TIS– FINAL PRESENTATION

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LEARNING FAIRNESS IN MULTI-AGENT SYSTEMS

MOTIVATION

In the same way fairness is crucial for a working society, the authors of the selected article argue that improving fairness in a Multi-Agent System can enhance its performance.

As most of today's methods focus primarily on maximizing individual or shared rewards without incorporating fairness, systems can become inefficient or even unstable.

FAIR-EFFICIENT NETWORK (FEN)

To overcome this balancing problem between fairness and efficiency, the authors propose their Fair-Efficient Network. This model introduces a hierarchical structure where a controller selects sub-policies to optimize the system's performance. The controller's main task will then be to maximize the "fair-efficient reward", by learning which sub-policy to select at each time, while the sub-policies learn to coexist.

FAIR-EFFICIENT REWARD

The article defines a fair-efficient reward for each agent that balances two key components:

- **Efficiency**: Measured as resource utilization, encouraging agents to optimize their use of shared resources.
- **Fairness**: Quantified by the coefficient of variation (CV) in agents' utilities, penalizing agents whose rewards deviate significantly from the average. This reward enables each agent to learn a policy that considers both their own and others' behaviors, promoting a more balanced distribution of resources.

WORK PERFORMED

PLANNED WORK

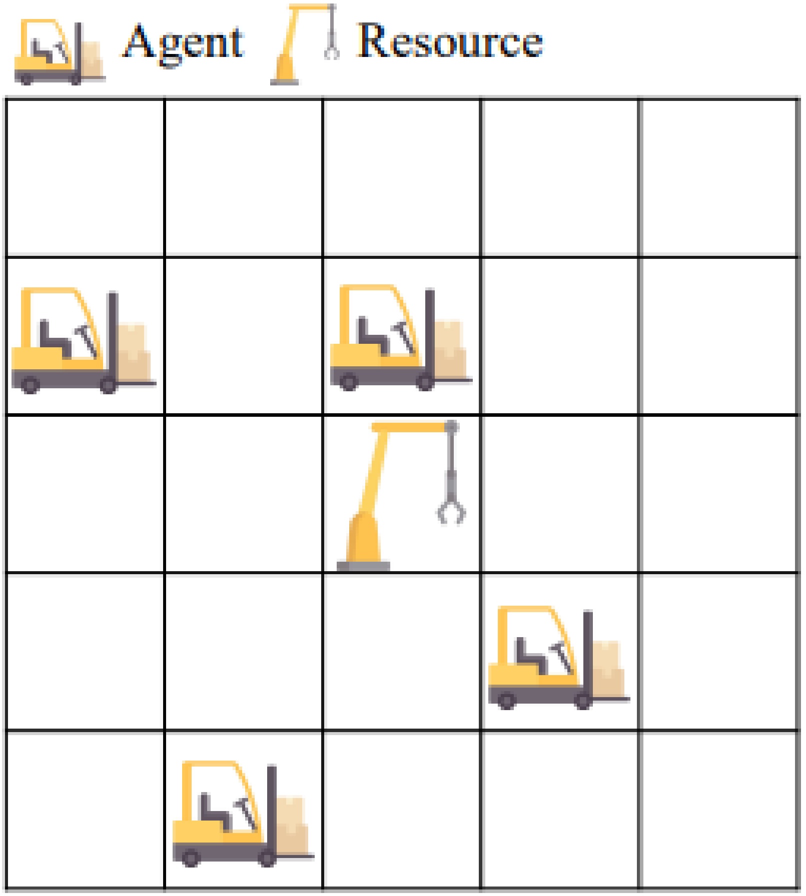
The group managed to follow the presented work during the middle presentation, starting with the study of the chosen paper.

With the theoretical part analyzed, which team member picked one of the presented experiments and manipulated the performance/fairness formula to evaluate the agents’ behaviors and outcomes.

JOB SCHEDULING

The first experiment had 4 agents and 1 resource at any given time present in the training environment and it was their objective to minimize the number of steps required to reach the resource while also learning to share it effectively.

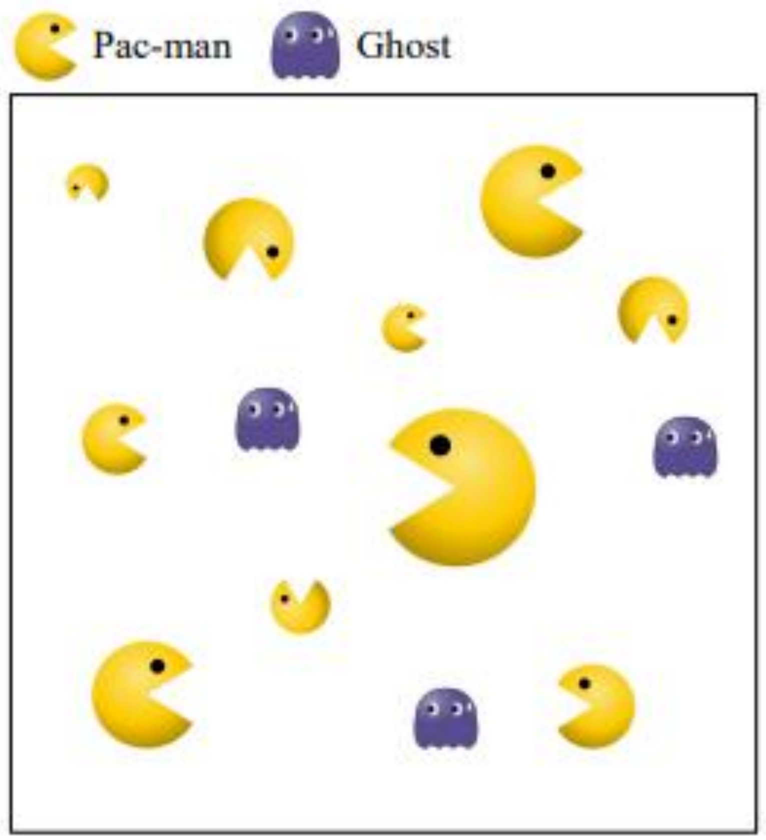
This scenario allowed us to simulate a team of workers learning how to plan the best routes as a group to reach the best individual and collective performances.



THE MATTHEW EFFECT

This effect can simply be put as "the rich get richer and the poor get poorer“, meaning that the available resources are unfairly distributed among those who already have more.

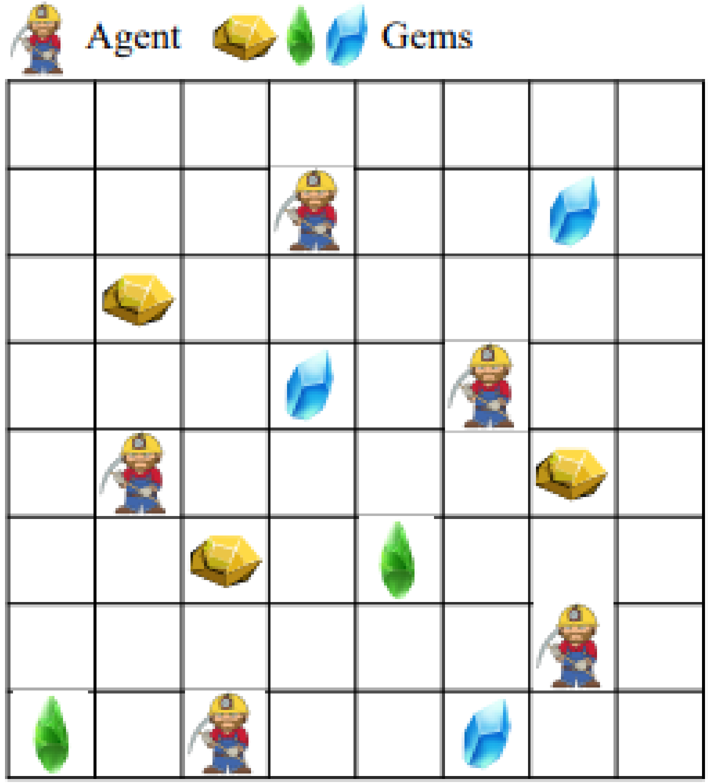
The main objective of this experiment was to see if the agents could learn how to mitigate this effect. To do so, a Pacman environment was created with 10 Pacmen(agents) of different sizes and speeds and a limited number of ghosts(resources).



MANUFACTURING PLANT

The last experiment required a more complex cooperation between agents due to the variety of resources available. Given 3 types of resources, the 5 agents had different individual objectives of which resources they had to collect.

Since there was a limited number of resources, once again the agents had to learn to work as a whole to allow each one to complete their goal.



EFFICIENCY/FAIRNESS BALANCE

Starting with the original FEN formula, the obtained behaviors and outcomes were the ones expected.

With the dominant agents having at the start a slight advantage causing some fairness imbalance, this soon would stop as the iterations kept running. By training the agents, fairness would soon be ideal without having significant drops in performance.

PERFORMANCE FOCUSED

This experiment was the ideal scenario to observe the Matthew effect in action. By changing the reward formula, where the ones that got more resources got the highest rewards, the dominant agents took advantage of features such as speed, size or closeness to resources.

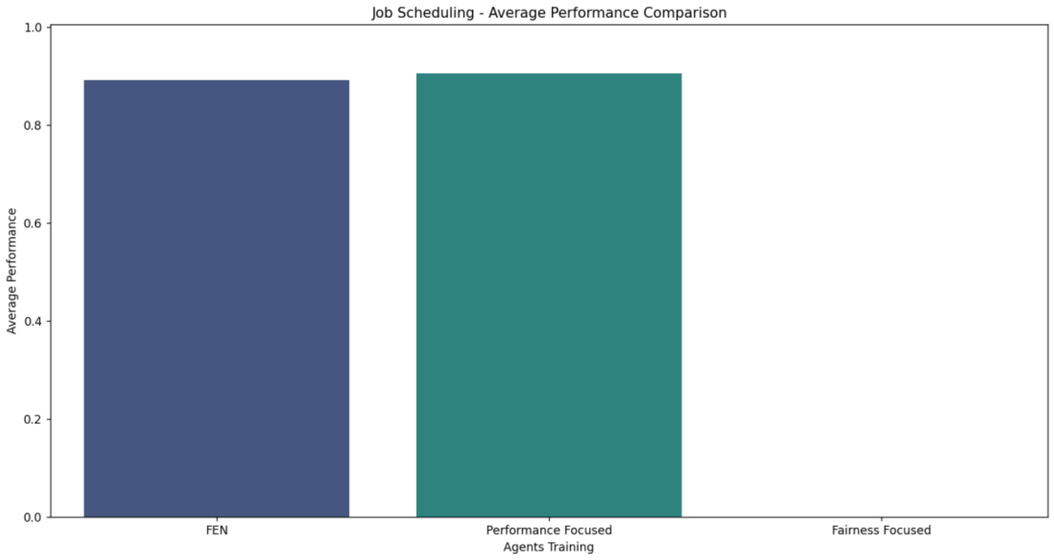
As expected, there was a significant increase in performance, but there was a severe fairness drop with the non-dominant agents having 0 resources multiple iterations in a row.

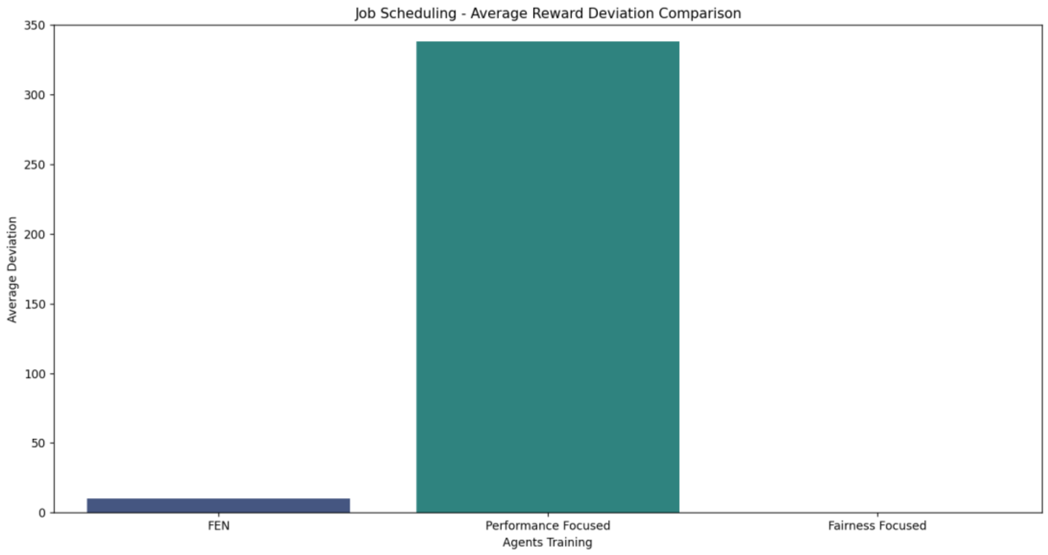
FAIRNESS FOCUSED

This experiment was the complete opposite of the previous one. Similar to the other experiments, where the dominant agents had a slight advantage at the beginning, the reward formula giving higher rewards for those that didn't deviate too much from the average resources obtained caused an interesting effect.

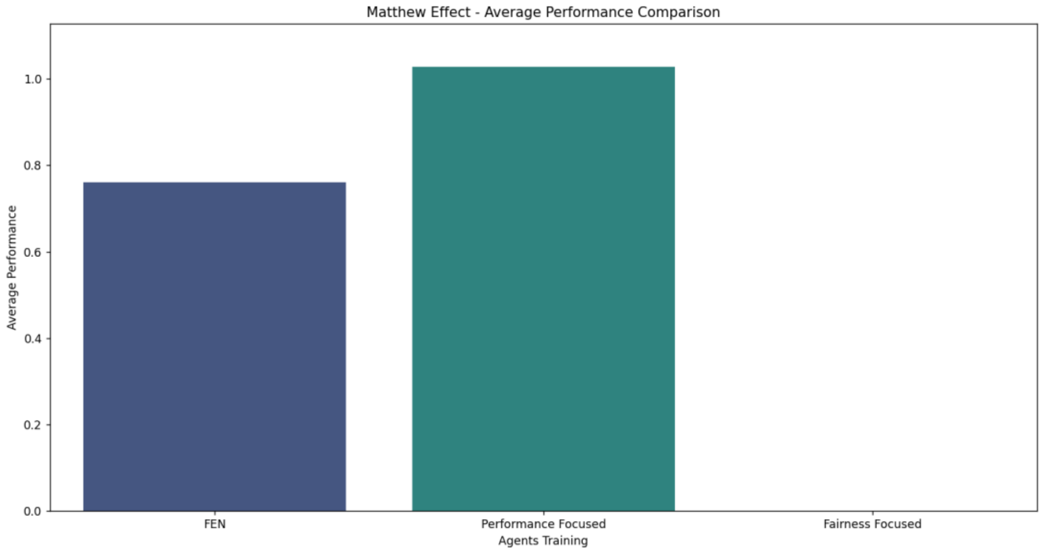
At some point during the training, all the agents simply ceased to try to get rewards to ensure no one had more than others. Fairness was then absolute, but the performance was 0.

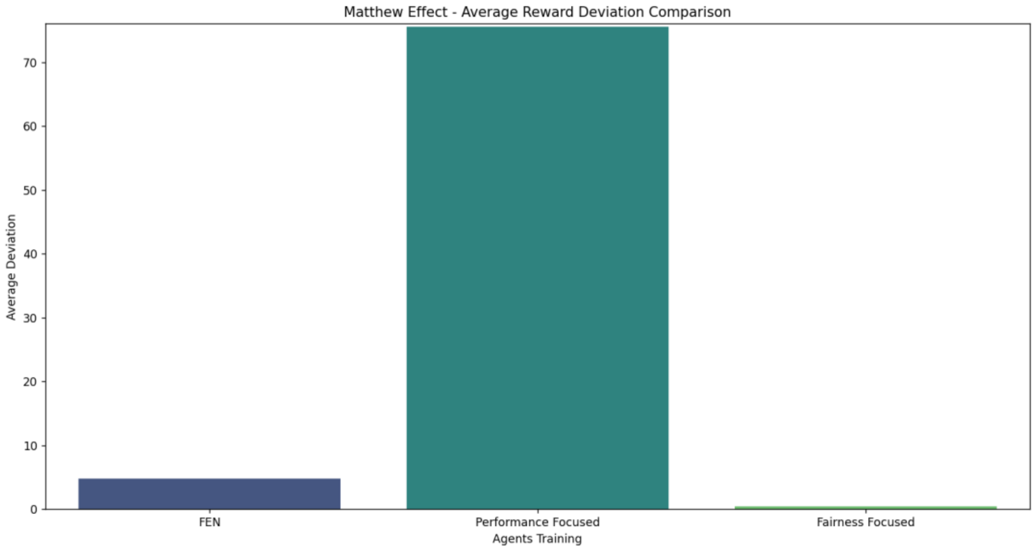
RESULTS COMPARISON - JOB SCHEDULING



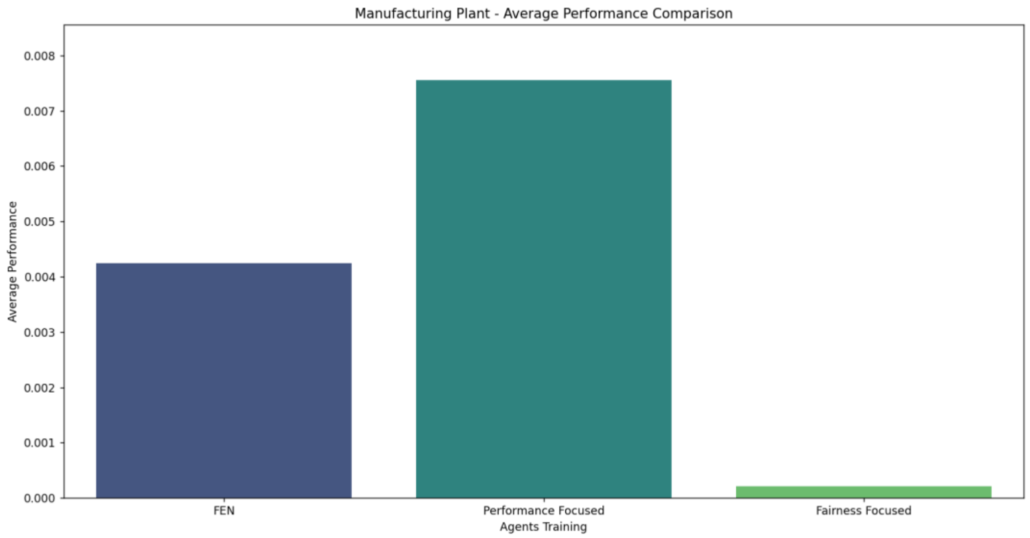


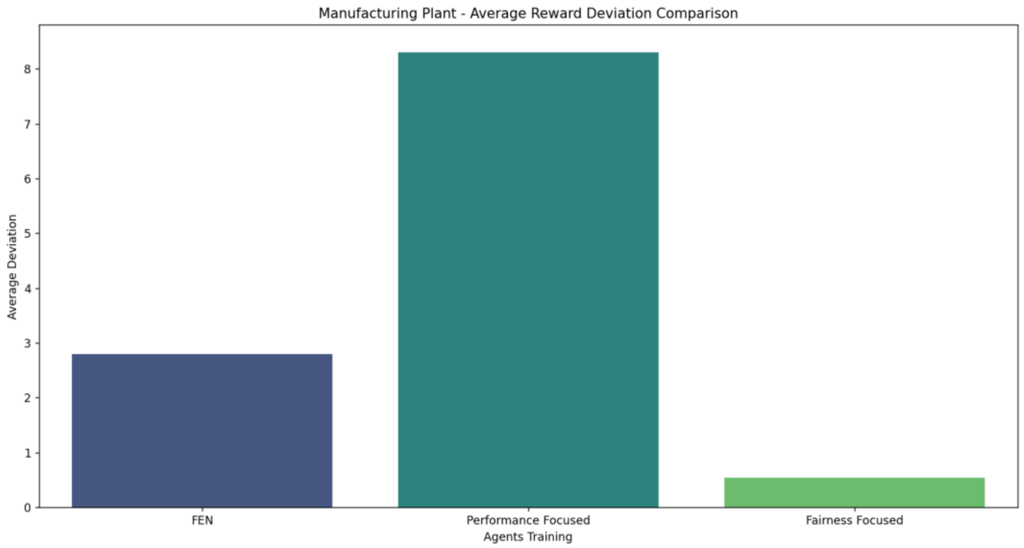
RESULTS COMPARISON – MATTHEW EFFECT





RESULTS COMPARISON – MANUFACTURING PLANT





RESULTS SUMMARIZED

Scenario	Dominance	Fairness	Efficiency
Efficiency Focused	Extreme	Low	Very high
Fairness Focused	Minimal	Very high	Close to 0
FEN	Moderate	High	High

MAIN DIFFICULTIES

OUTDATED CODE

This was the project's major difficulty, although the paper provided a detailed theoretical description that made it fairly simple to understand, the given code was quite old.

The first approach was to update the dependencies, but that created a never-ending "domino effect" of errors, so we instead created older virtual environments that could run the code with no issues.

HARDWARE LIMITATIONS

After the group managed to create an environment suitable to run the three experiments provided by the paper, it didn't take long for another problem to arise. Each experiment demanded powerful machines to fully train the agents for the expected iterations, so some changes were needed.

Since we didn't want to change the experiment's environment by manipulating the number of agents/resources, we decided to reduce the number of iterations.

CONCLUSIONS

FAIR-EFFICIENT NETWORK

The presented work gave an excellent solution to balance fairness and performance. As we could see, performance or fairness focused agents, in the long run, both fail to extract the most out of the different scenarios.

FEN manages to train the agents to deliver a good performance without sacrificing fairness, allowing them to create an ideal environment of cooperation.

FURTHER READING

Thank you for your attention, if you wish to take a closer look at the work performed, you can use this link to get access to our repository to analyze the code and the selected paper.