Evaluating Inter-Operator Cooperation Scenarios to Save Radio Access Network Energy

Xavier Marjou  
Orange Labs Lannion  
Lannion, France  
xavier.marjou@orange.com

Tanguï Le Gleau  
Orange Labs Lannion  
Orange  
Lannion, France  
tanguï.legleau@orange.com

Vincent Messie  
Orange Labs Lannion  
Orange  
Lannion, France  
vincent.messie@orange.com

Benoît Radier  
Orange Labs Lannion  
Orange  
Lannion, France  
benoit.radier@orange.com

Tayeb Lemlouma  
IUT Lannion  
IRISA  
Lannion, France  
tayeb.lemlouma@irisa.fr

Gael Fromentoux  
Orange Labs Lannion  
Orange  
Lannion, France  
gael.fromentoux@orange.com

Abstract—Reducing energy consumption is crucial to reduce the human debt’s with regard to our planet. Therefore most companies try to reduce their energetic consumption while taking care to preserve the service delivered to their customers. To do so, a service provider (SP) typically downscale or shutdown part of its infrastructure in periods of low-activity where only few customers need the service. However, an SP still needs to maintain part of its infrastructure “on”, which still requires significant energy. For example a mobile national operator (MNO) needs to maintain most of its radio access network (RAN) active. Could an SP do better by cooperating with other SPs who would temporarily support its users, thus allowing it to temporarily shut down its infrastructure, and then reciprocate during another low-activity period? To answer this question, we investigated a novel collaboration framework based on multi-agent reinforcement learning (MARL) allowing negotiations between SPs as well as trustful reports from a distributed ledger technology (DLT) to evaluate the amount of energy being saved. We leveraged it to experiment three different sets of rules (free, recommended, or imposed) regulating the negotiation between multiple SPs as well as trustful reports from a distributed ledger technology (DLT) to evaluate the amount of energy being saved. We leveraged it to experiment three different sets of rules (free, recommended, or imposed) regulating the negotiation between multiple SPs as well as trustful reports from a distributed ledger technology (DLT) to evaluate the amount of energy being saved. We leveraged it to experiment three different sets of rules (free, recommended, or imposed) regulating the negotiation between multiple SPs as well as trustful reports from a distributed ledger technology (DLT) to evaluate the amount of energy being saved.

Index Terms—RAN, energy-efficient, cooperative IA, MARL

I. INTRODUCTION

Reducing energy consumption is crucial to reduce human debt to our planet. Many governments and enterprises have taken action plans to significantly reduce their energy consumption in the coming years. Thus most services providers (SPs) strive to reduce their consumption by taking care not to impact the service delivered to their customers (e.g. [1], [2]). Typically, in periods of low-activity when only few customers need the service, they scale down or shutdown part of their infrastructure. For instance, during some low traffic hours at night, mobile network operators (MNOs) generally have few active subscribers and thus may shut down some frequency bands while only keeping alive one frequency band, usually the lowest-frequency band to provide cellular connectivity in a maximal geographical area (e.g. [3]).

However, most SPs still need to maintain part of their infrastructure on, which still requires significant energy. For instance, MNOs need to keep most part of their radio access network (RAN) active despite having few customers because the RAN needs to remain immediately reachable by any subscriber’s user equipment (UE).

In order to bring energy savings to a higher level, an uttermost solution might be to collaborate among SPs delivering the same type of service. Provided that an SP could serve all the users of others SP over a low-activity period, it could offer an on-guard service to serve the users of partner SPs during a low-activity period. For instance, an MNO could allow the other MNOs’ users to access its network via national roaming during this period. In exchange, the partner SPs might be on-guard during subsequent low-activity periods, allowing the SP to temporarily shutdown its whole infrastructure and achieve significant energy savings. However, would SPs cooperate? And if so, under which environmental constraints? Should there be no constraint so that SPs would freely interact, the cooperation dynamic nevertheless emerging naturally? Or should a supervisor at least recommend the SP to be on-guard? Or should a supervisor go even further and impose the SP to be on-guard?

To answer this question, we experimented a novel tit-for-tat cooperative framework integrating a central on-guard service, with a negotiation interface for on-guard service offer and demand between SPs, as well as a reporting interface to a distributed ledger technology (DLT), as shown in Fig. [1] We implemented the service as a reinforcement learning (RL) environment so that simulated agents, each representing an SP, could use an off-the-shelf RL-based policy to rationally interact with each other through the service which acts as an intermediary. The service could be configured and launched in one of the following modes: free, recommended or imposed; and it could also access trustful reports from the DLT to totalize the kWh being consumed by the on-guard SP.
We tested 12 independent scenarios: each of the three modes was tested with a set of 3, 4, 8, or 10 SPs. For each scenario, each SP used proximal policy optimization (PPO) \cite{10} as its RL policy; after training the SPs’ policies, we evaluated four cooperation metrics (efficiency, safety, incentive-compatibility and fairness) to evaluate the outcome of the scenario from an oracle perspective.

Among the tested modes, the results showed that the imposed scenario proved to be the best to meet the best cooperation properties among participating SPs.

A limitation of our work is that the quality of service (QoS) of the service provided during the collaboration was not taken into account, which could lead to tensions among the collaborative SPs in case the QoS is not acceptable to customers. We thus envisage to extend the framework with respect to QoS to enhance trust, especially in a use-case involving MNOs.

Another limitation is related to the key criteria of the agent’s policy. To ensure that the policy is efficient, safe, incentive-compatible and fair, additional work would be needed to ensure that a policy like PPO is robust against a variety of other policies that other SPs might use.

We believe that our findings are important to save energy because the cooperation is not limited to two SPs. On the contrary, the more cooperating SPs there are, the greater the energy savings are for each SP given that the order of magnitude of the energy savings is \((N - 1)/N\) for each of the \(N\) cooperating SPs, which should be compelling enough to gain attention.

II. RELATED WORKS

Axelrod’s tit-for-tat \cite{4} is a key algorithm regarding cooperation, as it is optimal on several aspects: in addition to being efficient with regard to the social welfare (sum of the utilities for each participant), it is also secure in the sense that a participant does not need to be afraid of being exploited, and incentive-compatible in the sense that its participation will encourage the other participant to play. In addition, the algorithm is provable: it stops cooperating upon detecting that the other participant has stopped cooperating; and is forgivable: it starts again cooperating upon detecting that the other participant cooperates again. However, the tit-for-tat algorithm is implemented in the agent’s side (i.e., the task to be done by the SP), which does not allow to cope with scenarios where an intermediary would be involved to possibly influence, slightly or strongly, the negotiation between the agents.

The work of Lerer and Peysakhovich \cite{5} brought considerable innovation introducing RL to lead cooperation between two agents. They avoid being trapped in a social dilemma by iterating interactions and finally act in ways that are simple to understand, nice (begin by cooperating), provable (try to avoid being exploited), and forgiving (try to return to mutual cooperation).

More recently, Zheng et all \cite{6} studied whether multiple agent reinforcement learning (MARL) could bring equality and productivity with AI-driven tax policies with a inner-outer loop. The inner loop allowed the agents to learn to maximize their utility by performing labor, receiving income, and paying taxes, while the outer loop allowed the intermediary (a.k.a. the regulator) to optimize taxes for any social objective. Though being extremely promising, this work does not seem to allow a read-only participation from the intermediary, which is one important mode to be evaluated.

III. MODEL

A. Social Dilemma

To give an intuition on how SPs may consider cooperating to save energy on low-activity periods, let’s model it as a social dilemma (SD) with the following costs associated to the three possible states of the SP’s infrastructure:

- \(o\) when the SP’s infra is off;
- \(a\) when the SP’s infra in active for its users only;
- \(g\) when the SP’s infra is on-guard for any user.

The matrix of Table I represents the possible cooperate (C) and defect (D) actions and payoffs when the SD is iterated twice (i.e., two consecutive negotiation cycles). Note that this representation is limited to two agents and that we only detail the four most relevant payoff values.

\[
\begin{array}{ccc|cc}
| & C & D \\
C & C2 & D2 & C2 & D2 \\
D2 & ... & D2 & ... & ...
\end{array}
\]

\[
\begin{array}{ccc|cc}
| & C & D \\
C1 & C2 & D2 & C2 & D2 \\
D2 & ... & D2 & ... & ...
\end{array}
\]

\[
\begin{array}{ccc|cc}
| & C & D \\
D1 & C2 & D2 & C2 & D2 \\
D2 & ... & D2 & ... & ...
\end{array}
\]

\[
\begin{array}{ccc|cc}
| & C & D \\
D1 & C2 & D2 & C2 & D2 \\
D2 & T = o + o & ... & D2 & ...
\end{array}
\]

By setting

- \(o = -0.01\) (the SP’s infra set to off costs nearly nothing)
- \(a = -0.90\) (the SP’s infra maintained on is expensive)
- \(g = -1.00\) (the SP’s infra maintained on for all users)

the payoffs become \(T = -0.02, R = -1.01, P = -2.00, S = -1.80\).

Hence, with such settings, this resulting dilemma leads to a prisoner’s dilemma as \(T > R > P > S\) (cf. \cite{4}). In this specific case, it is unknown if cooperation can emerge across iterations since \(2 * R = T + S\).
B. Architecture

To cope with scenarios involving the negotiation between multiple SPs as well as the possible intervention of the regulator, we used the architecture depicted in Fig. 1. All negotiation messages between the participating SPs go through a centralized on-guard service.

The service can be configured and observed by the regulator (e.g. to set specific rules, to provide an estimation of the energy consumed by each SP, or to configure a blacklisting policy, if any, as well as its duration).

In addition, an interface to a Distributed Ledger (DLT) reports a posteriori the energy (kWh) officially consumed by the SP being on-guard during the previous low-activity period. The service may thus update the total amount of kWh consumed by each SP in order to calculate the fairest sharing between SPs and possibly recommend or impose the SP to be on-guard for the next low-activity period. In the future, the DLT could also integrate other metrics for measuring the QoS of the service provided by the on-guard SP.

C. Environmental modes

The service can be instantiated in one of the following modes:

- **Free (F)**: the service makes no suggestion as to which SP(s) should be on-guard and act as a pure relay with regard to the SPs’ actions; it lets the SPs decide who is/are the on-guard SP(s) for the next low-activity period.
- **Recommended (R)**: at the initialization time of each new negotiation, the service suggests in the observation message which SP should be on-guard, selecting the SP that brought the lowest total amount of saved energy for the other SPs.
- **Imposed (I)**: in addition to suggesting which SP should be on-guard, the service also enforces offers coming exclusively from that SP. But it does not impose an SP to offer on-guard service to all demanding SPs. The service also temporarily blacklists an SP that has refused to be on-guard more than m times and can reinitialize it after a blacklisting period is finished. As a consequence, this mode takes advantage of the service’s central intermediary position to enforce provocation and forgiveness on behalf of the participating SPs; it also simplifies the strategy and makes it clear by announcing and imposing the SP to be on-guard. Note that these three properties are instead performed decentrally in [4].

D. Negotiation interface

The negotiation interface allows for actions from the SPs to the service. Each negotiation involves a set of messages between SPs to determine the SP, or the SPs, that will share its/their infrastructure for the next low-activity period.

The messages from an SP to the service contain a single action parameter containing a set of sub-actions. There are two types of sub-actions: an offer so that a SP \( i \) can offer another SP \( j \neq i \) to be on-guard (i.e., offer to serve SP \( j \)'s customers) and a demand so that a SP \( i \) can demand another SP \( j \neq i \) to be on-guard (i.e., demand to serve SP \( j \)'s customers).

The messages from the service to each SP contain an observation of the offers and demands from the other SPs to this SP, as well as a positive or negative reward proportional to the energy estimated to be saved or consumed during the next low-activity period based on the results of the current negotiation plus a small negative reward at each timestep in order to speed the negotiation.

E. POMDP

We consider N players, where each player represents an SP. The players repeatedly interact with each others across multiple negotiations, with each negotiation lasting multiple timesteps.

We formulate the negotiations as a variant of a decentralized partially observable Markov decision process (DEC-POMDP) [7] with individual rewards, thereby allowing choices to be made decentrally by the set of agents. Our variant is defined by a tuple \( \langle I, S, A, O, T, R, \gamma \rangle \) where \( I \) is the set of agents, \( S \) is the set of states and \( O : S \times I \rightarrow S \) is an observation function. \( A = A_1 \times \ldots \times A_N \) is the set of joint actions, and a joint action \( \vec{a} = (a_1, \ldots, a_N) \) transitions the state \( s \) to the next state following the stochastic function \( T : S \times A_1 \times \ldots \times A_N \rightarrow \Delta(S) \). At last, a personal reward function \( R : I \times S \times A \rightarrow \mathbb{R} \) gives a reward \( r^i \) to each player \( i \). The joint reward is denoted \( r = (r^1, \ldots, r^N) \). Each agent’s goal is to find a policy \( \pi_i : S \rightarrow \Delta(A_i) \) in order to maximise its expected discounted return defined by:

\[
G_{\pi_i}(s_0) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r^i(s_t, a_t) | s_0 \sim \pi_i, s_{t+1} \sim T(s_t, a_t)\right]
\]

\( \pi \) denotes the joint policy \( (\pi_1, \ldots, \pi_N) \).

IV. EXPERIMENTATION

A. Environment

The service was implemented as an RL environment that can be instantiated in one of the three modes (F, R or I). Each environment’s episode corresponds to a negotiation where the participating agents exchange messages to determine the on-guard agent for the next low-activity period.

For all modes, we used the same reward values: \(-1.00\) when an agent successfully negotiated to be on-guard; \(-0.9\) when an agent was not able to successfully find an on-guard SP; \(-0.01\) when an agent successfully found an on-guard SP; and \(-0.01\) for each other time-step to incite the agents to use the smallest number of messages during an episode. We set the maximal number of steps per episode to 10 in order to enforce short negotiations.

We implemented the environment as a Gym environment [8], a Python toolkit for developing and comparing RL algorithms. We used a multi-discrete binary value for the action space and also a multi-discrete binary value for the observation space, in order to faster the convergence of the RL training.

Regarding the interface between the environment and the DLT, we simulated energy consumption reports with a function...
adding a 10% random noise to the kWh estimated to be consumed by the on-guard SP.

B. Agents

We implemented the agents with RLlib [9], a Python library allowing for scalable MARL.

Regarding the RL policy algorithm, we selected Proximal Policy Optimization (PPO) for all agents as some of our pre-experiments showed that PPO [10] performed better than other algorithms (PG, A2C, A3C or MARWIL), which has also been successfully used in other MARL experiments [11]. Future work may experiment agents with different policies.

C. Cooperation properties

To evaluate the cooperation across episodes, we introduced four properties [12], also known as societal objectives [13]. Our three first metrics were adapted from [5] whereas the fourth property [12], also known as societal objectives [13].

After a training step $r$ involving $N$ agents, each agent $i$ acting on the behalf of one SP and performing actions based on its learned RL policy $\pi_i$, negotiate the on-guard service during $T_{\text{max}}$ episodes. $G_i(\pi, t)$ is the expected return, i.e. the sum of of discounted rewards received by an agent $i$ during one episode $t$ (i.e., one negotiation).

An efficiency property ($E$) measures how close the social welfare is from the optimum, which happens when all agents cooperate. The social welfare is the sum of expected returns over all agents. An optimal cooperating policy is noted $\pi_{i,C}$, whereas the worst cooperating policy is noted $\pi_{i,D}$.

$$E(\pi, r, t) = \frac{\sum_{i=1}^{N} G_i(\pi_i, r, t) - \sum_{i=1}^{N} G_i(\pi_{i,D}, r, t)}{\sum_{i=1}^{N} G_i(\pi_{i,C}, r, t) - \sum_{i=1}^{N} G_i(\pi_{i,D}, r, t)}$$

A safety ($SF$) property measures the risk taken by an agent $i$ and is defined as the difference, when all other agents defect ($\pi_{-i,D} = \pi_{j,j\neq i,D}$), between the expected return received by agent $i$ when trying to cooperate and the expected return it received when defecting. $(T - S)$ represents the maximal amplitude (cf. Section III-A) and, together with $+1$, allow to normalize $SF$ between 0.0 and 1.0.

$$SF(\pi_i, r, t) = \frac{G_i(\pi_i, \pi_{-i,D}, r, t) - G_i(\pi_{i,D}, \pi_{-i,D}, r, t)}{T - S} + 1$$

An incentive-compatibility property ($IC$) measures the capacity to incentivize cooperation and is defined as the difference, when all other agents try to cooperate ($\pi_{-i} = \pi_{j,j\neq i}$), between the expected return received by an agent $i$ when trying to cooperate and the expected return it received when defecting. $(T - S)$ represents the maximal amplitude (cf. Section III-A) and allows to normalize $IC$.

$$IC(\pi_i, r, t) = \frac{G_i(\pi_i, \hat{\pi}_{-i}, r, t) - G_i(\pi_{i,D}, \hat{\pi}_{-i}, r, t)}{T - S}$$

Finally, a fairness property ($J$) with $e_i$ equal to the total number of kWh saved by each agent at the end of an episode $t$ since the beginning of the evaluation after the training. In case of blacklisted agent(s), the Jain index was calculated based on the non-blacklisted agents.

$$J(\pi, r, t) = \frac{(\sum_{i=1}^{N} e_i, r, t)^2}{N \sum_{i=1}^{N} e_i, r, t^2}$$

D. Training and metrics measurement

We performed experiments with four different numbers of agents ($N = 3, 4, 8,$ or $10$) and three different modes on the environment side ($M = F, R,$ or $I$).

For each $(N, M)$ experiment, we first performed a set of 5 independent training runs. Each run was stopped when plateauing during 20000 timesteps. For each run, we launched 100 episodes and measured the cooperation properties by an oracle implemented in the environment. We then measured the distribution (mean and standard deviation) of these properties across the $5 \times 100$ episodes.

We limited the maximum number of agents to 10 because one important use-case assumption is that there should be only one on-guard SP and that it must have the possibility to host all the users of all SPs, which prevents experimenting a big number of agents. Another reason is that each training time increases quadratically with the number of participating agents. Future work may involve a game allowing for multiple on-guard SPs and thus a greater number of agents.

V. RESULTS AND DISCUSSION

A. Analysis of the scenarios

Table II and Fig. 2 display the obtained results.

| N | M | F | R | I |
|---|---|---|---|---|
| 3 | F | 0.00 ± 0.02 | 0.00 ± 0.02 | 0.00 ± 0.02 |
| 3 | R | 0.00 ± 0.04 | 0.00 ± 0.04 | 0.00 ± 0.04 |
| 3 | I | 0.00 ± 0.03 | 0.00 ± 0.03 | 0.00 ± 0.03 |
| 4 | F | 0.00 ± 0.04 | 0.00 ± 0.04 | 0.00 ± 0.04 |
| 4 | R | 0.00 ± 0.07 | 0.00 ± 0.07 | 0.00 ± 0.07 |
| 4 | I | 0.00 ± 0.02 | 0.00 ± 0.02 | 0.00 ± 0.02 |
| 5 | F | 0.02 ± 0.08 | 0.00 ± 0.00 | 0.00 ± 0.00 |
| 5 | R | 0.01 ± 0.02 | 0.00 ± 0.02 | 0.00 ± 0.02 |
| 5 | I | 0.00 ± 0.01 | 0.00 ± 0.01 | 0.00 ± 0.01 |
| 10 | F | 0.42 ± 0.47 | 0.99 ± 0.02 | 0.99 ± 0.02 |
| 10 | R | 0.18 ± 0.37 | 0.97 ± 0.03 | 0.97 ± 0.03 |
| 10 | I | 0.09 ± 0.01 | 0.94 ± 0.04 | 0.94 ± 0.04 |

In most scenarios with free modes, the efficiency was close to 0.0. The incentive to play was also close to 0.0: if an SP tried to cooperate with other cooperating SPs, its expected return did not increase; However the safety remained close to 1.0, suggesting that an SP did not take many risks by trying to cooperate. The results led to unfair fairness scores, although being calculated on the rare successful transactions.

In all scenarios with imposed modes, $E$ remained close to 1.0. Recall that when $E$ is close to 1.0, each of the $N$
agents saves $N - 1/N$ of energy per low-activity period. Thus, as energy savings increase with $N$, a maximum number of cooperating SPs is nevertheless desirable. This can also be noticed with the values of IC: indeed, when all but one agent collaborate, the more agents there are, the bigger the regret for the defecting agent. In addition, the results also showed excellent results for the safety and fairness scores. Such successful and reiterated cooperations suggest that a strong control from a regulator can be beneficial for all agents, provided that this control is aligned with convincing rewards for the agents. Otherwise the agents would likely have no incentive to cooperate and would stop performing offers.

In scenarios with recommended modes, there were two subsets of results. With $N=3$ or $N=4$ agents, the mean efficiency remained close to zero, as in the free modes; similarly, the incentive-compatibility was also close to zero and the safety remained high indicating no risk to play. Instead, with $N=8$ or $N=10$ agents, the recommended modes demonstrated more and more efficiency, although being subject to important variance across different runs and although fairness remained limited. This suggests that recommending the agent to be on-guard in the observation is a useful hint for most agents but is not sufficient to trigger a virtuous equilibria among multiple agents; The fact that efficiency sometimes emerged when $N \geq 8$ might be due to the few agents who have early discovered cooperation by chance and who have progressively influenced the behavior of other agents. Consequently, future work should strive to investigate the reasons for the successful cases and identify whether cooperation could be stabilized with additional hints or different reward, which, if successful, would result in a smoothly controlled mode would be very appealing.

A limitation of this work is that the QoS provided during the cooperation is not taken into account, which could lead to tensions among SPs in case of low QoS. As a consequence, future work should also integrate QoS.

Note: These results are purely technical and do not presume whether any of the mode would be allowed by a real regulator.

VI. CONCLUSION

We described a trusted and collaborative framework based on MARL allowing a regulator to test different rules in order to supervise negotiations related to energy savings, such as RAN energy savings, and also allowing service-providers to train and evaluate their policy regarding such a participation.

The analysis of cooperation metrics showed that successful cooperation emerged upon tightly constrained rules enforcing the scheduling of the SP to be on-guard. However cooperation hardly emerged from loosely constrained rules, although there might be room for improvement.

As such, we believe that this framework might be beneficial to evaluate cooperative scenarios to significantly reduce energy consumption.

REFERENCES

[1] F. E. Salem, T. Chahed, E. Altman, A. Gati and Z. Altman, “Optimal Policies of Advanced Sleep Modes for Energy-Efficient 5G networks” 2019 IEEE 18th International Symposium on Network Computing and Applications (NCA), 2019, pp. 1-7, doi: 10.1109/NCA.2019.8935062.

[2] K. Kanwal, G. A. Salfar, M. Ur-Rehman and X. Yang, “Energy Management in LTE Networks,” in IEEE Access, vol. 5, pp. 4264-4284, 2017, doi: 10.1109/ACCESS.2017.2688584.

[3] ITU-T, "Smart Energy Saving of 5G Base Station: Based on AI and other emerging technologies to forecast and optimize the management of 5G wireless network energy consumption", ITU-T report, 2021.

[4] R. Axelrod, WD Hamilton, "The evolution of cooperation", science 211 (4489), 1390-1396

[5] Adam Lerer and Alexander Peysakhovich, "Maintaining cooperation in complex social dilemmas using deep reinforcement learning", 2018, Arxiv 1707.01068

[6] Stephan Zheng and Alexander Trott and Sunil Srinivasa and Nikhil Naik and Melvin Gruesbeck and David C. Parkes and Richard Socher, "The AI Economist: Improving Equality and Productivity with AI-Driven Tax Policies", 2020, Arxiv 2004.13332.

[7] Daniel S. Bernstein, Shlomo Zilberstein, and Neil Immerman, “The Complexity of Decentralized Control of Markov Decision Processes”, CoRR, 2013, Arxiv 1301.3836.

[8] Greg Brockman and Vicki Cheung and Ludwig Pettersson and Jonas Schneider and John Schulman and Jie Tang and Wojciech Zaremba, “OpenAI Gym”, 2016, Arxiv 1606.01540.

[9] Eric Liang and Richard Liaw and Philipp Moritz and Robert Nishihara and Roy Fox and Ken Goldberg and Joseph E. Gonzalez and Michael I. Jordan and Ion Stoica, "RLlib: Abstractions for Distributed Reinforcement Learning", 2018, Arxiv 1712.09381.

[10] John Schulman and Filip Wolski and Prafulla Dharwal and Alec Radford and Oleg Klimov, "Proximal Policy Optimization Algorithms", 2017, Arxiv 1707.06347.

[11] Chao Yu, Akash Veli, Eugene Vinitsky, Yu Wang, Alexandre M. Bayen and Yi Wu, "The Surprising Effectiveness of PPO in Cooperative, Multi-Agent Games", CoRR, 2021, Arxiv 2103.01955

[12] Leibo, Joel Z et al. “Scalable Evaluation of Multi-Agent Reinforcement Learning with Melting Pot”, 2021, Proceedings of the 38th International Conference on Machine Learning

[13] Allan Dafoe, Edward Hughes, Yoram Bachrach, Tantum Collins, Kevin R. McKee, Joel Z. Leibo, Kate Larson and Thore Graepel, Open Problems in Cooperative AI, preprint, 2020, Arxiv 2012.08630.

[14] Jain, Rajendra K. and Chiu, Dah-Ming W. and Hawe, William R., “A Quantitative Measure Of Fairness And Discrimination For Resource Allocation In Shared Computer Systems”, 1984