

Learning to Run a Power Network with Trust

Enhancing power system operation through online analytics

Antoine Marot, Benjamin Donnot, Karim Chaouache, Adrian Kelly, Qiuhua Huang, Ramij-Raja Hossain, Jochen L. Cremer

Credits





Adrian Kelly



ELECTRIC POWER RESEARCH INSTITUTE

Qiuhua Huang



Ramij-Raja Hossain

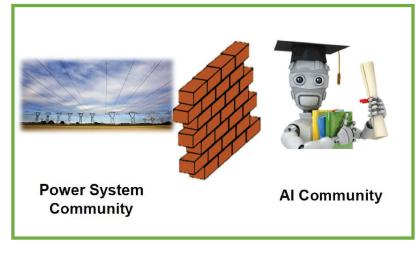
TUDelft Jochen L. Cremer

Antoine Marot, Benjamin Donnot, Karim Chaouache

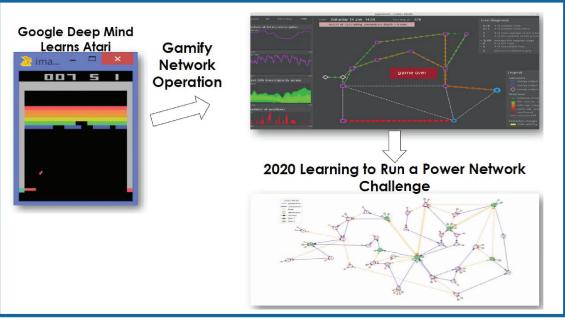
Gamify power system challenges



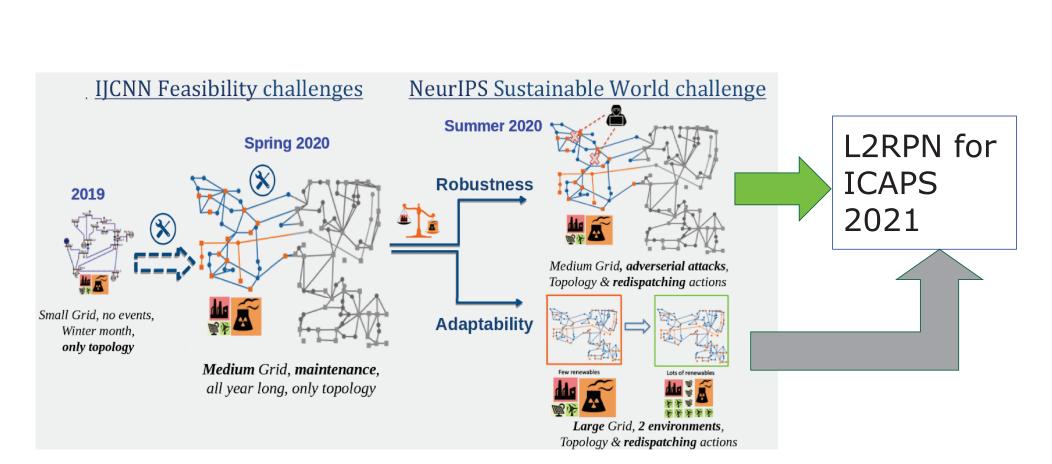
Problem



Approach



https://icaps21.icaps-conference.org/Competitions/

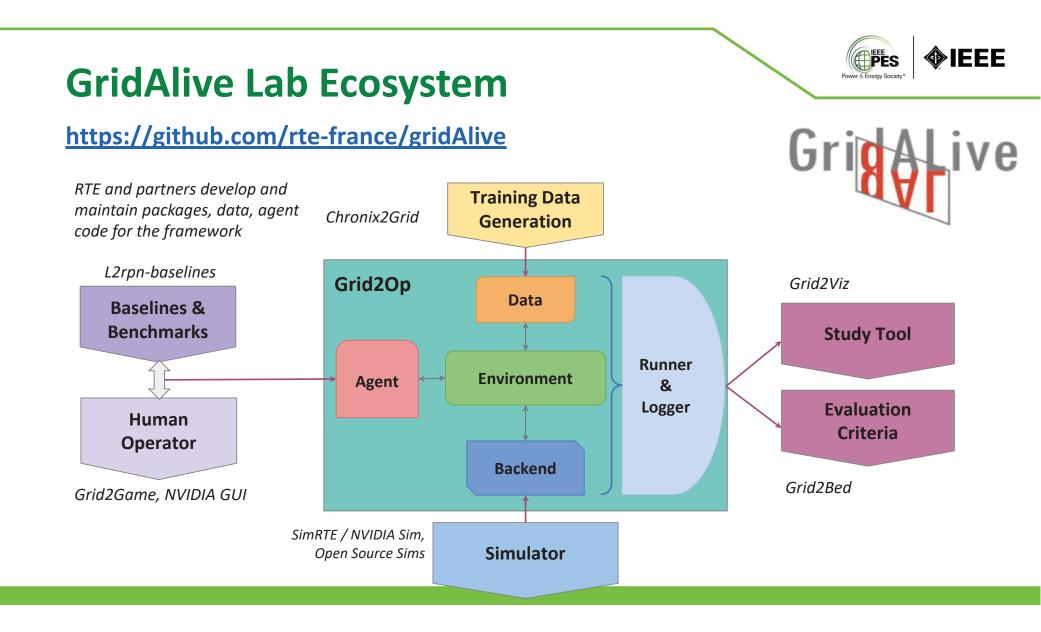


IEEE

PES

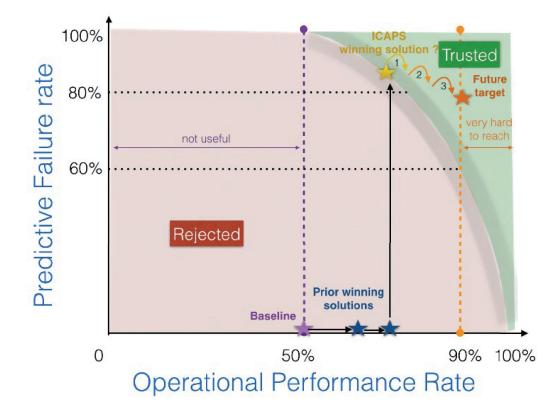
Power & Energy Society

Competitions from 2019->2021





Vision for L2RPN 2021: Can we trust AI?



Marot, Antoine, Benjamin Donnot, Karim Chaouache, Adrian Kelly, Qiuhua Huang, Ramij-Raja Hossain, and Jochen L. Cremer. "Learning to run a power network with trust." *IEEE Power Systems Computing Conference, 2022, arXiv preprint arXiv:2110.12908* (2021).



Contributions

Sequential Decision Making formulation for human-AI trustbuilding concept

Developing "trust" concept through the L2RPN framework and environment

Analysing the open competition results to evaluate this concepts and determine promising directions

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Modelling operator / agent trust Pitfalls



Out of the Loop

- Automated actions take human operator "out of the loop"
- Need to direct operator attention when required to act in an emergency, uncertain situation
- Acts as a proxy for credibility
- Modelled as the agent directing attention to specific areas or assets on the network



Boy Who Cried Wolf

- Need to avoid over alarming, or alarming inaccurately.
- Need to keep the operators attention and trust.
- Acts as a proxy for reliability and intimacy
- Model the operator's attention numerically with a budget, which degrades and upgrades depending on alarm load.

Two approaches to quantify the limits of human to agent/algorithm Interactions







Passive

Level of confidence quantified for each suggested automated action/prediction -> operator can act accordingly

 Requires a lot of supervision and hard to evaluate the agent's performance

Active

Receive a signal of 'low confidence' to actively warn the operator of risky or uncertain conditions ahead.

IFFF

- Can be framed as a sequential decision-making problem with some budget
- Can be evaluated relative to the ultimate outcome.
- Concepts used in semi-autonomous driving cars today

Trust framework

Trusted Advisor Book – Charles Green



Credibility

Increases when the agent is transparent and explains the proposed action

L2RPN: Modelled by the agent presenting the **alert time and location** to the operator



Reliability

An agent acts consistently for similar situations and "knows" the limits of its capabilities

L2RPN: Modelled by operational performance and **alerting capability** evaluation



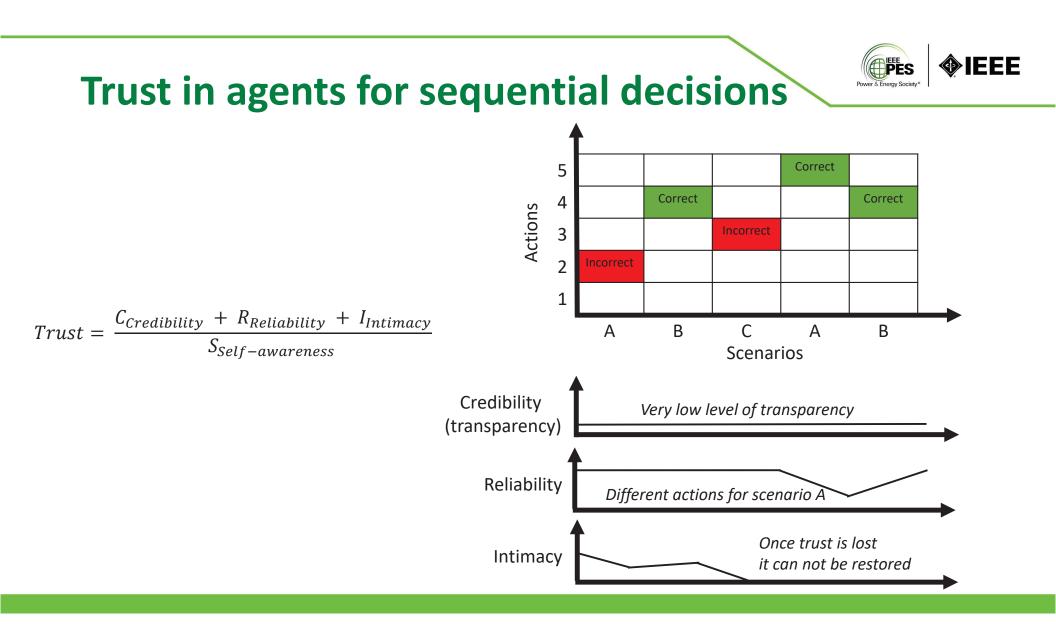
Intimacy

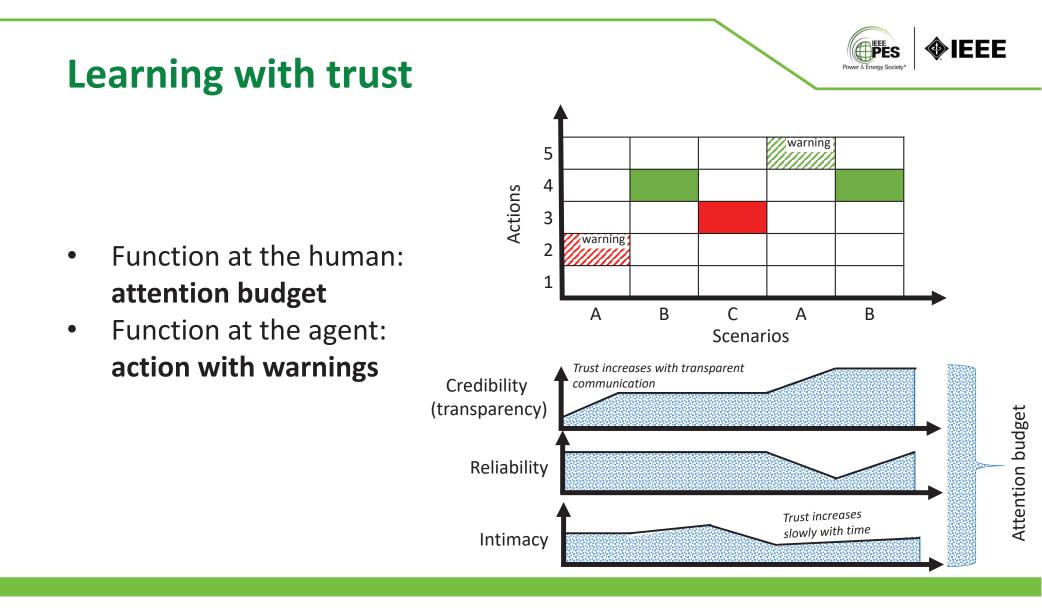
The relationship quality over time with relevant interactions and reduced misunderstandings

L2RPN: Modelled by the attention budget of the operator

An AI agent can increase its trustworthiness by reducing conflicting evidence and by increasing the amount of evidence it has gathered

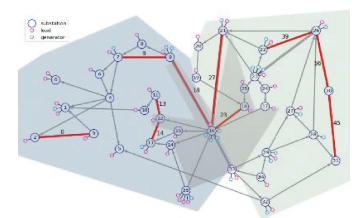


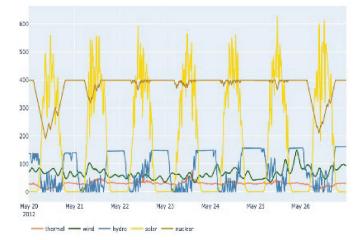






2021 L2RPN ICAPS competition format





Environment: Simulated grid with 24 5-minute resolution weekly scenarios, and considering:

- Physical limits of transmission lines and generators
- Minimum intervals for actions on the same equipment
- Maintenances and adversarial attacks

Actions: (>70k discrete actions and 20-dimensional continuous actions)

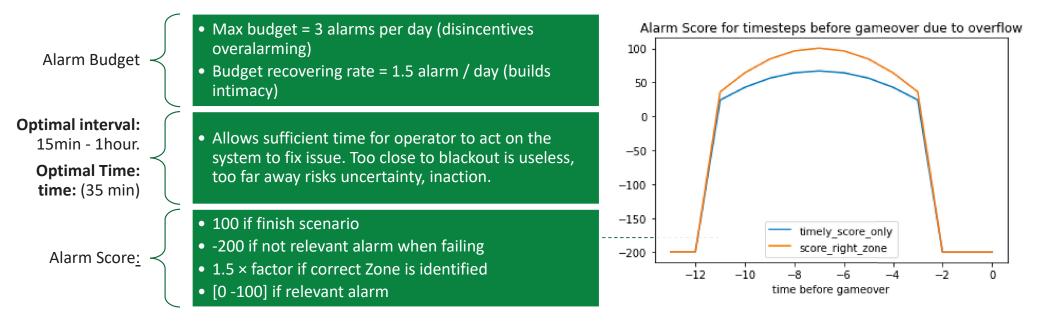
- "Cheap" topology changes (discrete) that allow for line dis-/re-connection and substation nodal re-configurations.
- Costly production changes (continuous) through redispatching or RES curtailment.

Score = 0.3 * Alarm Score + 0.7 * Operational Score

100 (if agent completes episode) OR 100*(Time of Alarm * Alarm Area) Linearised (Cost of Losses + Costs Redispatch + Cost of Blackout)

Alarm and operator's attention modelling





Incentives for agents to send alarms in a selective and relevant time range before failure so that operators can focus on that task with enough time to study & act

Encourage agents to still finish scenarios and not fail on purpose



L2RPN 2021 results and leaderboard

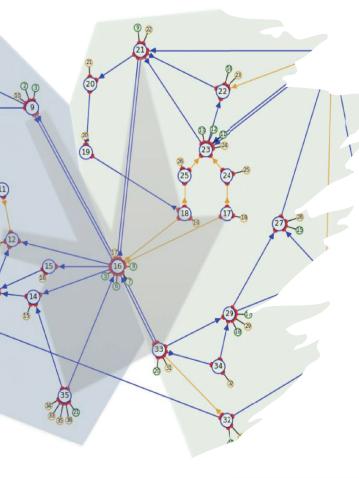
#	User	score 🔺	operational cost 🔺	attention cost	Computation time	
1	xd_silly	57.45 (1)	59.80 (1)	51.94 (1)	548.72 (10)	Polixir Technologies, China
2	SupremaciaChina	47.63 (2)	54.69 (2)	31.17 (2)	1465.96 (17)	Horacio Martinez, Argentina
3	maze-rl	46.81 (3)	54.18 (3)	29.61 (3)	787.32 (15)	Enlite Al, Austria
4	IndigoSix	33.75 (4)	45.57 (4)	6.17 (4)	768.10 (14)	Wuhan Uni, China

Attention cost (or Alarm Score) was an important factor for the final ranking

There was an incentive for participants to integrate this feature in their agent

Information on the winning teams' strategies can be viewed at https://www.youtube.com/watch?v=WOt8xgpC370 - search "L2RPN"

Analysis of best two agents



 1^{st &} 2nd agents operated the network on 16 out of 24 blind. 7 of the failed scenarios were common.

≫IFFF

- Failed Scenarios:
 - 1st sent alarms correctly on 7 of 8,
 - 2nd: sent alarms on 5 of 8.
- Alarms are sent between 15-35 mins before failure. Evidence of operators' attention budget diminishing (<1) for some failed scenarios.
- One Failed Scenario: Both agents alarm correctly, but didn't locate the area correctly. The prediction and planning skillset is good over reasonably long periods.
- 1st agent:
 - cautious with alarms keep an average attention budget of 2.5 per day (versus 2.2 for 2nd place)
 - attention below 1 only 1.5% of the time (versus 10% for 2nd place)
 - efficient with actions: Used less actions per week (avg:23.5 max:38) than 2nd (avg:26.5 max:64).
- 2nd agent is greedier than the 1st in general.



Conclusions

- On the journey towards creating trustworthy AI-based assistants for future network operators, we have proposed a trust framework that builds on the reliability, credibility and intimacy model of trust, by explicitly considering the human operators' mental workload and capability of addressing issues when early warning and relevant network information are provided.
- Through the L2RPN with trust competition in 2021, we have successfully designed a realistic active warning environment to experiment and evaluate trust between humans and agents.
- Winning teams have achieved the best alarm scores overall, in combination with the best operational performance, and demonstrated good reliability. By relying mostly on rule-based alarms, there however remains room for improvement on the credibility and intimacy aspects. Learning-based alarm agents could help address in the future these open questions.

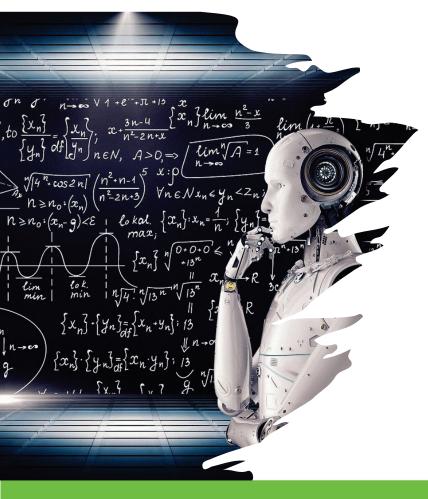


Discussions and next steps

- Extending the frameworks
- Work with winning agents
- Utilizing the L2RPN and wider AI/ML community through competition
- Building on GUIs such as NVIDIA: <u>https://github.com/NVIDIA/energy-sdk-l2rpn</u>
- Working with domain experts (operators) to test and benchmark agent performance and trust
- Expanding the trust framework
- Expanding the networks and action space
- Continued developments and community building.



Useful links



- L2RPN 2021 Competition Page: <u>https://competitions.codalab.org/competitions/33121</u>
- L2RPN 2022 Irina Competition: https://codalab.lisn.upsaclay.fr/competitions/5410
- Join the L2RPN mailing list: <u>https://l2rpn.chalearn.org/</u>
- Join the L2RPN Discord Channel: <u>https://discord.gg/cYsYrPT.</u>
- Visit <u>www.EPRI.com/L2RPN</u>
- View L2RPN 2021 ICAPS Competition Summary: https://www.youtube.com/watch?v=WOt8xgpC370
- Join Development Community:
 - <u>https://github.com/rte-france/gridAlive</u>
 - <u>https://github.com/rte-france/Grid2Op</u>

