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Algorithms for Resource Exchange in Networks

The Influence of homo- and heterogeneous Strategies in Resource Exchange Environments on the approximation of Equilibria

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01. Introduction

Resource exchange networks are becoming more prevalent in every day life. For example **energy sharing neighbourhoods** like the **Brooklyn Microgrid** or **file sharing services** like **BitTorrent**.
These networks have similar characteristics which allows them to be modelled using the same framework. Participants are modelled by **nodes** (**agents**) in a graph and the option for the agent to give to another agent is represented by an **undirected edge** between these nodes.
In previous studies, few strategies have been compared.
This research investigates how different agent strategies change whether and the speed at which **Equilibrium** states are approximated.

02. Research Question

How do the different strategies and pairs of strategies affect the approximation of an equilibrium in a sharing economy?

1. **Which** strategies **approximate** an equilibrium allocation?
2. How do the different strategies compared to each other measured by the **percentage distance** from the Pareto optimal allocation?
3. How do the different strategies compare to each other measured by the **number of iterations** needed to get arbitrarily close to the Pareto Optimal allocations?

Nomenclature

Loss : The normalized distance from a market equilibrium allocation vector to the current market vector
x_{ij} : Allocation from agent i to agent j
$\vec{x}_i$: the allocation vector of agent i
v_i : Value of agent i's resources
U_i : Total utility obtained by agent i
ρ_i : Sharing ratio of i, calculated by taking the average total utility of i divided by the average value of i's endowment

03. Agent Strategies

1. **Greedy**: Agent aims to maximize its utility by giving to the neighbour with the **lowest Sharing ratio**, with the expectation the agent will reciprocate the sentiment next round
2. **Proportional**: Agent **reciprocates proportionally** to the utility it received from its neighbours last round.
3. **Egalitarian**: Agent aims to **minimize** the **inequality** between neighbours by minimising the differences in Sharing ratio's.
4. **Imitation**: Agent aims to maximise its own utility by **copying** the **most successful strategy** of its neighbours.
5. **Satisficing**: Agent aims to maximize its utility **up to** their **aspiration level**, after which it is satisfied and maintains the previous allocation.
6. **Petty**: Agent is focussed on **exact reciprocation** of the utility received the previous round.

Homogeneous simulation means that **every agent** in the network uses the **same** strategy/combination of strategies.

Heterogeneous means **each agent** can have its **own** strategy/combination of strategies.

05. Mathematical Description

Greedy: $$\vec{x}_i(t) = \max_{\vec{x}_i}(\hat{U}_i(t+1))$$

Proportional: $$x_{ij}(t+1) = D_i(t+1)\cdot\frac{v_i\cdot x_{ji}(t)}{\sum_{k\in\mathcal{N}_i} v_k\cdot x_{ki}(t)}$$

Egalitarian: $$x_{ij}(t+1) \propto \left(\max_{k\in\mathcal{N}_i}\rho_k(t) - \rho_j(t)\right)$$

Imitation: $$s_i(t+1) = \begin{cases} s^{max}(t) & \text{if } s_i(t)\notin\mathcal{M}(t) \\ s_i(t) & \text{if } s_i(t)\in\mathcal{M}(t)\end{cases}$$

Satisficing: $$\vec{x}_i(t+1) = \begin{cases}\vec{x}_i(t) & \text{if } \rho_i(t)\geq\alpha_i \\ \vec{x}_i^{greedy} & \text{if } \rho_i(t)<\alpha_i\end{cases}$$

Petty: $$x_{ij}(t+1) = x_{ji}(t)$$

06. Methodology

Using the definitions of the strategies and transforming them into strategies that can be used by agents in the simulation environment.
The only information an agent has about other agents is their sharing ratio and their strategy (only necessary for the imitation strategy).
Simulations are performed using **5 graph types** (complete, random, grid, scale-free and small-world graphs) and **mixes of agent strategies** (pure- and mixed strategies, and homo and heterogeneous populations).
Simulations are run with **30 agents** for **400 iterations**, to minimize the influence of run to run variance each simulation is repeated 30 times.

07. Results

All graphs are **log-log graphs**, the **closer** to **0** the strategy gets the **better**.

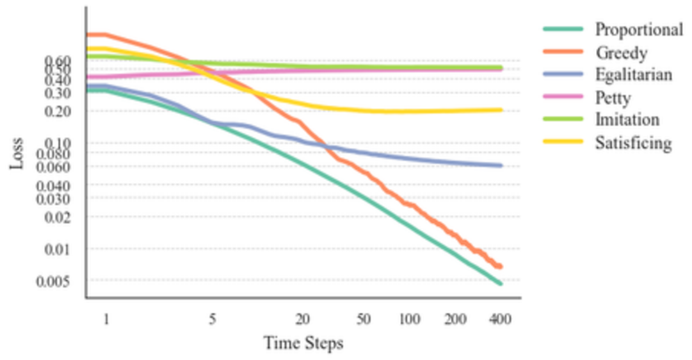

Fig 1: Result of the pure strategy simulations

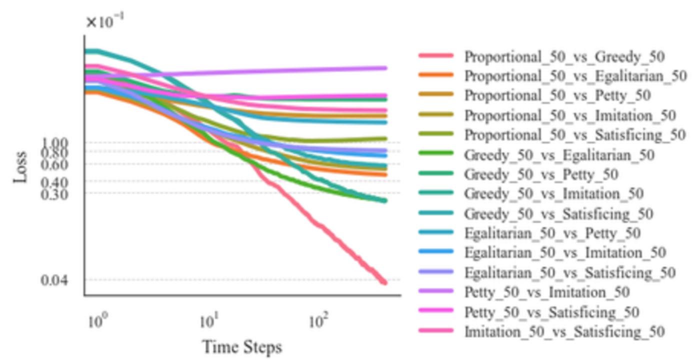

Fig 2: Result of the homogeneous simulations

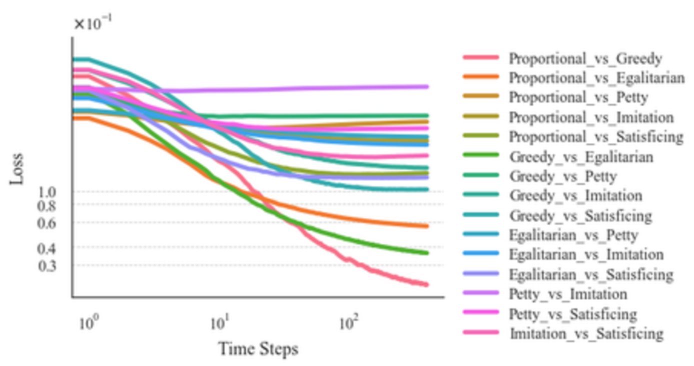

Fig 3: Result of heterogeneous simulations

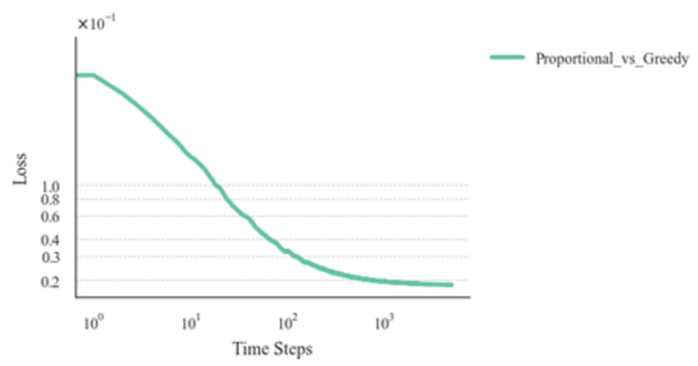

Fig 4: Simulation of 5000 iterations of the heterogeneous mix of proportional and greedy agents

08. Conclusion

- From the **first simulation**, visualised in fig.1, we concluded that only the **greedy** and **proportional** strategies **converge** in a **asymptotic** manner
- Other pure strategies do **not approximate** an equilibrium
- From the **second simulation**, visualised in fig.2, we conclude that only the **greedy with proportional** strategy converges asymptotically.
- Furthermore, combinations of egalitarian with greedy and proportional come in a close second
- From the **third simulation**, visualised in fig.3, we conclude that there seem to be **no** strategies who converge to the equilibrium.
- To investigate further, in the **4th figure** the results of a simulations of **5000 iterations** was done to investigate the findings of the third simulation further. Here we conclude that the **heterogeneous** simulation of the **greedy** and **proportional** does **not converge asymptotically** to an equilibrium state for all graph types.

09. Future work

- Formalise a proof that proportional and greedy agent environments do not necessarily asymptotically converge to an equilibrium allocation.
- Investigate simulations with agents who follow 3 or more strategies.
- Investigate simulations where agents have the option to keep or drop connections with other agents affects.