FACULTY OF ENGINEERING
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Forecasting and generative modeling of the Belgian electricity market

February Intermediate Report

Master Thesis

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1 Intermediate Results

1.1 Net Regulation Volume Moddeling

Using a generative model, we try to predict the NRV for the next day. The model is trained on historical data and uses multiple input features to model the NRV. The data for the input features can all be downloaded from Elia Open Data.

1.1.1 Input Features

The generative model uses multiple input features to predict the NRV.

- NRV History (NRV of yesterday)
- Load Forecast (Forecasted load of tomorrow)
- Load History (Load of yesterday)
- Wind Forecast (Forecasted wind of tomorrow)
- Wind History (Wind of yesterday)
- Implicit net position (Nominal net position of tomorrow)
- Time features (Day of the week + quarter of the day)
- Photovoltaic Forecast*
- Photovoltaic History*

* These features are not used currently, the data was not available. These features can easily be added without changing any code.

1.1.2 Models

In the intermediate report of November, baselines were discussed. Now, other more advanced models are used. Samples must be generated using the model, this means the model can't just output one value but a distribution is needed. Quantile Regression can be used for this task. The model then outputs the values of multiple quantiles. For example, the model outputs the value for which 10% of the data is lower, the value for which 50% of the data is lower, etc. This way, the model outputs a distribution which can be used to sample from. The NRV predicitons are done in a quarter-hourly resolution. To predict the NRV for the next day, 96 values need to be sampled. This can be done in an autoregressive manner. The model outputs the quantiles for the first quarter-hour, a sample is drawn from this distribution and this sample is used as input for the next quarter-hour. This process is repeated 96 times.

Model	**test_L1Loss**	**test_CRPSLoss**
Linear Model	101.639	68.485
Non Linear Model	102.031	68.968
LSTM/GRU Model	104.261	66.052

Table 1: Performance of Autoregressive Models

At the moment, I am experimenting with a diffusion model to generatively model the NRV but more research and expermimenting needs to be done.

1.1.3 Charging Policy

Using the predicted NRV, a policy can be implemented to charge and discharge a battery. The goal of the policy is to maximize the profit made by selling the stored electricity. A simple policy is implemented to charge and discharge the battery based on 2 thresholds determined by the predicted NRV. The policy is evaluated on historical data and the profit is calculated. To determine the charge and discharge threshold, 1000 full NRV predictions are done for the next day and for each of these predicitions, the thresholds are determined. Next, the mean of these thresholds is used as the final threshold.

Policy	**Total Profit (€)**	**Charge Cycles**
Baseline (charge: 150, discharge: 175)	251,202.59	725
Baseline (yesterday imbalance price)	342,980.09	903
GRU Predicted NRV (mean thresholds)	339,846.91	842
Diffusion Predicted NRV (mean thresholds)	338,168.03	886

Table 2: Comparison of Energy Storage Policies Using Predicted NRV. Battery of 2MWh with 1MW charge/discharge power. Evaluated on data from 01-01-2023 until 08-10-2023.

The recommended charge cycles for a battery are <400 cycles per year. The policy also needs to make the charge cycles are below 400. A penalty parameter can be introduced and determined so that the policy is penalized for every charge cycle above 400. The policy can then be optimized using this penalty parameter. I am currenlty experimenting with this.

2 Schedule next months