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On using reinforcement learning to increase stability in smart electricity grids

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Over the years interest in renewable energy sources is growing and the amount of electricity provided by such resources, such as photovoltaic (PV) or wind energy is increasing. The supply of renewable energy sources is highly dependent on environmental changes and therefore hard to predict and adjust. As a response, new methods have been proposed to shift control to the demand side of the electricity grid. Furthermore, it can be seen that there is a shift from a situation in which the supply of electricity is managed by a small group of very large suppliers to a larger group of smaller suppliers (e.g. wind farms or households with PV panels).

In order to maintain balance between supply and demand, any shortages or excesses of electricity are resolved by trading on the reserve market. Due to minimum production rates that are required to trade on this market, small suppliers can not participate in this trade. However, as this group becomes larger it would be a great addition to the reserve markets when it comes to maintaining stability in the grid. One solution to add these smaller parties to the electricity grid is to bundle groups of small prosumers into a cluster, controlled by an aggregator. The aggregator can then offer a certain range of power within which it is able to ramp the amount of consumption (or production) up or down.

In this thesis it is shown how reinforcement learning can be applied to successfully learn the boundary conditions within which an aggregator can safely ramp up or down its consumption. Furthermore, Neural Fitted CACLA (NFCACLA) is proposed as a new reinforcement learning algorithm, which is a neural fitted variant on the existing CACLA algorithm [1].

Two reinforcement learning agents were implemented in an internal simulation environment, developed by TNO (The Netherlands Organisation for Applied Scientific Research), used for simulating smart electricity grids. The PowerMatcher [2] was used to coordinate the supply and demand within the simulated grid through dynamic pricing.

The first agent was trained using the CACLA [1] algorithm, an Actor-Critic model that uses function approximators to approximate both the value and policy functions of the model to deal with a continuous state and action space. The second agent was trained with the newly introduced, NFCACLA algorithm: a model-free batch learning algorithm, inspired on the CACLA and NFQCA [3] algorithms.

The agents were trained and tested in a simulation containing 100 households equipped with a PV panel and either a heatpump (80 households) or a micro-CHP (20 households), which is a cogeneration device for generating both heat and power. Historical data was used to simulate weather conditions and imbalance demand for the month of March 2013. The results were compared with a baseline in which the agent offered a fixed percentage of its available flexibility.

Results of the experiments were both measured in terms of imbalances that were resolved and caused by trading, as well as the financial costs and gains that were made. Table 1 shows a summary of the results of the best performances for the baseline and both RL agents. The optimal performing baseline was when the agent offered 50% of its available flexibility.

Table 1. Results of RL agents versus baseline results

agent	resolved imb.	caused imb.	difference	gains	costs	profit
baseline (50%)	751.56 kW	507.15 kW	244.42 kW	€18.29	€5.97	€12.32
CACLA	734.21 kW	552.96 kW	181.25 kW	€18.04	€7.35	€10.69
NFCACLA	577.41 kW	383.68 kW	193.72 kW	€17.61	€4.71	€12.90

Over all results a number of observations can be made. The first observation is that the caused and resolved imbalances were generally lower when boundaries were set by the NFCACLA agent, even when larger portions of the available flexibility were offered. A second observation is that the amount of electricity was generally lower than the boundaries that were provided by the agents. This means that the actual trades had a smaller impact on the grid than the boundaries had allowed for. Finally, the NFCACLA agent is able to make a larger profit than the baseline, even though the amount of traded electricity is smaller.

In conclusion, this thesis shows that RL can be used for trading electricity on the reserve market. However, simpler solutions might prove more successful. One of the downsides in the scenario with which the simulations were performed, is that the balancing trades on the reserve market were rather small, thus having a small impact on the cluster itself as well. In order to test the usefulness of RL additional experiments should be done to test the resilience of the agents when larger amounts of imbalances are traded on the reserve market, such that the boundaries are more stressed.

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