarter
2.3.3.	Experimental investigation of the developed methods and their evaluation (validation, Verification and calibration of the developed agent models)	2025 y. III quarter	2026 y. III quarter
2.3.4.	Identification and tuning parameters for multi-agent systems	2025 y. III quarter	2026 y. III quarter
2.4.	Analysis of got facts, summing-up, drawing conclusions:		
2.4.1.	Summarising the theoretical study.	2025 y. IV quarter	2026 y. IV quarter
2.4.2.	Summarising the empirical study.	2025 y. IV quarter	2026 y. IV quarter
2.4.3.	Analysis and description of the results and drawing conclusions.	2025 y. IV quarter	2026 y. IV quarter

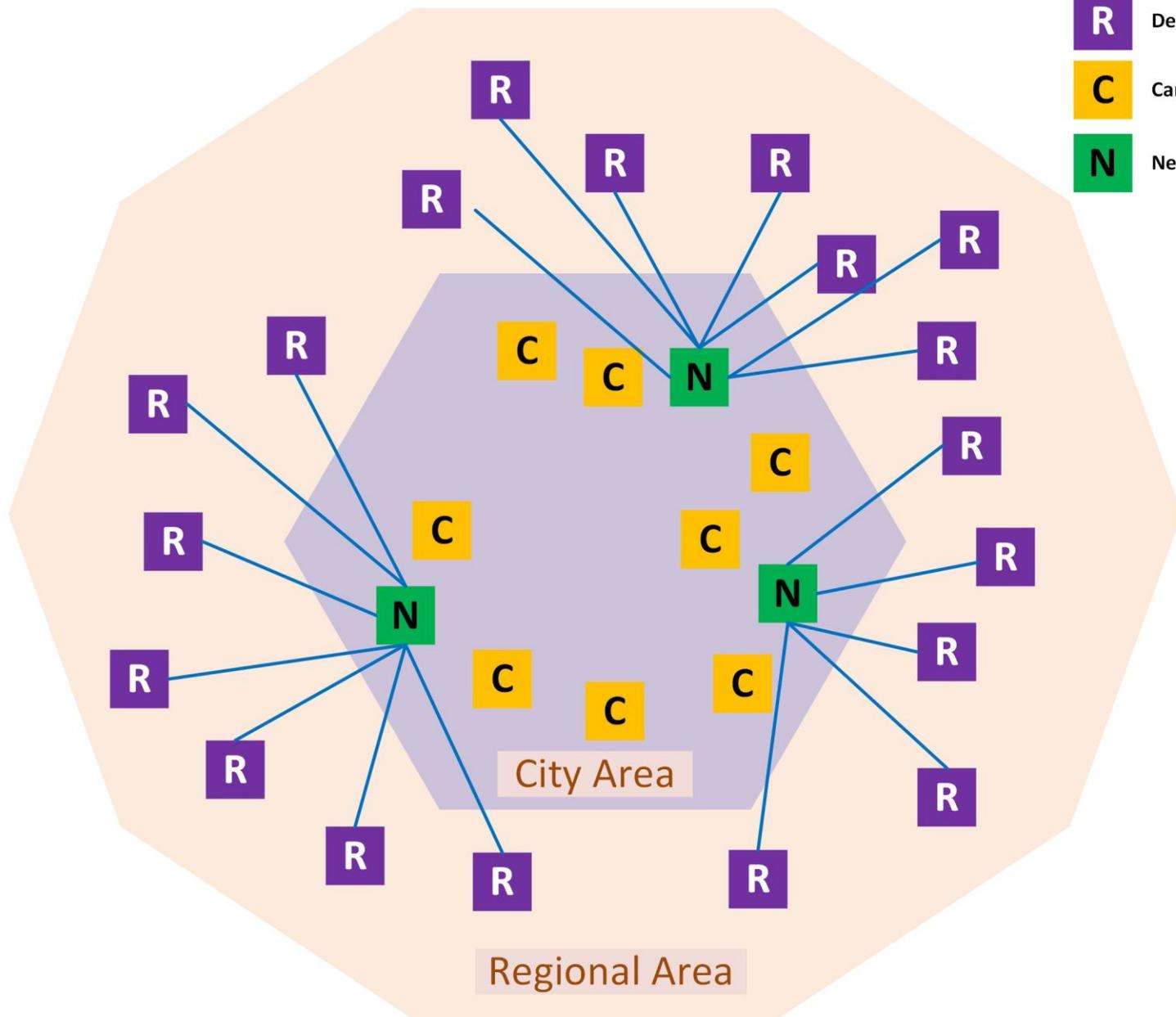
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**Research
Plan
(Last 6
Months)**

Motivation

- Facility Location Problem, specifically with the **park and ride model**, to solve the **uncertainty behavior** of the customer, and find a **Robust combination solution** on binary and proportional customer behavioral models under both objectives in a maximization manner.
- The multi-agent system used in this situation is studied further with a **negotiating agent** to find **non-dominated solutions** and finally to find a robust solution.

- R** Demand Points - Regional
- C** Candidate Locations - City
- N** New P&R Hubs (Proposed)



Park & Ride model

Research Objective

- Develop a Multi Agent System (MAS) for FLP
- Model binary and proportional customer behaviors

Identify:

- Non-Dominated Facility Location solutions
- Single robust solution

Previous Work (MAS)

- Ranking-based candidate selection
 - Voting and MAPN negotiation strategies
 - Dominance-based Pareto filtering
 - Verified using complete enumeration
- **Limitation:**
 - Efficiency and Negotiation coordination required improvement
 - Robust Solution Selection method need improvement
 - Improvements to Verification and Validation for MAS results

Key Improvements

- Learning-based solution generation
- Separate **proposal & evaluation phases**
- Duplicate control mechanism
- Lightweight **FIPA ACL communication**
- Efficient **MAPN-based negotiation**

MAS Workflow (New System)

- Initialization of agents and parameters
- Proposal phase (generate candidate solutions)
- Evaluation phase (compute utilities)
- Dominance filtering (update Pareto set)
- Iteration update (repeat until termination)
- Robust Solution Finding (MMD based Knee Selection)

Learning-Based Solution Generation

- Ranked candidate locations
- Probability-based selection (Roulet-wheel)
- Roulette-wheel sampling
- Balances **exploration & exploitation**
- **Key Result:**
- High acceptance rate (92 - 95%)

FIPA-ACL Communication

Message Type	Performative	Sender > Receiver
proposal_request	request	Base Agent > Behavioral Agent
proposal	propose	Behavioral Agent > Base Agent
evaluation_request	request	Base Agent > Other Behavioral Agent
evaluation	inform	Behavioral Agent > Base Agent
termination	inform	Base Agent > All Agents

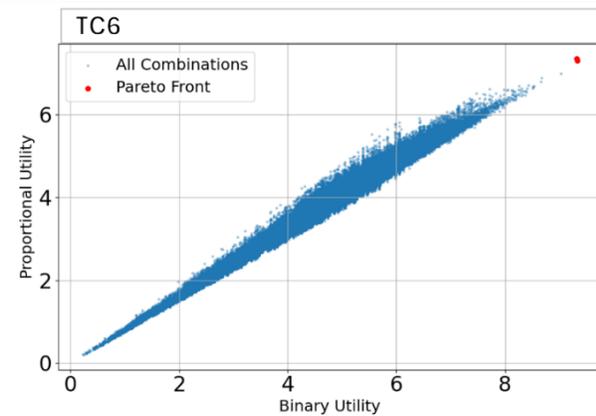
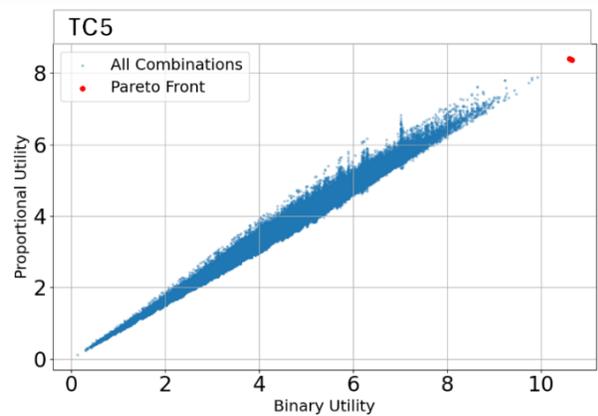
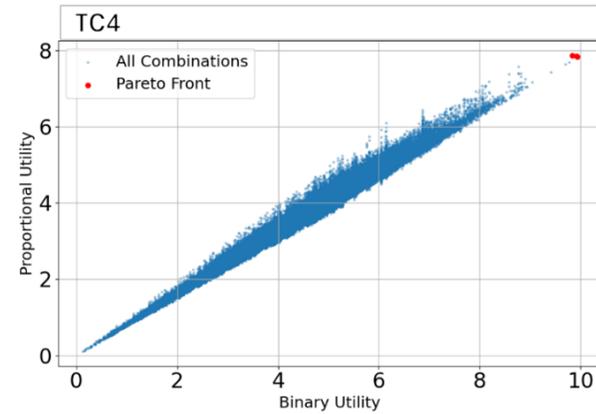
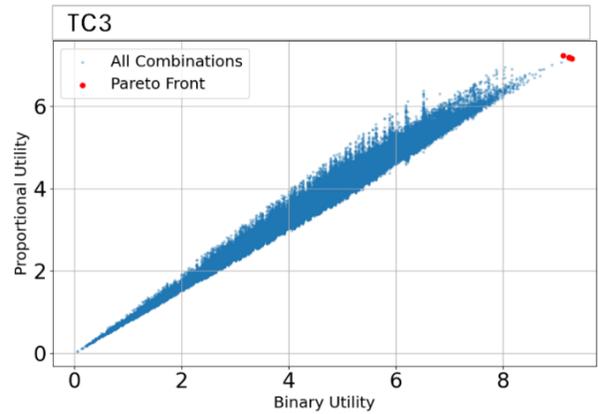
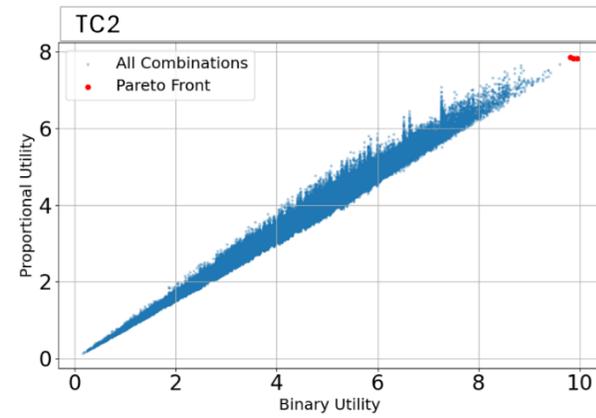
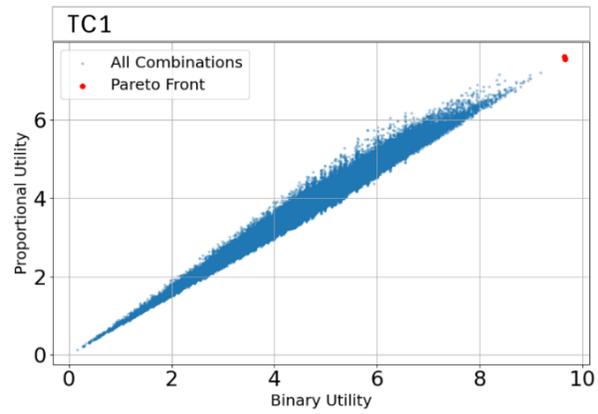
- Lightweight **FIPA-ACL messaging**
- Standardized message structure
- Supports **proposal & evaluation exchange**
- Enables clear and structured agent coordination

Experimental Setup

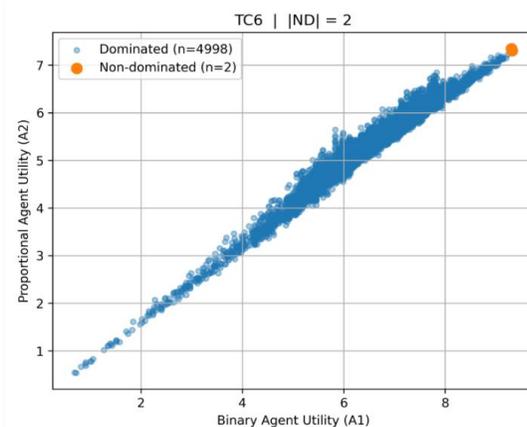
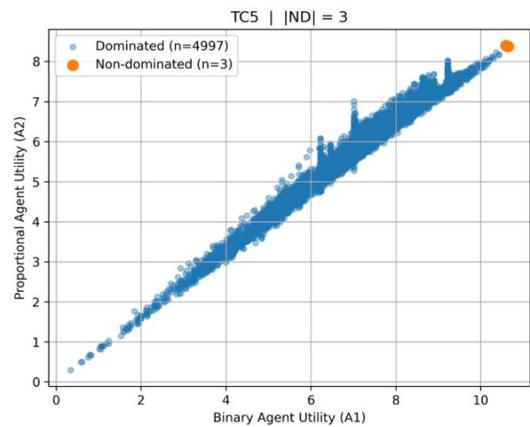
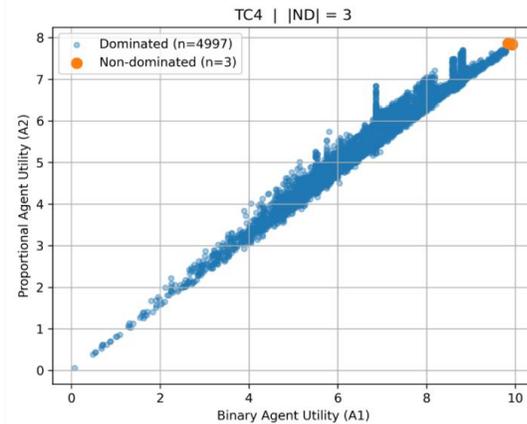
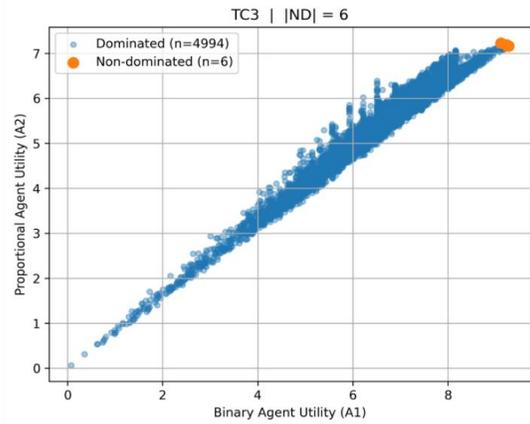
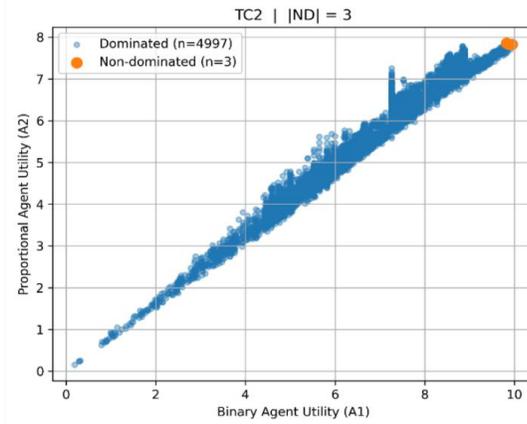
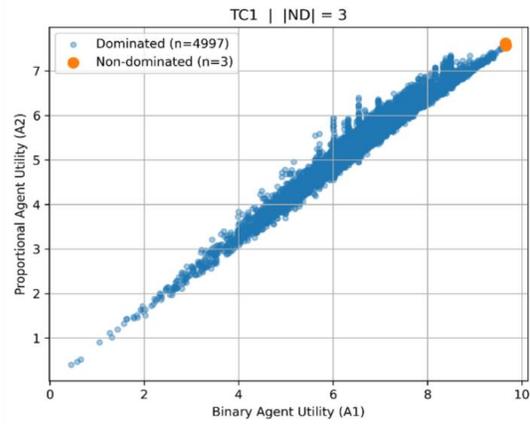
Parameter	Value
Candidate locations	283
Demand regions	440
Facilities selected (k)	3
Test cases	6
Max iterations	2500

Verification Results – Complete Enumeration

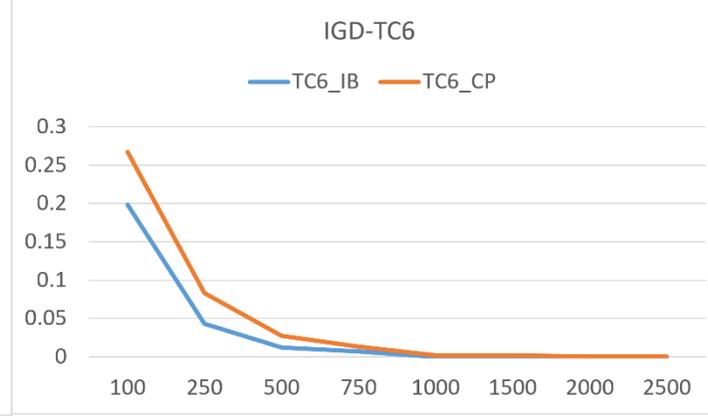
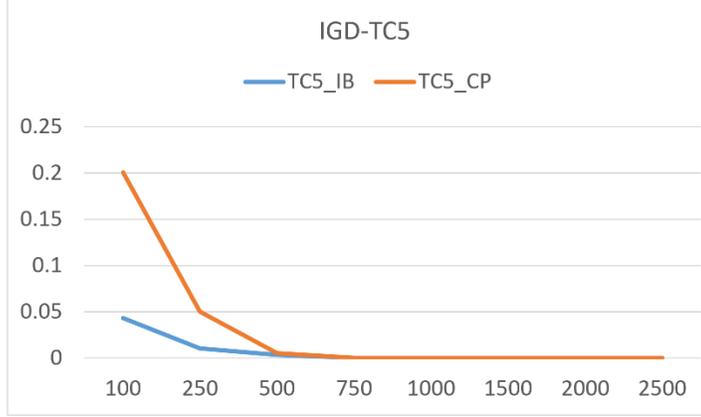
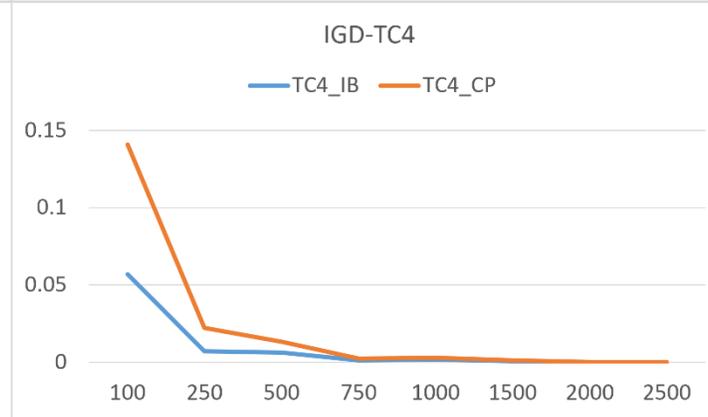
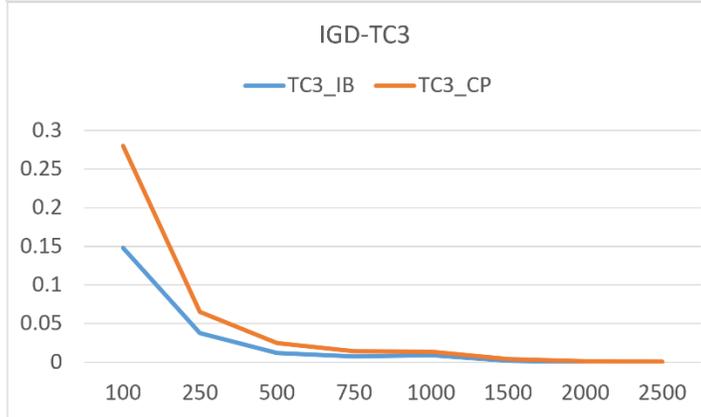
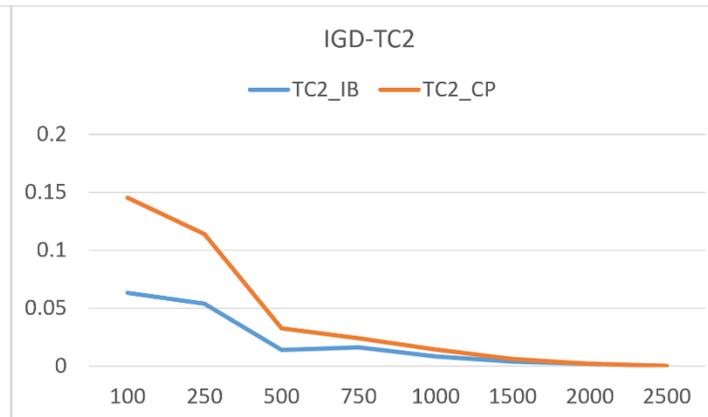
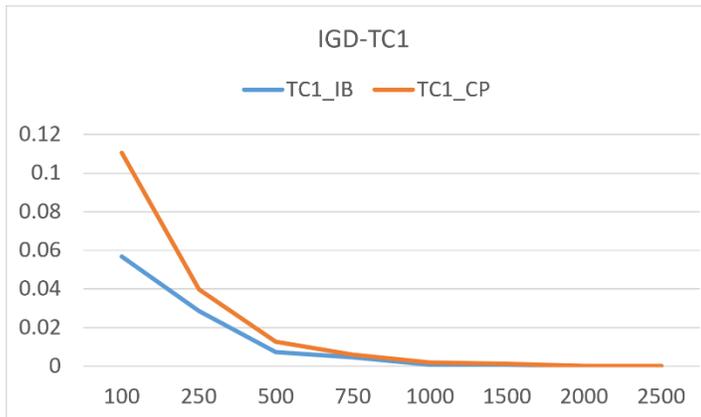
Test Case	Size	Solutions	Utility Values (U_bin, U_prop)
TC ₁	3	[146, 255, 274]	(9.6630, 7.5600)
		[20, 157, 274]	(9.6621, 7.5787)
		[20, 255, 274]	(9.6529, 7.6191)
TC ₂	3	[130, 219, 265]	(9.9483, 7.8261)
		[58, 155, 265]	(9.8752, 7.8306)
		[58, 219, 265]	(9.8218, 7.8556)
TC ₃	6	[127, 240, 265]	(9.2781, 7.1645)
		[127, 240, 244]	(9.2517, 7.1703)
		[127, 192, 265]	(9.2415, 7.1839)
		[77, 192, 265]	(9.2327, 7.1907)
		[127, 192, 244]	(9.2221, 7.1921)
		[77, 88, 244]	(9.1176, 7.2294)
TC ₄	3	[146, 174, 252]	(9.9289, 7.8319)
		[96, 174, 252]	(9.9239, 7.8472)
		[155, 174, 252]	(9.8407, 7.8606)
TC ₅	3	[113, 212, 265]	(10.6488, 8.3754)
		[180, 212, 265]	(10.6291, 8.3803)
		[212, 233, 265]	(10.5972, 8.3991)
TC ₆	2	[113, 252, 274]	(9.3250, 7.3044)
		[113, 174, 252]	(9.3126, 7.3472)



COMPLETE ENUMERATION PARETO FRONT



MAS RESULTS



Convergence & Efficiency

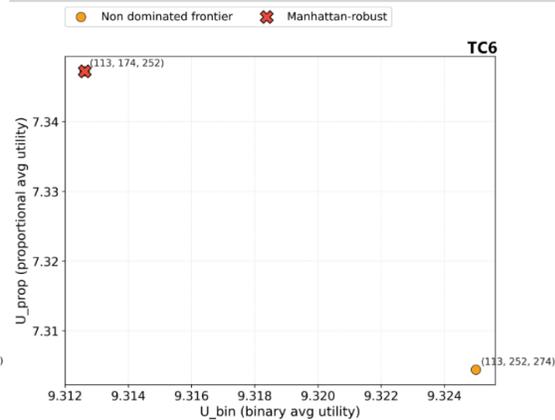
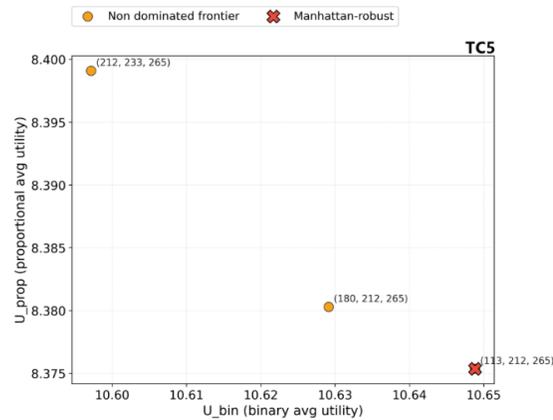
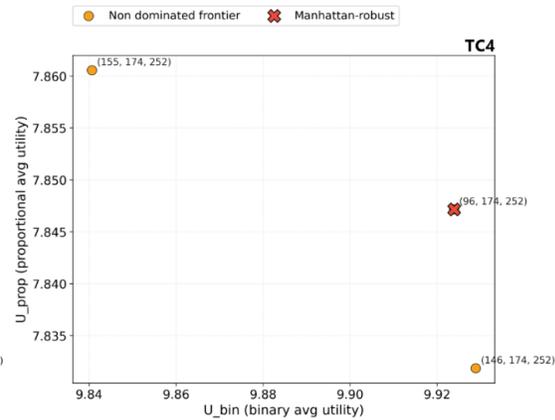
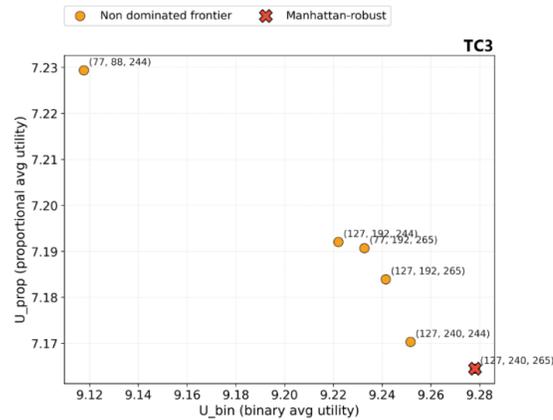
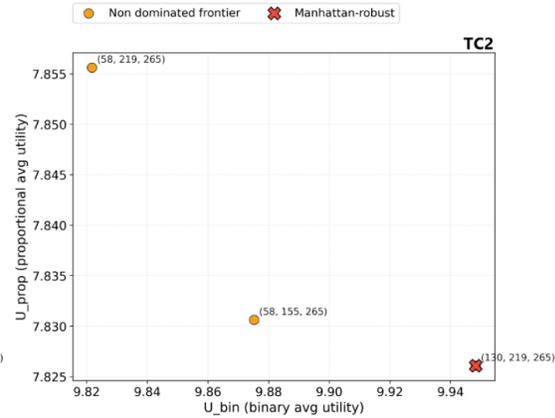
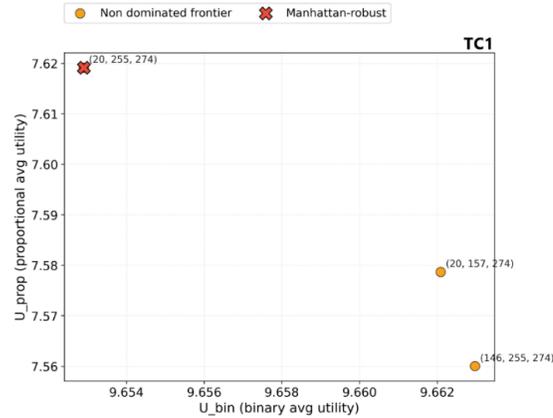
- IGD → converges to ~0
- Stable convergence within **2000–2500 iterations**
- **Evaluation Cost:**
 - 3.7M (Complete Enumeration)
 - ~5k (MAS)
- **Key Message:**
 - ~99.8% reduction in computational effort

Efficiency of the Negotiation Process

Test Case	Generated Solutions (A1/A2)	Unique Solutions after Local Filtering (A1/A2)	Local Duplicate Rejections (A1/A2)	Base Agent Rejections (A1/A2)	Rejection Rate (%) (A1/A2)
TC ₁	2766 / 2802	2586 / 2596	180 / 206	86 / 96	93.49 / 92.65
TC ₂	2695 / 2739	2562 / 2566	133 / 173	62 / 66	95.06 / 93.68
TC ₃	2770 / 2789	2575 / 2584	195 / 205	75 / 84	92.96 / 92.65
TC ₄	2775 / 2788	2589 / 2593	186 / 195	89 / 93	93.30 / 93.01
TC ₅	2774 / 2837	2580 / 2599	194 / 228	80 / 99	93.01 / 91.93
TC ₆	2727 / 2765	2576 / 2580	151 / 185	76 / 80	94.46 / 93.31

Robust Solution

- MMD-based knee-point selection
- Identifies a **balanced compromise solution**



Conclusion and Future

- MAS reconstructs the Pareto-optimal front
- Achieves high computational efficiency
- Enables robust decision-making under uncertainty

Final Takeaway:

- MAS is an effective approach for FLP under behavioral uncertainty

Future Directions

- Advanced learning (RL / bandit-based methods)
- Enhanced negotiation strategies (agent & mediator level) to make more efficient
- Scalability analysis for larger data set with candidate locations, demand points larger K values etc...
- Robustness under richer uncertainty scenarios

THANK YOU

