AI for energy: a bright and uncertain future ahead

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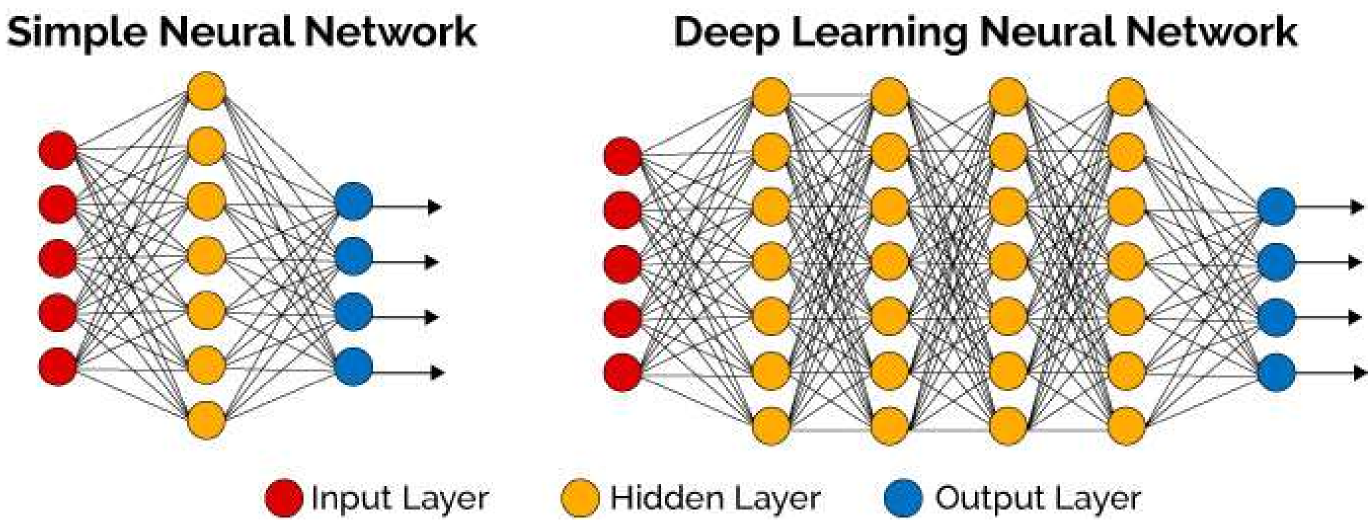
“Recent” changes in AI: 1. Deep neural nets



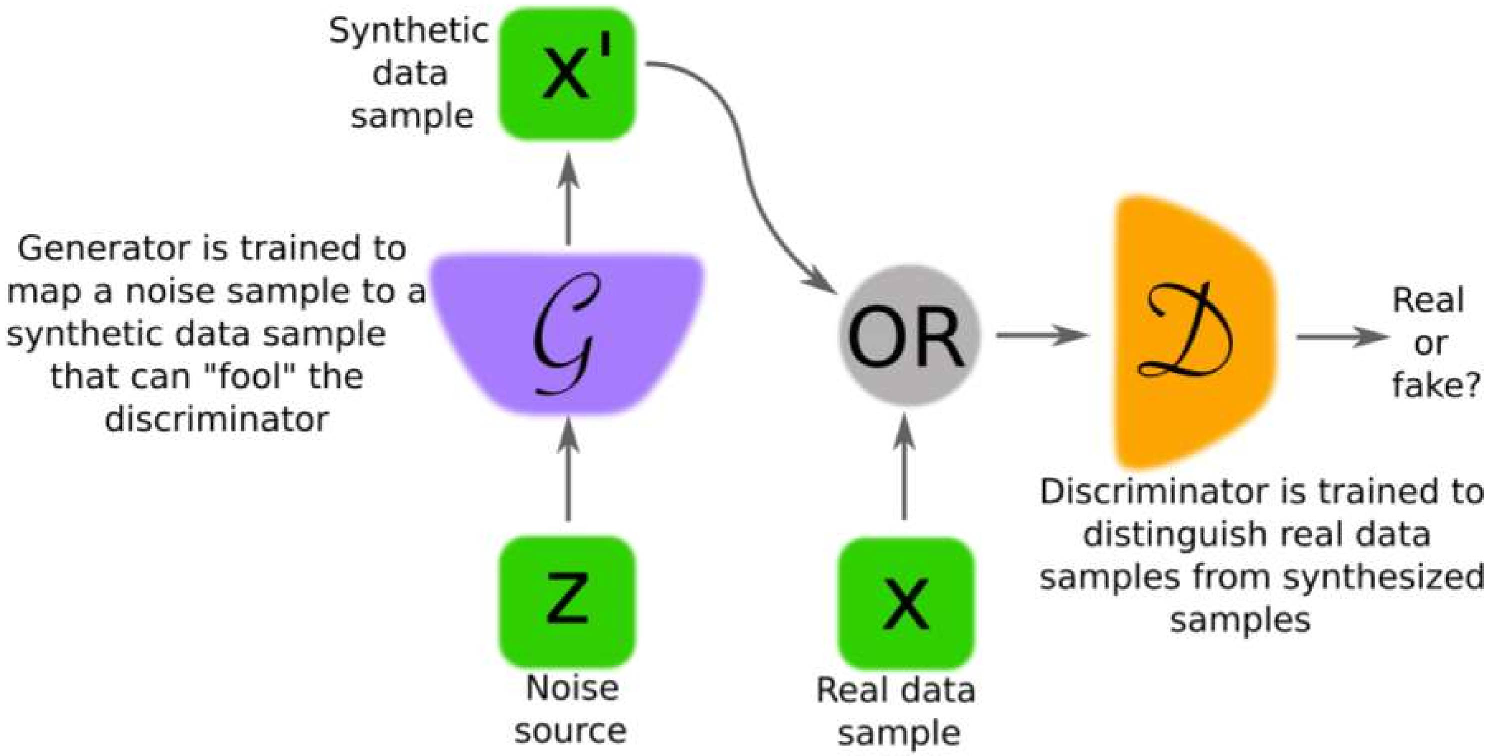
A deep-learning neural network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers. No universally agreed upon threshold of depth separates shallow learning from deep learning, but most researchers agree that deep learning involves a chain of transformations from input to output higher than 2.

1. Outperform supervised learning algorithms but more tuning is often necessary as well as much higher computational costs for training.

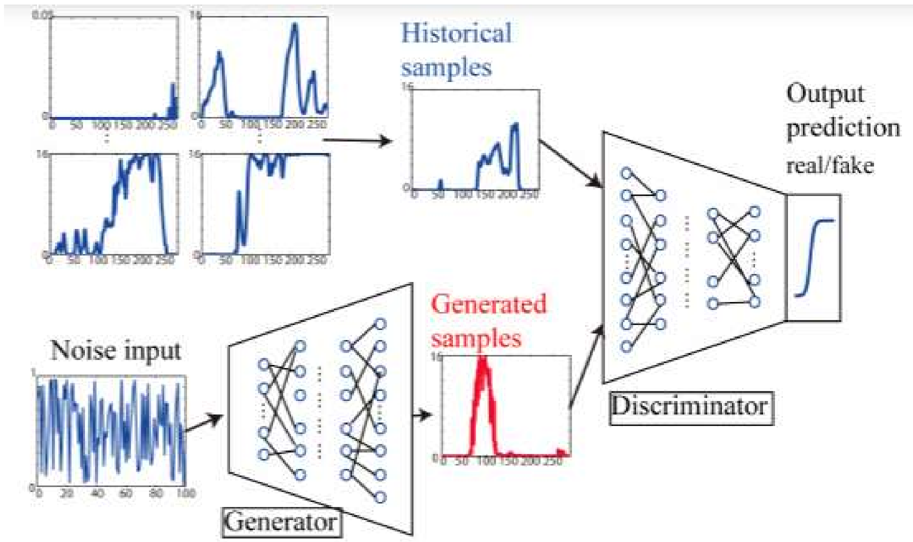
2. Dedicated hardware architectures have been developed for training and executing those networks (e.g., GPU networks).

3. Open-source software libraries for designing and training DNNs are available and very well created. The most popular ones include: PyTorch (Facebook's AI Research Lab) or Tensorflow (Google Brain).

2. Generalised adversarial nets (GANs)

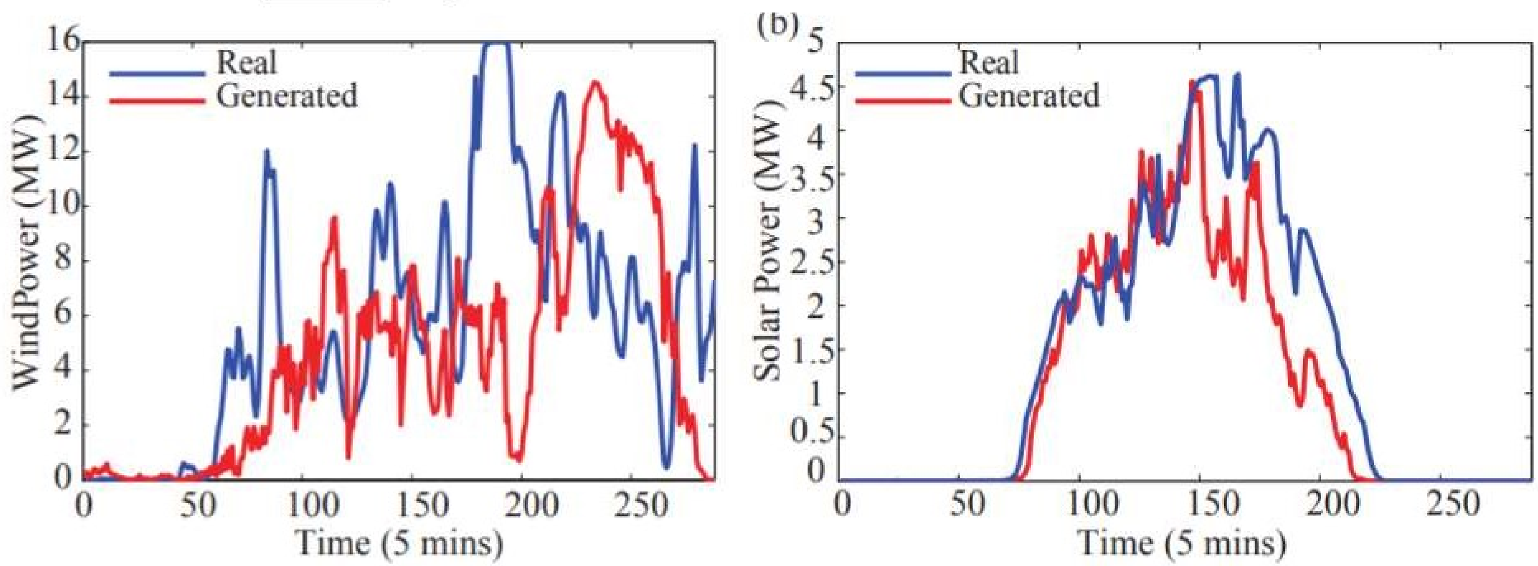


Examples of Photorealistic GAN-Generated Faces.Taken from Progressive Growing of GANs for Improved Quality, Stability, and Variation, 2017



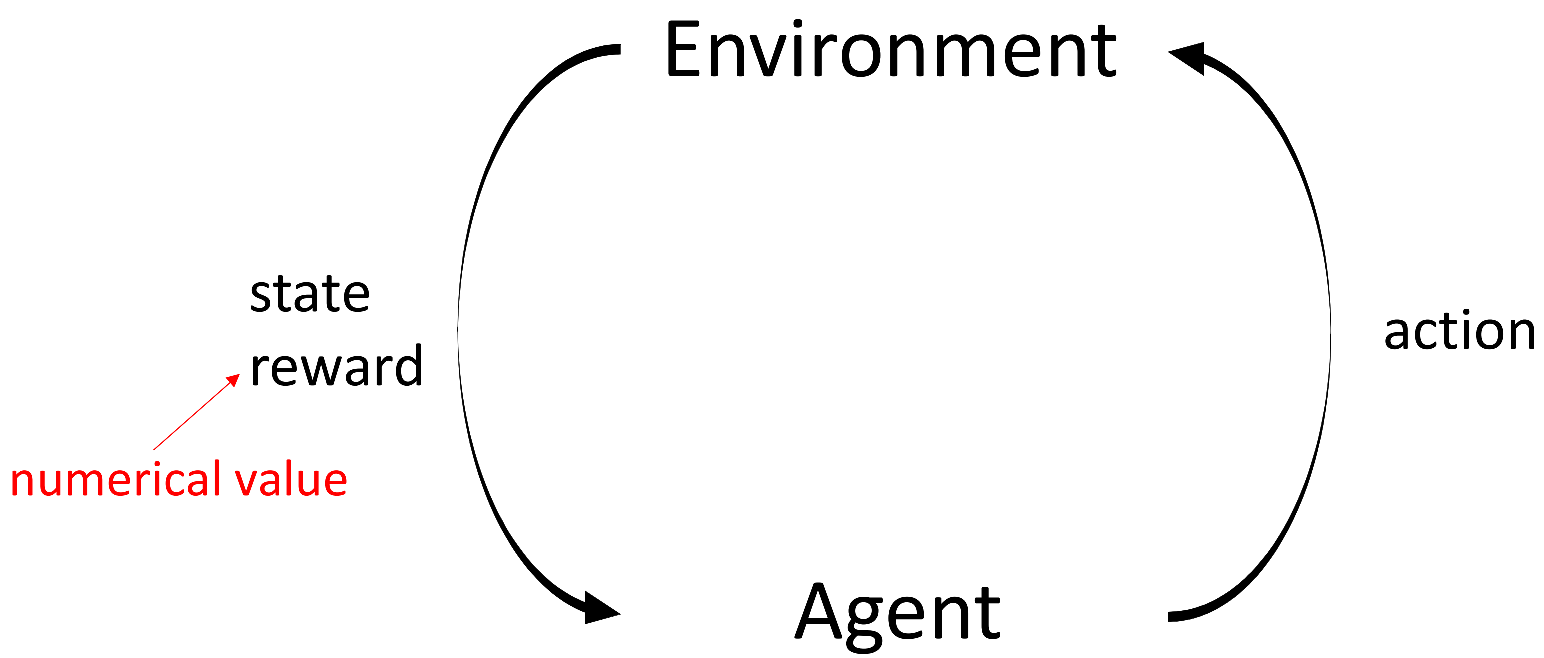
Left: The architecture of a GAN used for a wind/solar generation scenario.

Below: Generated scenarios versus real-life ones.



Figures taken from: "Model-Free Renewable Scenario Generation Using Generative Adversarial Networks". Yize Chen, Yishen Wang, Daniel Kirschen and Baosen Zhang, 2018.

3. Powerful new reinforcement learning agents



Lee Sedol, is a former South Korean professional Go player with a 9 dan ranking.

He was defeated by the computer program AlphaGo (based on RL algorithms combined with DNN) in a series in March 2016.

On 19 November 2019, Lee announced his retirement from professional play as artificial intelligence had created an opponent that "cannot be defeated."

+ the energy market

State: (i) the battery level (ii) *Everything you know about the market*
Reward: The money you make during the market period.

The battery setting for the next market period.

The battery controller

Table 1. Summary of RL considerations for electric power system control/decision

Problem	Type of control	RL method	Reference(s)
Electricity market simulation	Market decision	Q-learning	Harp et al. (2000) Rahimiyan et al. (2010) Nanduri and Das (2007) Lincoln et al. (2012) Kim et al. (2016) Krause et al. (2006)
Transient angle instability	Emergency	Q-learning	Ernst et al. (2004) Glavic (2005) Glavic et al. (2005a) Glavic et al. (2005b) Li and Wu (1999)
		Fitted Q iteration	Ernst et al. (2009)
		Policy search	Mohagheghi et al. (2006)
Oscillatory angle instability	Emergency	Q-learning	Ernst et al. (2004) Wang et al. (2014) Glavic et al. (2005a) Ademoye and Feliachi (2012) Karimi et al. (2009)
Voltage control	Normal	Q-learning	Xu et al. (2012) Vlachogiannis et al. (2004)
AGC (Automatic) generation control)	Normal	$Q(\lambda)$ with elig. traces	Yu et al. (2011)
		Q-learning	Daneshfar and Bevrani (2010) Ahamed et al. (2002)
		$R(\lambda)$	Yu et al. (2012b)
Economic dispatch	Normal	Q-learning	Jasmin et al. (2011) Yu et al. (2016)
Wide-area control	Emergency	TD	Yousefian et al. (2016)
		Q-learning	Yan et al. (2016) Hadidi and Jeyasurya (2013)
Households control	Normal	Q-learning	Wang et al. (2016) Yan et al. (2016)
Wind generation control	Normal	Q-learning	Wei et al. (2015) Tang et al. (2015)
		$Q(\lambda)$	Yu et al. (2012a)
Demand control	Normal	Fitted Q iteration	Ruelens et al. (2016) Vandael et al. (2015)
System restoration	Restorative	Q-learning	Ye et al. (2011)
Congestion management	Emergency	Q-learning	Zarabbian et al. (2016)
Microgrids control	Normal	Q-learning	Khorramabady et al. (2015) Li et al. (2012)
		Policy search	Venayagamorthy et al. (2016)

Table taken from: "Reinforcement Learning for Electric Power System Decision and Control: Past Considerations and Perspectives". M. Glavic, R. Fonteneau and D. Ernst. Proceedings of the 20th IFAC World Congress.

Learning:

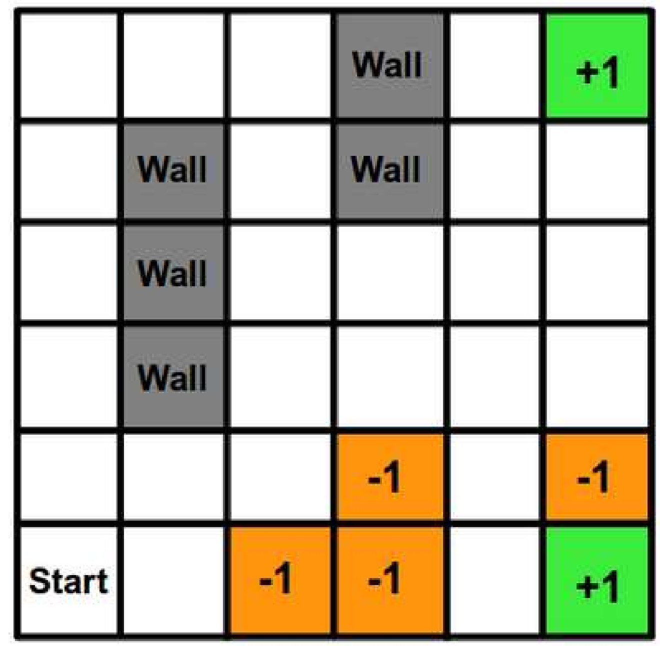
Input : x_t, u_t, r_t and x_{t+1}

$$\delta \leftarrow (r_t + \gamma \max_{u \in U(x_{t+1})} Q(x_{t+1}, u)) - Q(x_t, u_t)$$

$$Q(x_t, u_t) \leftarrow Q(x_t, u_t) + \alpha\delta$$

Exploration/exploitation: Do not always take the action that is believed to be optimal to allow exploration.

Generalisation: Generalise the experience gained in certain states to other states.

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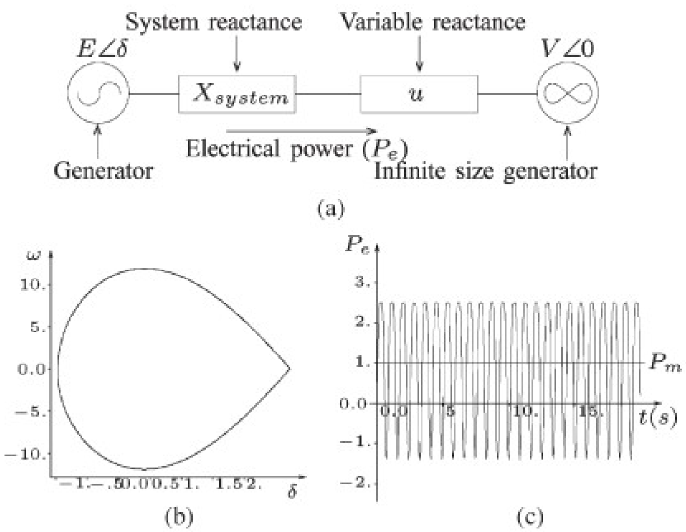
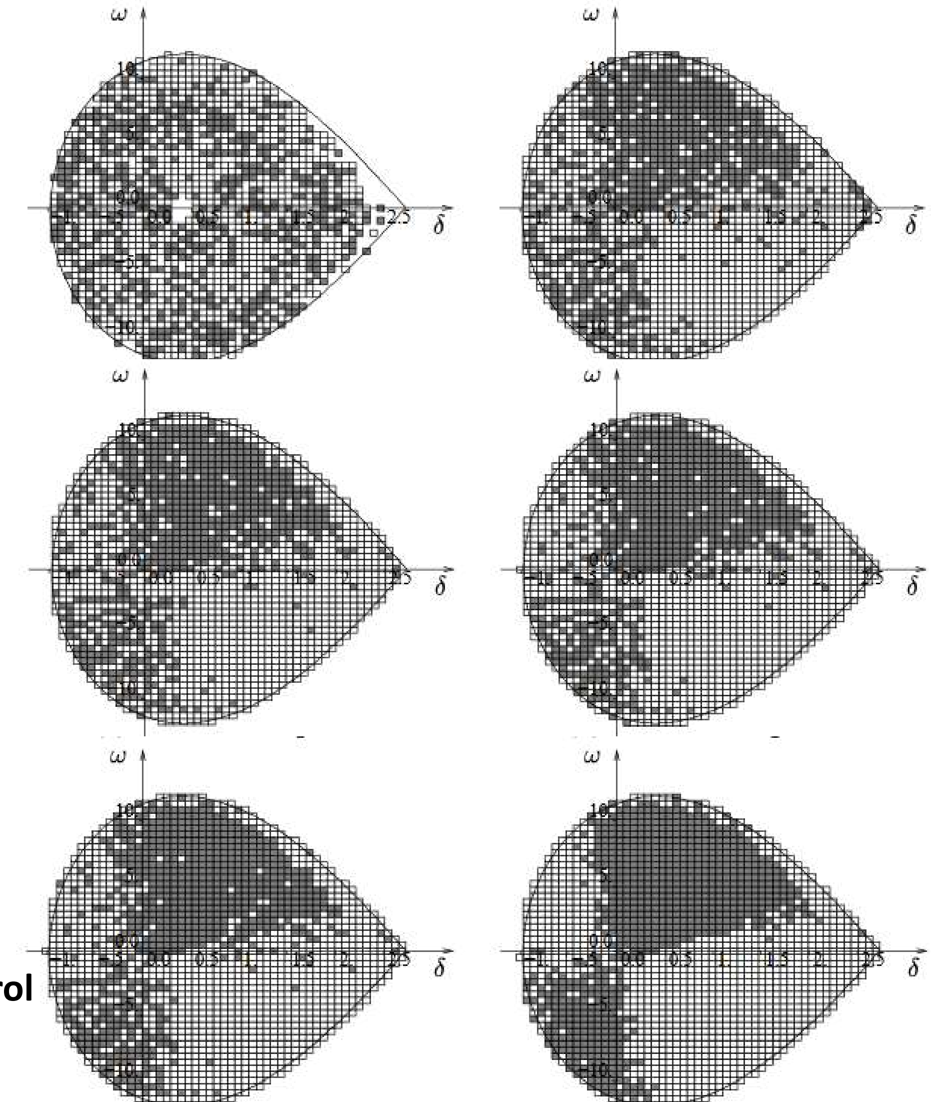
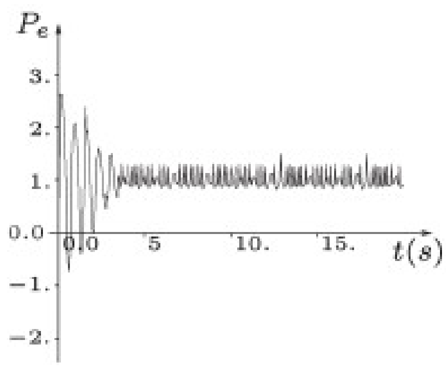
OXYGEN



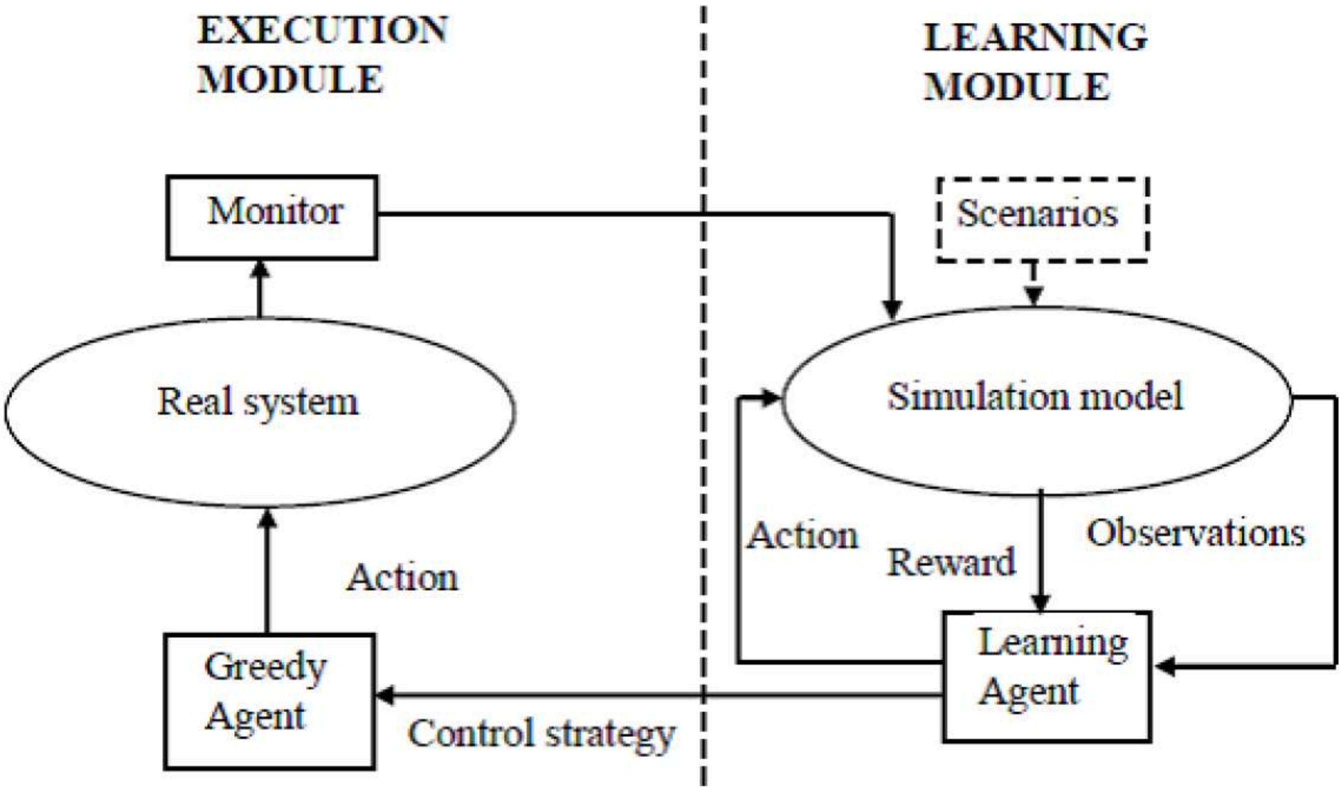
Learning phase



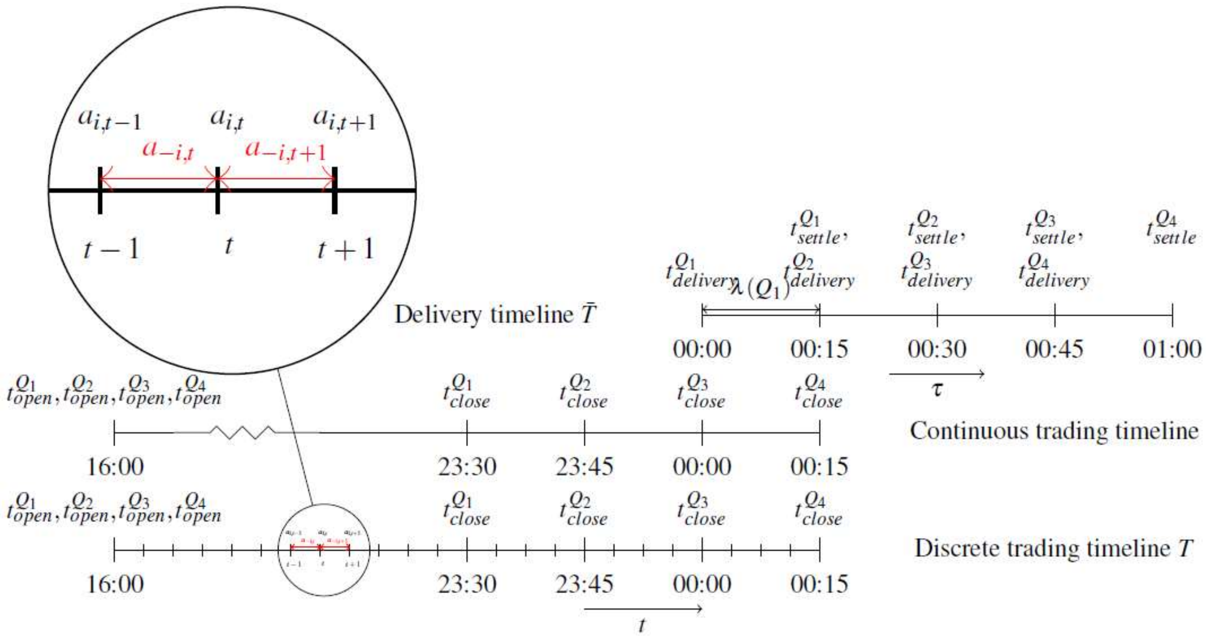


Effect of the resulting control policy

First control law for stabilizing power systems every computed using reinforcement learning. More at: “Reinforcement Learning Versus Model Predictive Control: A Comparison on a Power System Problem”. D. Ernst, M. Glavic, F.Capitanescu, and L. Wehenkel. IEEE Transactions on Syestems, Man, An Cybernetics—PART B: Cybernetics, Vol. 39, No. 2, April 2009.


EXECUTION MODULE
LEARNING MODULE
Monitor
Scenarios
Real system
Simulation model
Action
Action
Reward
Observations
Greedy Agent
Learning Agent
Control strategy

RL for trading flexibility in the intraday market



Order book

i	**Side**	v **[MW]**	p **[€/MWh]**
4	"Sell"	6.25	36.3
2	"Sell"	2.35	34.5
1	"Buy"	3.15	33.8
3	"Buy"	1.125	29.3
5	"Buy"	2.5	15.9

Taken from: "A Deep Reinforcement Learning Framework for Continuous Intraday Market Bidding". Ioannis Boukas et al., 2020.

RL for trading flexibility in the intraday market (Contd.)

Very complex decision-making problem.

Good results could be obtained by using the RL Fitted Q Iteration algorithm (FQI) combined with DNNs.

Trajectories generated artificially on the order the book.

1.5% increase in profit!

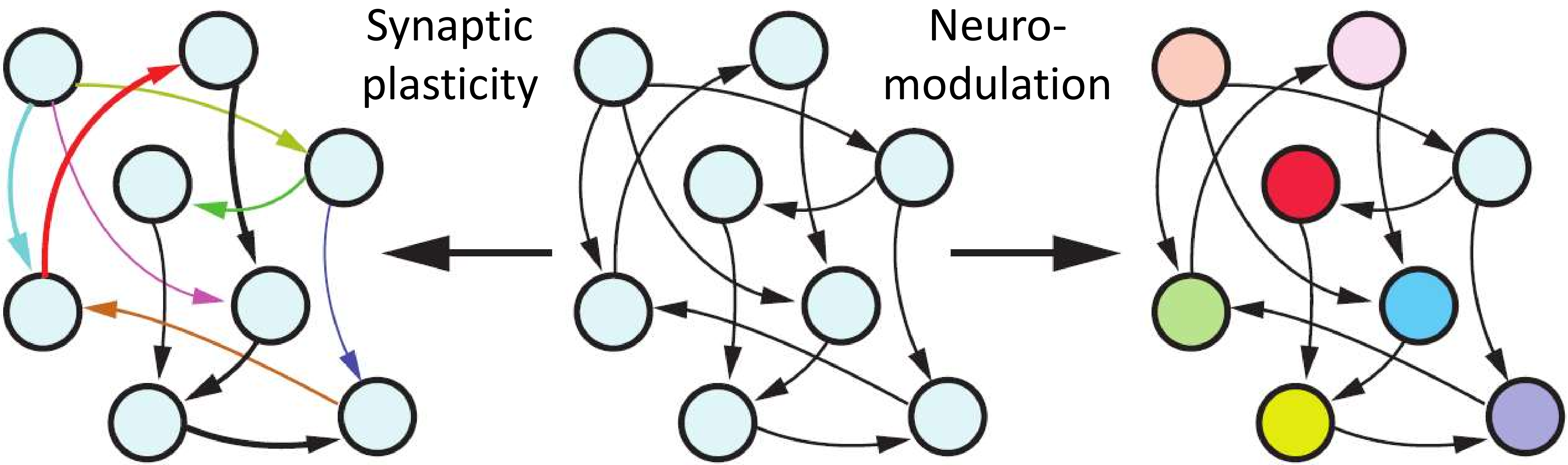
Table 4. Descriptive statistics of the returns obtained on the days of the test set for policies π^{FQ} and π^{RI}. The last column also provides the corresponding profitability ratios.

	π^{FQ} **returns (€)**	π^{RI} **returns (€)**	**r (%)**
mean	8583	8439	1.50
min	2391	2366	−0.73
25%	5600	5527	0.23
50%	7661	7622	0.87
75%	10823	10721	2.22
max	37902	36490	6.56
sum	935552	919871	1.7

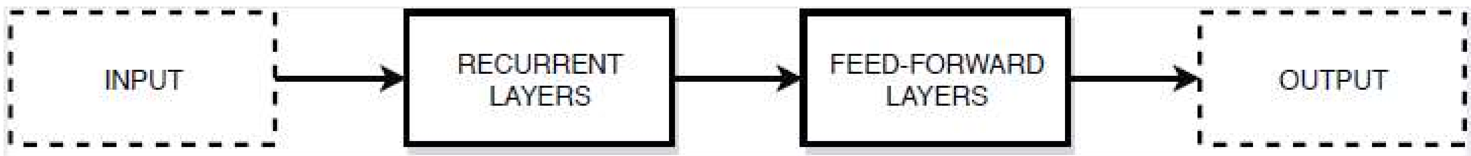
“A critical present objective is to develop deep RL methods that that can adapt rapidly to new tasks.”

Deepmind, “Learning to reinforcement learn.” (2016).

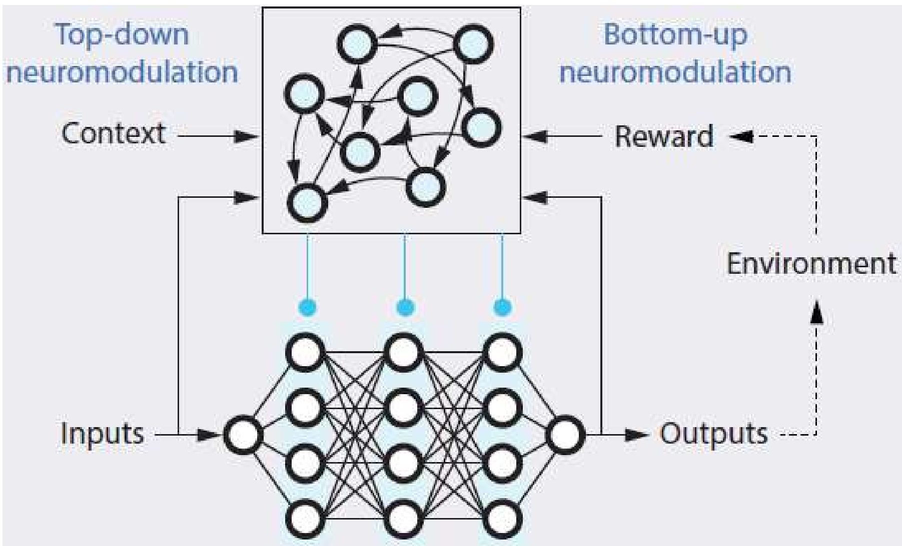
Walking: a meta-RL problem solved through synaptic plasticity and neuro-modulation

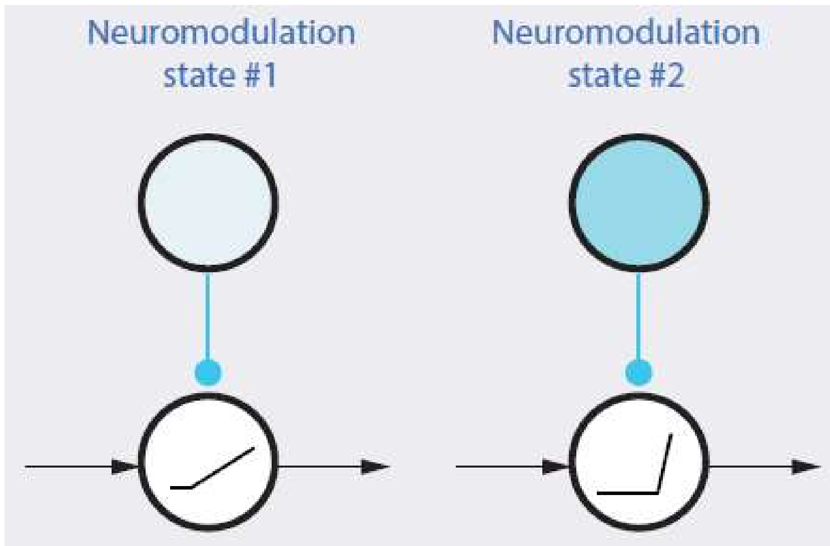


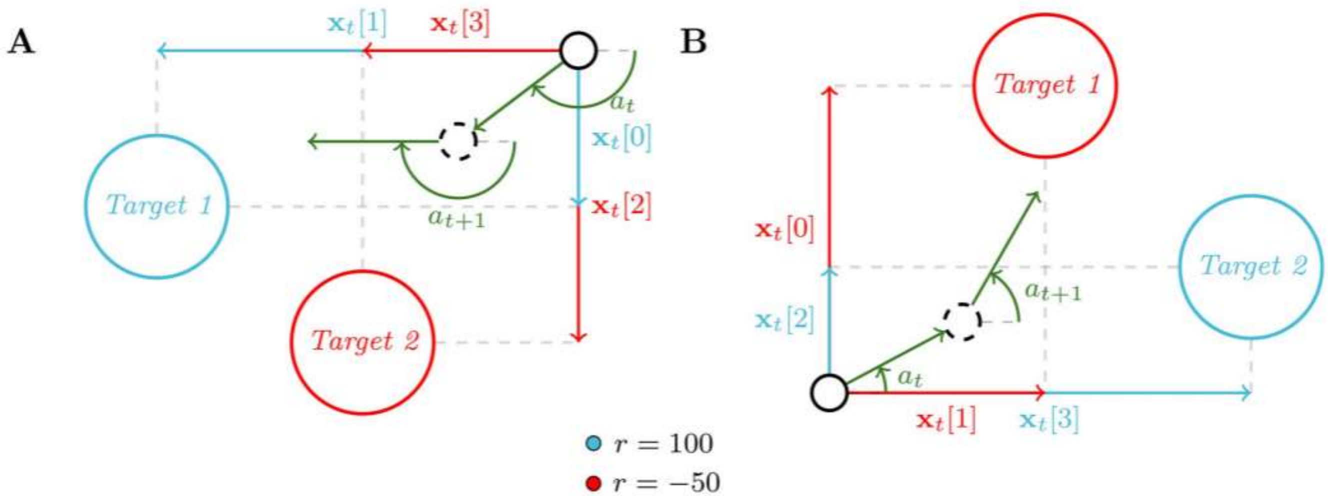
Classical architecture for solving meta-RL problems:



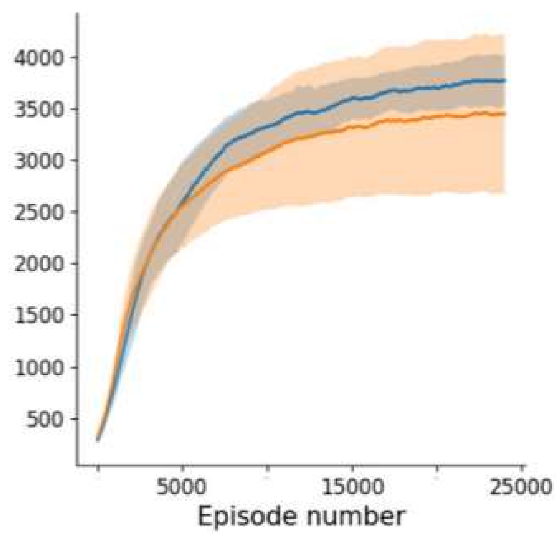
Our new architecture:



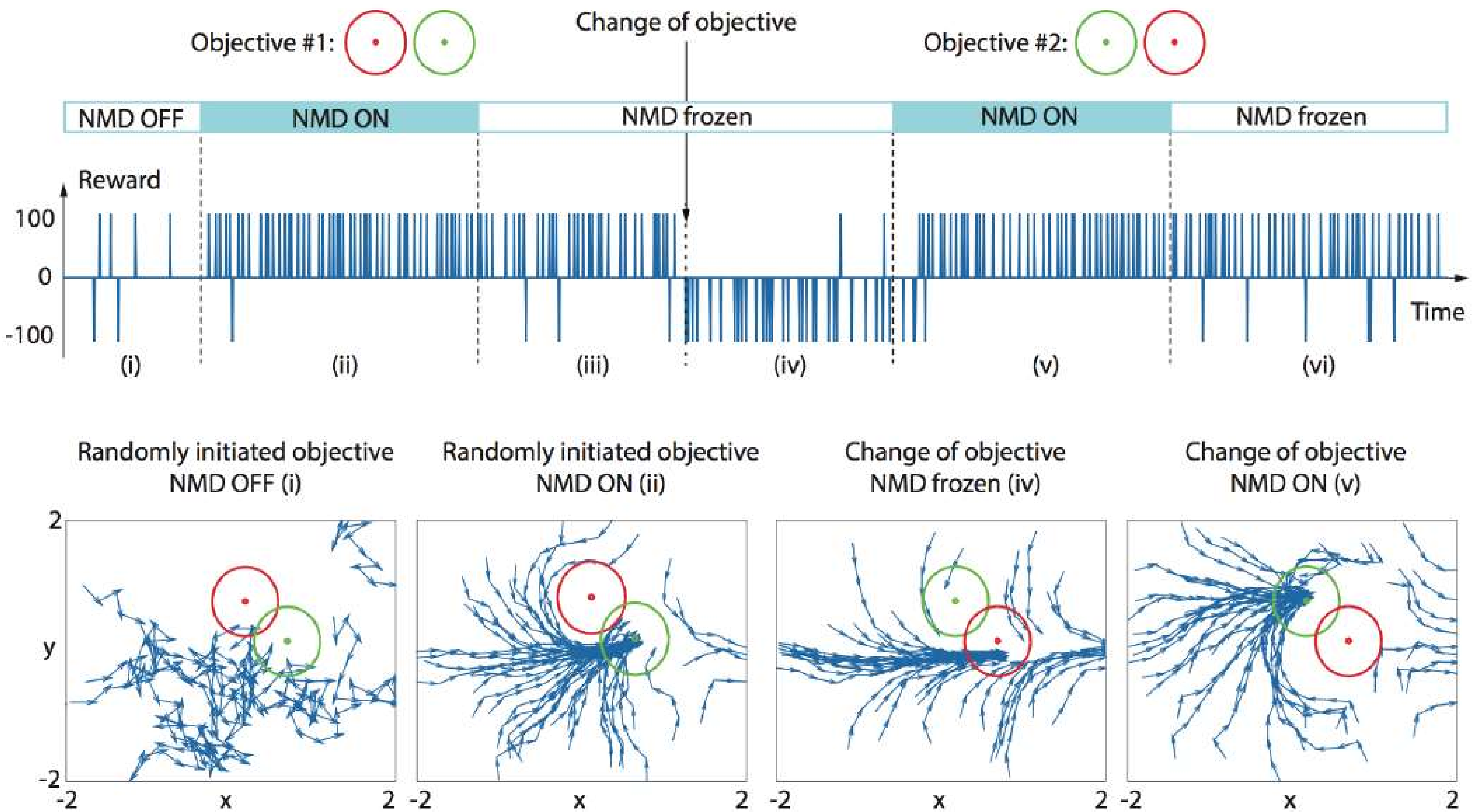




Benchmark description: The RL agent has to navigate on a plane to reach the blue target that leads to high rewards. The environments differ through the positions of the target.



Results: Blue curve represents the neuromodulated neural net. Orange curve represents the classical architecture.



More: "Introducing neuromodulation in deep neural networks to learn adaptive behaviours". N. Vecoven, D. Ernst and G. Drion, 2020.

A question that I was asked a few months ago, and my answer

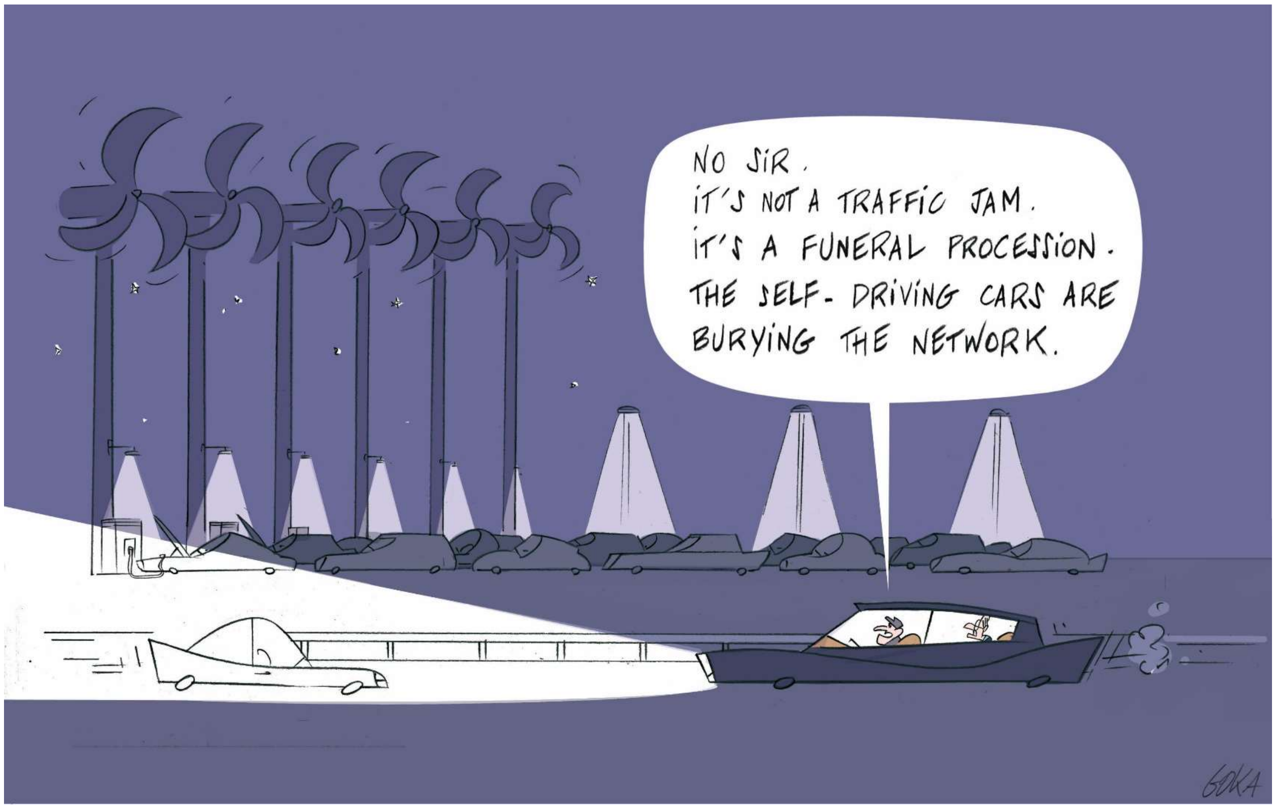
What types of power system problems can one resolve with machine learning?

We could potentially address them all, but I fear that the power system community will not address many of them in the future. Why? Because the power system community will never be able to attract enough bright machine-learning scientists who prefer the high-paying salaries of major companies and corporations (e.g., Facebook, Google) or working on problems related to robotics that they believe are ‘fancier’. The power system community should therefore scale back its ambitions to build a very intelligent grid and focus on the building of grids which do not require a lot of intelligence to be effectively operated.

But what if big tech was disrupting the energy industry with its fancy AI solutions?

Autonomous electrical vehicle going out to collect electricity that is discharged into domestic batteries afterwards.

No need to be connected to the electrical grid anymore.



Self-driving EV cars could be charged next to electricity sources at a cheap price. Afterwards, EVs could directly sell their electricity (without using the grid) to any electricity consumer at a higher price. As such, they will act as a true competitor for the utility grid.