

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
- Use ranked solutions in the MAS
- Voting Base Agent Negotiation
- MAPN Dominance Negotiation
- FIPA-ACL Light-weighted Simplified Method
- Complete Enumeration
- Test Cases and Results
- Summary and Future Plan

Courses of Study Plan

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

Publication Plan

Year of	Atte	ending Con	ference		Publications					
Study	International		National		With impact factor			Without Impact factor		
	Pla n	Implem ented	Plan	Implemented	Plan	Implem ented	Conditi on	Plan	Implement ed	Condition
1st (2023/2024)				1 (doctoral consortium — DBIS-2024)						
2 nd (2024/2025)			1 (progress writing an abstract for DAMSS conference)							
3 rd (2025/2026)	1				1			1		
4 th (2026/2027)	1				1					
Total	2		1	1	2			1		

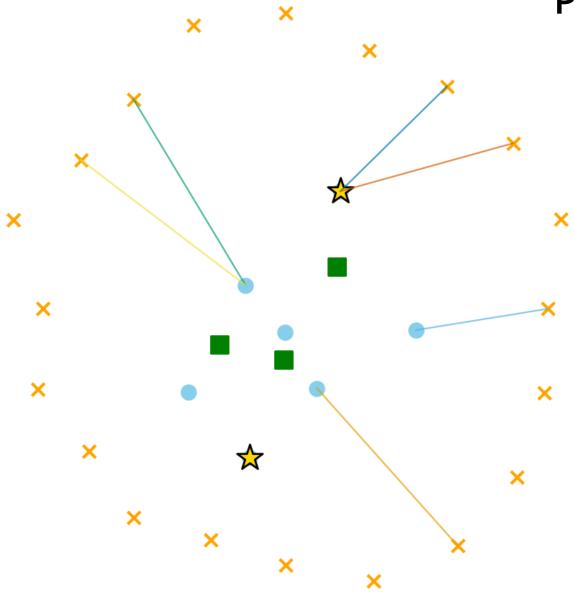
2.2.	Theoretical study:		
2.2.1.	Analysis of scientific (and other) literature of Competitive Facility Location and Multi-Agent Base solutions.	2025 y. I quarter	2025 y. III quarter
2.2.2.	Selection and description of implementing multi- agent systems for facility location problem	2025 y. I quarter	2025 y. III quarter
2.2.3.	Creation of optimised algorithms for facility location using identified parameters over agent/s of the multi-agent system.	2025 y. I quarter	2025 y. III quarter
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

Research Plan (Last 6 Months)

Motivation

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

Park & Ride Problem



- × Regions demand
- Cities candidate sites
- Existing P&R hubs
 - Selected new hubs example

Objectives of the study

Find the non-dominated set efficiently

• On this objective, it is necessary to prioritise the most suitable candidates to select for earlier evaluation of utility values through Binary and Proportional agents.

Utilise an agent communication model to find a non-dominated candidate combination set.

• This should be working on a standardised communication method and protocol. But needs to be suitable with existing requirements.

Find the robust solution based on the non-dominance frontier

• Find and evaluate available frontier methods to select a suitable solution for the current scenario. This should meet the solution for the uncertainty of the customer behaviour.

Verify the selected output is valid and correct

• The MAS system's given results should be verified with the standard practical method.

Utility models and Objective

Binary (winner-takes-all):

• Each demand point picks the single most attractive site; we capture it if one of our k sites is best (ties split).

Proportional (share-by-attractiveness):

• Each demand point splits among all sites in proportion to attractiveness; we capture our share.

maximize both *U*bin and *U*prop

 Use the Pareto set to manage trade-offs before picking a robust single combo.

Use of Ranked Solutions with MAS Agentsiversity

- Each agent (Binary / Proportional) keeps its own rank table over candidate sites, reflecting behaviour-specific attractiveness.
- Ranked candidates can be used by the agents by prioritising higher ranks to propose for negotiation.
 - Voting Base Negotiation
 - MAPN (Mediated Alternating-Proposal Negotiation; dominance-based)

Voting-based negotiation - Phase 1 (Ballottersity Building)

- Input: Union of each agent's Top-N ranked sites.
- Process: For each k-combo, both agents compute utilities and apply per-agent rules (utility threshold, rank-match) → cast YES/NO.
- Outcome: Keep Both_Accept combos in a ballot table; later run Pareto filtering on these.

per-agent voting rules

- Utility threshold, eg 75% of the maximum utility Value
- Rank-match e.g., at least two of the candidate locations should be within Top M of the agent ranked candidate list

Voting-Based Negotiation — Phase 2 (Mediation + Top-N Expansion)

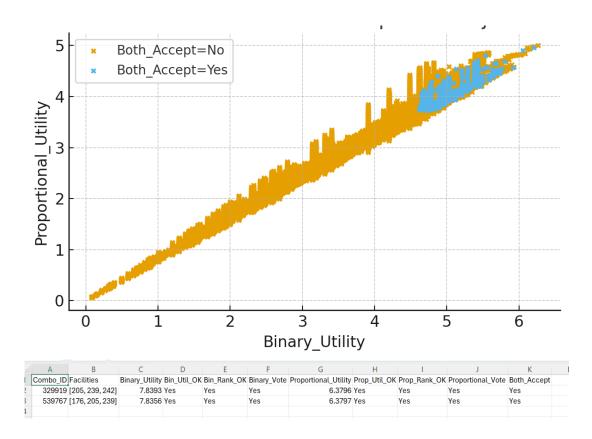
• Convert Both_Accept combinations (Phase-1) into a final ε-Pareto front and expand Top-N only if the frontier is too small, narrow, or stagnant.

Top N expansion factors

- The number of Pareto points
- Diversity of the Pareto front measured in average pairwise L1 distance
- no improvement (best utilities or archive quality) over a last round.

Utility spread over Accepted vs Rejected University from the Ballot table and Final Pareto Set

	Α	В	С	D	E	F	G	Н	1	J	K
	Combo_ID	Facilities	Binary_Utility	Bin_Util_OK	Bin_Rank_OK	Binary_Vote	Proportional_Utility	Prop_Util_OK	Prop_Rank_OK	Proportional_Vote	Both_Accept
	7242	[137, 211, 213]	6.2618	Yes	No	No	5.0031	Yes	Yes	Yes	No
	29747	[211, 213, 116]	6.205	Yes	Yes	Yes	4.9545	Yes	Yes	Yes	Yes
	7250	[137, 211, 101]	6.2039	Yes	Yes	Yes	4.9817	Yes	No	No	No
	7291	[137, 213, 245]	6.1751	Yes	No	No	4.9733	Yes	Yes	Yes	No
	29847	[211, 101, 116]	6.1475	Yes	Yes	Yes	4.9323	Yes	No	No	No
	30167	[213, 116, 245]	6.1164	Yes	No	No	4.9255	Yes	Yes	Yes	No
	7391	[137, 101, 245]	6.1091	Yes	No	No	4.9555	Yes	Yes	Yes	No
	29738	[211, 213, 96]	6.0855	Yes	No	No	4.8383	Yes	Yes	Yes	No
)	30763	[101, 116, 245]	6.0508	Yes	Yes	Yes	4.9069	Yes	Yes	Yes	Yes
	29800	[211, 96, 101]	6.0367	Yes	Yes	Yes	4.8261	Yes	No	No	No
2	30095	[213, 96, 245]	6.024	Yes	No	No	4.8123	Yes	Yes	Yes	No
3	26173	[189, 211, 213]	5.9782	Yes	Yes	Yes	4.8312	Yes	No	No	No
1	30531	[96, 101, 245]	5.9591	Yes	No	No	4.8033	Yes	Yes	Yes	No
5	26181	[189, 211, 101]	5.9338	Yes	Yes	Yes	4.8103	Yes	No	No	No
5	7343	[137, 96, 101]	5.9331	Yes	No	No	4.5803	Yes	Yes	Yes	No
7	29744	[211, 213, 233]	5.9317	Yes	Yes	Yes	4.8064	Yes	No	No	No
3	30530	[96, 101, 116]	5.9173	Yes	Yes	Yes	4.5685	Yes	Yes	Yes	Yes
9	26222	[189, 213, 245]	5.9043	Yes	No	No	4.8095	Yes	Yes	Yes	No
)	7387	[137, 101, 233]	5.8964	Yes	Yes	Yes	4.6239	Yes	No	No	No
	29844	[211, 101, 233]	5.8884	Yes	Yes	Yes	4.7861	Yes	No	No	No
}	7281	[137, 213, 96]	5.8862	Yes	No	No	4.5521	Yes	Yes	Yes	No
3	30094	[213, 96, 116]	5.8715	Yes	No	No	4.5426	Yes	Yes	Yes	No
ļ	7287	[137, 213, 233]	5.8672	Yes	No	No	4.6117	Yes	Yes	Yes	No
5	6956	[137, 189, 101]	5.8648	Yes	Yes	Yes	4.5992	Yes	No	No	No



MAPN (Mediated Alternating Proposal Negotiation, dominance-based)

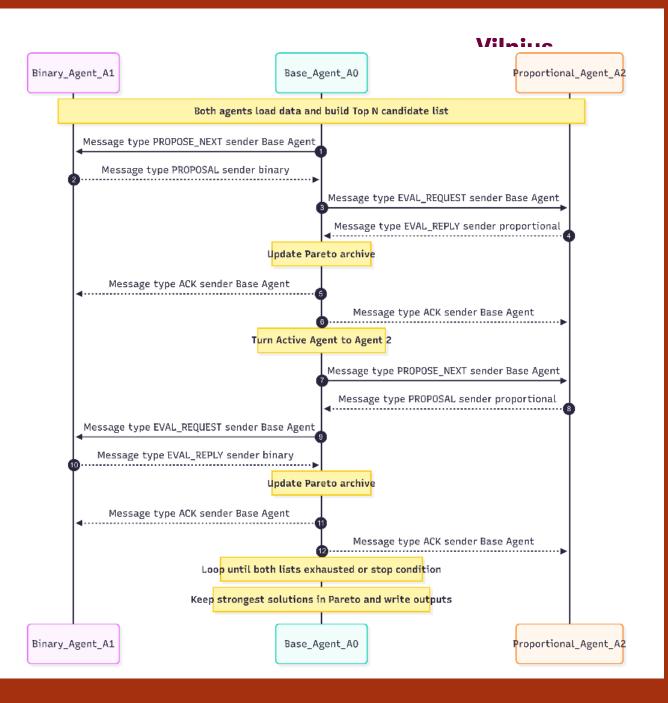
- Binary agent (A1), Proportional agent (A2), Base agent (A0).
- Each agent utilizes its own behaviour Top-N lists of candidate locations.
- Agents take turns proposing a combo; the peer evaluates; the base agent updates an ε-Pareto archive (insert if non-dominated, prune dominated).

 Outcome: A compact nondominated set is maintained online, ready for robust selection.

FIPA-ACL (Simplified) Envelope & Rationale

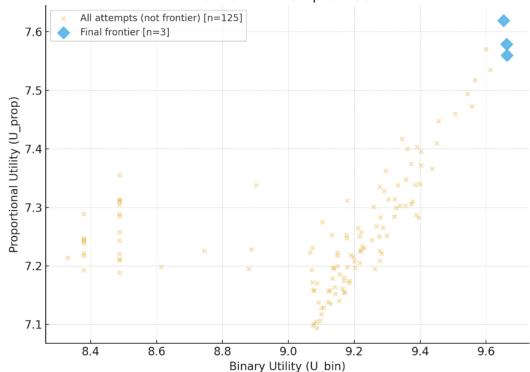
- Full FIPA has 13 fields; This MAS keep 6
- speed, clarity, and easy logging

```
"performative":"pr",
"sender":"agent1",
"receiver":"agento",
 "conversation_id":"pp-20250914-42",
"reply_with":"Booo1",
"content":{"combo":[146,255,274],"
utility":9.6620}
```



Final Non-Dominated set

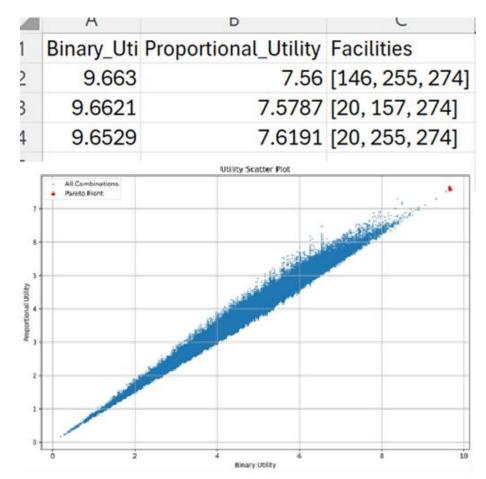




	Α	В	C	D	Е	F	G	Н
	rank	а	b	С	k	U_bin	U_prop	source
2	1	146	255	274	3	9.662967377958001	7.5600258306249835	binary
3	2	20	157	274	3	9.662086058255126	7.578686530169721	binary
1	3	20	255	274	3	9.652902375742302	7.6191380683403445	proportional
5								

Complete Enumeration — Verification & Validation of MAS

- Establish a ground-truth Pareto set to verify MAPN/voting outputs.
- Evaluate all (Lk) combinations; compute Ubin, Uprop; extract the exact Pareto front



Vilnius

Comparison MAS MAPN with Complete Enumerated Pareto Results

Test Case	CityQualities	MAS Pareto Size	Enum Pareto Size	Overlap (%)
TC1	cityQualities_1.dat	3	3	~100%
TC2	cityQualities_2.dat	3	3	~100%
TC ₃	cityQualities_3.dat	6	6	~100%
TC4	cityQualities_4.dat	3	3	~100%
TC ₅	cityQualities_5.dat	3	3	~100%
TC6	cityQualities_6.dat	2	2	~100%

Robust Solution Finding Methods

- **Distance-based**: Manhattan, Euclidean, Chebyshev
- Rank-based: TOPSIS, VIKOR
- Curvature-based: Knee point

- Most methods (Manhattan, Euclidean, Chebyshev, VIKOR, Knee) select (20,157,274) after normalization.
- TOPSIS depends on normalization type (vector \rightarrow (20,255,274); min—max \rightarrow (20,157,274)).

Summary: Insight Future plan

- The voting frontier indicated that accepted combinations are located in the upper right corner of the scatter plot, suggesting that voting negotiation led to higher quality outcomes.
- MAPN-Dominance-based MAS for CFLP gave better results compared with the Pareto front generated with complete enumeration.

- Improving logic of the agents (reinforcement learning)
- Improving communication and negotiation strategies.
- Finding robust solutions (s) for facility location problems
- Extending experimental investigation to more test cases and data

THANKYOU