University of Pannonia
Faculty of Information Technology
Doctoral School of Information Science and Technology

USE OF FORECASTING AND OPTIMIZATION TOOLS TO INCREASE THE FLEXIBILITY OF THE TRANSFORMING POWER SYSTEM

Thesis booklet
Author: István Gusztáv Balázs

Supervisors: Dr. Attila Fodor, Dr. Attila Magyar

Veszprém
2024

1 Introduction

The rise of Distributed Energy Resources (DERs) is transforming power systems from centralized to decentralized structures. Traditionally, large generation sources fed power into transmission grids, which then delivered it to end users. Power flowed one way from high-voltage transmission to low-voltage systems, centralized, predictable generation balanced supply and demand. However, the increase in distributed and renewable generation (projected to grow from 21% in 2010 to 44% in 2030) introduces variability, making the load-following generation paradigm unsustainable.

DERs, including solar panels, wind turbines, and electric vehicles, enable consumers to become energy producers. While this supports renewable energy integration, it complicates supply-demand balance due to intermittent energy generation. The unpredictability of DERs necessitates improved forecasting and control. Variability increases supply-demand imbalances, demanding flexible resources to maintain grid stability. Frequency and voltage regulation are critical, as fluctuations can disrupt electrical equipment and cause outages. Managing peak loads and preventing network congestion become more challenging with DER integration.

Necessity of Digitalization

DER impacts require enhanced digitalization for real-time monitoring, improved communication between transmission and distribution system operators (TSO-DSO), and integration of flexible consumers. Digitalization is essential for adapting to the evolving energy ecosystem, ensuring stability and efficiency. Digital platforms enable seamless communication between participants, exchanging critical data on energy production, consumption patterns, and grid performance. Demand response programs, supported by digital technologies, adjust consumer energy usage to balance supply and demand. Smart meters and home energy management systems empower consumers to aid grid stabilization.

Digital technologies optimize renewable energy use. Advanced control systems, IoT devices, and AI algorithms enhance the predictability and management of renewable outputs, mitigating variability challenges. As DERs rise, digitalization becomes crucial for modern power systems, providing tools to manage decentralization and maintain grid stability and efficiency.

Research Questions

A fundamental question of the digitization of the electricity sector is whether it is possible to formulate methods that can be automated in order to increase the efficiency and utilization of the system, and make it cheaper and safer to operate. Although there are centralized actors in the electricity industry, it is largely driven by market processes and market actors that follow the operating rules of the electricity system and aim to achieve economic benefits.

Another way to make efficient use of the system is to involve previously passive actors in its operation, of which the involvement of energy consumers is a typical example. It is true for consumption in general, but for household consumption in particular, that its inherent flexibility capacity is not systematically exploited. As a first step, we need to know the amount that is available to the consumer at any given moment as a potential consumption reduction or increase.

In this thesis the following research questions will be addressed:

1. How accurately and by what methods the system imbalance, the difference between aggregated generation and consumption, can be predicted in the short term, so that the necessary measures can be taken in advance to stabilize the grid?
2. How a market-based aggregated portfolio using different technologies can derive economic benefits from imbalance forecasting and parallel activities in different but interconnected energy markets through automated strategies?
3. What methodology can be employed to quantify and predict the up-and-down flexibility of a residential house, defined as the ability of a system to adjust its power consumption or generation in response to fluctuations?

2 Advancements in the field

2.1 Short-term system imbalance forecast of the power grid

The imbalance between supply and demand is a critical factor in the operation of the power system, as it leads to a change in the system frequency [1]. Therefore, it is essential to be able to predict its value from historical, measured and forecast data. Based on the assumption that system imbalance is correlated with measured values of system variables (solar and wind generation, load, system imbalance) as well as predictions of exogenous variables, I propose a multi-step version of the Autoregressive Distributed Lag (ARDL) model for the short-term forecast of system imbalance. The proposed forecasting model has been compared with a long short-term memory network-based procedure as well as with an extra trees regression model using real data. The results show that the proposed multistep autoregressive forecasting model outperforms the others in all three evaluation metrics. Since, in many cases, it is sufficient to specify the sign of the imbalance, this paper introduces the concept of sign accuracy as a function of the predicted imbalance and evaluates it for the investigated solutions.

This section presents a forecasting method predicting system imbalance with a 2-hour lead time and quarter-hour resolution using publicly available data. The forecasting employs an ARDL (Autoregressive Distributed Lag) model for time-series data [2]. The method relies heavily on the autoregressive property of the imbalance and on the appropriate compilation of publicly available explanatory variables that are correlated with the imbalance. By using the predictor variables associated with each step of the multi-step forecasting horizon, I also utilize past observed and future known inputs. The proposed ARDL method, together with two non-linear benchmark models (ETR [3] and LSTM [4]) and an ARIMAX model, were subjected to a comparative analysis using the same prepared and processed input data. Results show that ARDL, despite being simpler, offers comparable accuracy to other state-of-the-art methods.

Given imbalance and explanatory time-series data, the goal is to provide a multi-step forecast of system imbalances at forecast execution time t for the current and subsequent quarters $t{+}0$, $t{+}1$, ..., $t{+}7$. This is achieved by creating separate lag structures of the feature set and training ARDL models for each forecast timestep. Both training and verification are performed on historical data, adhering to the rules of temporal availability of plan and measured data. The quality of the prediction is evaluated using metrics commonly used in the literature and compared to the performance of leading non-linear machine learning methods.

An important consideration in the selection of independent variables was that they should be publicly available in sufficient quantity to be used to train the model. Given that my aim is a short-term forecast using a sliding window approach, it is expected that they will be available at the time of forecasting for the period in question. The 'Metered' type of variables are not available in the forecast period, only values from the past can be used. 'Planned' variables are available both for the current time interval and for the future time interval. Typical examples are schedules that are submitted by market participants as part of the day-ahead or intra-day processes, or forecasts that are published by the TSO. 'Fixed' variables are available for both past and future, however, only the forecast interval is used here.

I propose a linear multihorizon imbalance forecasting method that uses both past values of the outcome variable and exogenous variables, and provides flexibility in the design of the lag structure. The basic ARDL structure includes a lagged dependent variable, a set of lagged independent variables, and possibly exogenous variables. The model can be estimated using ordinary least squares (OLS) regression or other estimation techniques. The general ARDL model applied is specified by Equation 1 :

$$Y_t = \delta_0 + \sum_{p=1}^{P} \phi_p Y_{t-p} + \sum_{k=1}^{M} \sum_{j=1}^{Q_k} \beta_{k,j} X_{k,t-j} + \underbrace{Z_t \Gamma} + \epsilon_t, \tag{1}$$

where

- Y_t: the forecasted value of the dependent variable at t,
- Y_{t-p}: values of the dependent variable at $t-1, t-2, \ldots, t-p$,
- P: maximal lag of Y,
- $X_{k,t-j}$: k^{th} independent variable at $t-1, t-2, \ldots, t-j$ periods,
- Q_k: maximal lag of X_k,
- M: number of lagged variables,
- Z_t: fix non-lagged independent variable at time period t,
- ϵ_t assumed to be i.i.d.,
- $\delta, \phi, \beta, \gamma$ are estimated modell parameters.

The ARDL model according to Equation 1 calculates the value of the next time period after the observations. This is called single-step forecasting because we only need to forecast one step. However, in this case we are interested in several quarters of an hour, several steps need to be predicted at the same time, so this is a multi-step time series forecasting problem. In order to use the ARDL approach for a multi-step forecast, the predicted value of the dependent variable from the previous step is used to train a separate model with different variables and lag structures. The model is illustrated in Figure 1. The forecast is made at the time t for the time intervals between t and $t + 8$. I assume that for both the dependent and independent variables, observations are already available for time period $t - 1$. The value of the Fixed variable (Z in Equation 1) is known for the given interval t. From these inputs, the ARDL model calculates the value of the dependent variable value for period $t + 1$ (FC_{t+1}). In the same period t, the forecast for the interval $t + 1$ is also computed (FC_{t+1}). To do this, the existing observations of the dependent variable are used as predictors, along with its forecast for the previous interval ($t + 0$) and the value of the fixed variable for $t + 1$. For Step $t + 2$, the set of observations remains the same, but the predictors for $t + 0$ and $t + 1$ of the dependent variable are added to the set of predictors. Multi-step forecasting is implemented iteratively, with different steps using different variable and lag structures, thus training a separate ARDL model for each step.

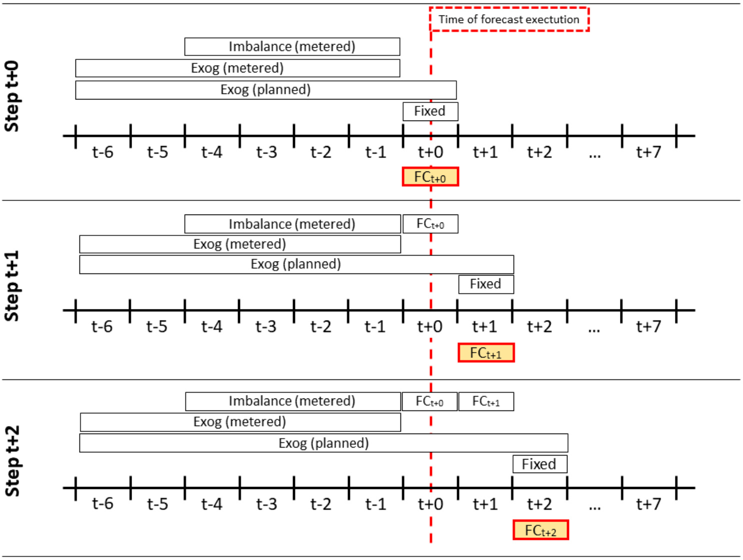

Figure 1: Lag structure of the predictor variables. A separate model is traned for each step. FC refers to the forecasted values of imbalance.

As shown in Figure 1, to train the model for each step, the predictor set must be constructed by adding the prediction of the previous step to the predictor set. After a model has been trained for a prediction step, the corresponding prediction is made, and then the next step is trained

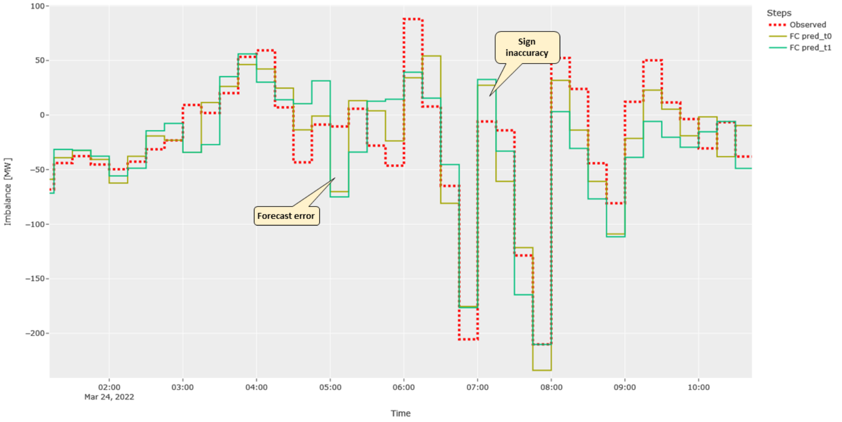

Figure 2: Sample of observed imbalance and prediction

by adding that prediction to the set of predictions. The forecast follows a similar logic. The forecast that is associated with a step is both the final result and the input for the forecast of the next step.

Real data was used to verify the method described above. The data are available on the Hungarian TSO website and the ENTSO-E Transparency Service. The train period is quarter hours between January 2021 and February 2022, the test period is between March 2022 and December 2022. In these intervals, all quarter-hour values have been taken into account.

Figure 2 shows a snippet of the imbalance forecast. A solid line is the forecast value and a dashed line is the observed value for the same quarter of an hour. The time series 'FC pred_t0' represents the prediction step 'Step t+0' as shown in Figure 1. For a given time stamp, there are several predictions (t0-t7), but for the sake of clarity, only $t+0$ and $t+1$ are shown in the figure. The forecast error is the difference between the observed and the predicted value.

In addition to the magnitude of the error, the sign accuracy is of particular importance. Sign accuracy is important because the value, or more precisely the sign, of the system imbalance is used to build logic that encourages power system actors to reduce the system imbalance. Therefore, in addition to the well-known metrics, I present an independently developed metric for evaluating sign accuracy. The Sign Accuracy Percentage

(SAP) is calculated by dividing the number of correct predictions of the direction (Equation 2) by the total number of predictions (Equation 3). In addition, a threshold value is applied so that SAP is only calculated for forecasts with an absolute value that is greater than the threshold value.

$$
\begin{aligned}
SA^{True}_{step,\tau} &= \sum_t \Big[(FC_{t+step} \geq \tau \land Y_{t+step} > 0) \lor \\
&\qquad (FC_{t+step} \leq -\tau \land Y_{t+step} < 0)\Big] \\
SA^{False}_{step,\tau} &= \sum_t \Big[(FC_{t+step} \geq \tau \land Y_{t+step} < 0) \lor \\
&\qquad (FC_{t+step} \leq -\tau \land Y_{t+step} > 0)\Big]
\end{aligned}
\tag{2}
$$

$$
SAP_{step,\tau} = \frac{SA^{True}_{step,\tau}}{SA^{True}_{step,\tau} + SA^{False}_{step,\tau}} * 100, \tag{3}
$$

where

- $[condition]$ is the Iverson bracket, denoting a number that is 1 if the *condition* in square brackets is satisfied, and 0 otherwise,
- $SA^{True}_{step,\tau}, SA^{False}_{step,\tau}$: number of correct and incorrect directional predictions given a threshold value τ and a forecast window *step*,
- FC_{t+step}: imbalance forecast of interval $t + step$ executed at time interval t,
- Y_{t+step}: measured imbalance of interval $t + step$,
- τ: threshold value, $0 \leq \tau$ only forecast over τ or $-\tau$ are considered,
- $SAP_{step,\tau}$: sign accuracy percentage.

The results of the ARDL model have been compared with the benchmark models (ARIMAX, ETR, LSTM). Although several studies use the methods selected for the benchmark, the literature on short-term imbalance forecasting is not very rich, and comparisons can be valid only if the models are run on the same assumptions and data. To this end, the benchmark models were not only presented but also applied and implemented to the problem at hand. The results are summarized in Table 1. For mean absoulute error (MAE) and root mean squared error (RMSE), a lower value indicates better forecasting efficiency. For SAP, a higher value is favorable because the value indicates the percentage of forecasts above 40 MW and below -40 MW that correctly predict the system direction. The performance of ARDL is better than the benchmark models in the first 4 intervals, i.e. the first 1 hour. In the second hour, ARIMAX performs slightly better.

Table 1: Comparison of prediction results using 5 months of test data

Metric	Step	ARDL	ARIMAX	ETR	LSTM
MAE	Step 0	28	54	32	46
	Step 1	40	55	45	55
	Step 2	49	58	53	64
	Step 3	55	59	59	71
	Step 4	63	66	67	73
	Step 5	69	69	73	75
	Step 6	73	71	77	79
	Step 7	76	73	80	86
RMSE	Step 0	37	67	43	62
	Step 1	53	69	61	73
	Step 2	66	75	72	84
	Step 3	75	76	81	94
	Step 4	86	84	92	98
	Step 5	94	86	101	100
	Step 6	101	92	108	107
	Step 7	105	93	113	117
SAP	Step 0	98	89	97	91
	Step 1	94	88	92	86
	Step 2	90	87	88	82
	Step 3	88	85	85	80
	Step 4	84	84	82	78
	Step 5	81	82	78	76
	Step 6	78	80	76	73
	Step 7	76	80	74	69

I have demonstrated the ARDL model's effectiveness in forecasting power system imbalances, essential for maintaining stability. Comprehensive evaluations using real-world data show ARDL's performance compared to benchmark models. The multi-step forecasting approach enhances the ability of system operators to manage imbalances, with the innovative sign accuracy metric providing reliable directional forecasts. The ARDL model's computational efficiency and high predictive accuracy make it a practical tool for real-time power system management.

2.2 Trading activity simulation of an aggregated power portfolio

The penetration of distributed, weather-dependent generation over conventional large power plants has increased worldwide. This shift, coupled with technological and market operation advancements, allows the development of portfolios that optimally use different generation and consumption technologies (e.g., weather-dependent and conventional generation units, controllable and non-controllable consumers, energy storage) [5]. Managing portfolios that include a mix of generation and consumption assets involves a range of strategies, covering both internal optimizations and market participation. This section presents a combined technical and market model to simulate potential operational strategies, generating time-series data representing energy transactions, revenues, and costs for an aggregator managing diverse assets based on realistic scenarios.

I consider a reasonably accurate model of the current functioning of the European electricity market. This model depicts market participants operating in electricity markets with different time horizons and balancing control markets. It also depicts market participants adapting to the market's process, timing requirements and settlement rules. I have created an aggregator model that includes generation, consumption and storage assets with different technologies. This model operates within a real operational framework. The assets comprising the portfolio are coordinated and operated by an aggregator role in different electricity markets with the objective of maximizing economic benefits, subject to the technical constraints of the assets that make up the portfolio. The model simulates a 12-month reference period using historical time-series data and real market parameters. It treats the portfolio as a price taker, unable to influence commodity prices due to market competition. The simulation involves a decentralized aggregator portfolio with a consumer, weather-dependent solar (PV) generator, and battery energy storage, forming an individual balancing group. My work addresses both the internal modeling complexity arising from the inhomogeneity of the portfolio and the multi-market nature of the modern electricity industry, while incorporating imbalance forecasting in order to profit from deliberate schedule deviations.

PV generation can be flexibly scheduled and provides real-time control options for pre-scheduled dispatch, balancing services, and real-time adjustments. The consumer has a passive role, with planned production consumed based on availability and planned needs, and remaining production sold in the market. Energy storage can provide scheduled usage and real-time control options for charging and discharging, providing balancing services. The aggregator operates in the Day-Ahead and Intraday Market (DAM, IDM), Imbalance Market, Balancing Capacity Market (aFRR) nad the Balancing Energy Market (aFRR).

Market transactions are priced using the HUPX (Hungarian Power Exchange) DAM hourly and IDM quarterly average prices for the reference period. Among the balancing services, the aggregator participates in the aFRR (automatic frequency restoration reserve) market. The model takes into account the possibility of hourly bidding in the aFRR market and the possibility of intra-day (T-25 minutes) bidding in the intraday market. Reserves and activated quantities are based on a pricing strategy that can be set in the model. The offer prices are calculated based on a pre-fixed ratio of the moving average price of the market offers already known at the time, and in the case of negative aFRR energy bids, a fixed negative price was considered in order to avoid loss periods during activations. The timings used by the model correspond to real market rules for the different activities. The model calculates the energy flows for each element of the portfolio and its energy market components on the basis of the forecasts, the set parameters and the situations that occur in each period (schedule deviations, contracted reserves, activations) and their subsequent resolution. The objective function is to maximize the economic profit resulting from the balance of market transactions.

Two scenarios are evaluated. "Basic Functions" scenario is a traditional approach where solar production meets consumer demand, with excess sold in the market. The aggregator controls the battery and solar panel to maintain the schedule. In the Extended Functions scenario, the portfolio actively participates in balancing markets and provides aFRR services via batteries and solar. System imbalance forecasting helps increase revenue through deliberate schedule deviations. The two scenarios presented cover the two extreme cases of possible operating models and market strategies, but in the space between them other intermediate operating approaches are conceivable.

The results show significant differences between the scenarios in terms of energy flows and financial outcomes. Figure 3 compares the expected energy flows for the two scenarios during this day. For the Basic Functions case, it is easy to follow the process of scheduling and internal utilization of generation. During the night, consumption is entirely from the public grid, then increasingly offset by PV generation, and finally PV generation is also used for external sales. In the case of the "Extended Functions", there are significant deviations from the market schedule due to the influence of both

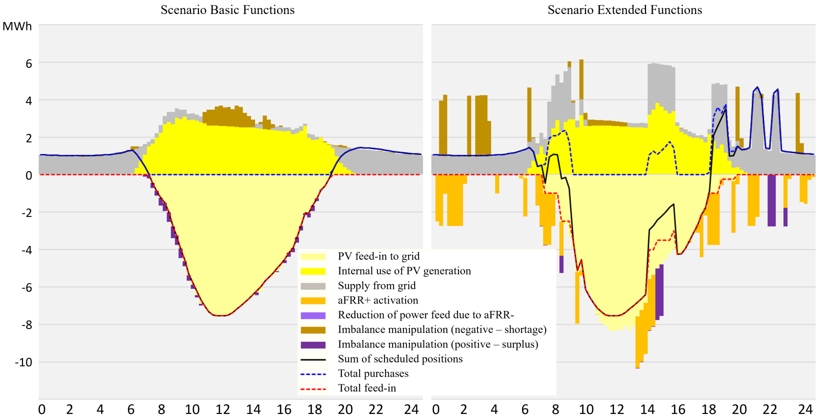

Figure 3: Energy flows for the scenarios

aFRR demand and balancing energy. In addition, it is worth noting the frequent surge in the level of purchase from the public grid, which is often necessary due to the urgency to recharge batteries.

While above I have shown the differences between the scenarios through selected examples, the following graph summarize the figures for the whole year 2022 for the two scenarios. Figure 4 summarizes the cash flows. The balance of organized electricity market transactions are significantly negative on an annual basis in the extended case. However, this is convincingly compensated by the revenues that can be generated by the use of balancing reserves. The frequent need to recharge the battery almost doubles the expenditure on system charges. The positive balance of imbalance energy is also doubled due to system imbalance forecasts. The overall monetary difference is quite impressive, even though we know that this is not the total annual cash flow of the portfolio, and that there is a significant difference between the two cases for both Operational Expenditure (OPEX) and Capital Expenditure (CAPEX) - of course, the picture would be complete if these were taken into account.

By bringing together distributed generation and consumption units, it is possible to create a portfolio of a size and composition that can overcome barriers to entry and compete effectively in different markets. My model demonstrates how different generation and consumption technologies can work together in complex market conditions. The results demonstrate the potential variability in effectiveness that the same set of tools can exhibit

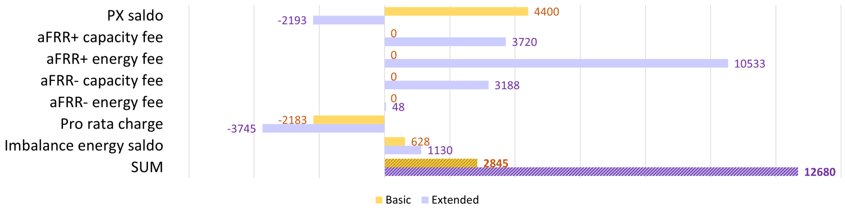

Figure 4: Summary of annual cash flows for the scenarios [EUR, in thousands]

under different operational strategies. More complex strategies typically require more intricate organizational, process, and IT support structures, leading to increased risks and higher implementation costs.

2.3 Quantifying the power flexibility of a residential household

Flexibility in energy systems involves modifying generation or consumption patterns in response to external signals, such as price changes or activations, to maintain system balance or grid power flows. This concept is essential for compensating for the inherent variability and uncertainty of renewable energy sources like wind and solar power. As these variable renewable energy sources become more prevalent, interest in flexible resources — including demand response, dispatchable generation, transmission interconnection, and storage technologies — has grown. In this context, residential energy systems, equipped with devices such as heat pumps (HPs) and stationary batteries, can play a pivotal role in providing this necessary flexibility [6]. This section proposes a framework for the estimation, as well as the prediction of the power flexibility of residential prosumers. In order to quantify the residential buildings' demand flexibility, a thermoelectric simulation model of a typical residential house was developed based on first engineering principles. Based on the calculated flexibility values, a prediction method was used to give a short-term forecast of the prosumer flexibility. The results were validated by simulation experiments incorporating real data for four different scenarios.

To study demand flexibility, I assumed a residential building located in Hungary. The building is equipped with an electric heating system, a separate water heater, a home energy storage system, and rooftop PV panels (see Figure 5).

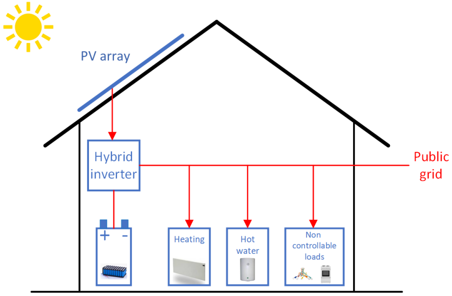

Figure 5: High-level model of the system. Line segments without arrow heads represent bidirectional power flow.

A thermal model was developed for the space heating and hot water system. The energy required is supplied from the PV system, energy storage, or the grid. A conventional greedy algorithm was implemented to control the operation of the energy storage system when no external flexibility regulation is applied. The objective is to minimize grid usage. The model is designed to describe the dynamic behavior of the energy consumption of a typical house with a garden. The aim of the model is not to show perfect quantitative behavior with the real system; rather, it is expected that the essential dynamic transients characterizing each module will be recognizably and correctly described by the model.

Hot water is supplied by an electric water tank (DHW tank) containing m_w kilograms of water. A setpoint (T_w^{sp}) specifies the maximum temperature of the water, and a thermostat controls the heating cycles. The thermostat switches the heater off at the setpoint and turns it on when the temperature drops below the setpoint by a threshold value (T_w^{th}). When the heater is on, a heating wire warms up the water by η_w efficiently consuming a constant level of power (P_w).

A water tank model calculates the water temperature dynamics (Equation (4)). The water temperature change ($\frac{dT_w(t)}{dt}$) has three main inputs: heat provided by the heater ($\frac{dQ_w^g(t)}{dt}$), hot water consumption ($\frac{dQ_w^c(t)}{dt}$), and heat losses ($\frac{dQ_w^{hl}(t)}{dt}$). When hot water is consumed, the same amount of cold water ($\frac{dm_w^c(t)}{dt}$) fills the tank. The inflow water temperature is the same as the outside temperature ($T_a^{out}(t)$); thus, consumption cools the tank. The heat outflow is proportional to the temperature difference between the cold and the tank water ($T_w(t)$). Heat loss is calculated considering a heat loss parameter (hl_w) and the difference between water and room temperature (T_a^{in}). The room temperature is an output signal of the heating subsystem.

The energy balance of the hot water subsystem is expressed by the following equations:

$$\begin{aligned}
Cons_w(t) &= P_w^{max} \cdot Reg_w(t) \\
\frac{dQ_w^g(t)}{dt} &= Cons_w(t) \cdot \eta_w \\
\frac{dQ_w^c(t)}{dt} &= (T_w(t) - T_a^{out}(t)) \cdot \frac{dm_w^c(t)}{dt} \cdot C_w \\
\frac{dQ_w^{hl}(t)}{dt} &= (T_w(t) - T_a^{in}) \cdot m_w \cdot hl_w \\
\frac{dT_w(t)}{dt} &= \left(\frac{dQ_w^g(t)}{dt} - \frac{dQ_w^c(t)}{dt} - \frac{dQ_w^{hl}(t)}{dt}\right) \frac{1}{m_w \cdot C_w},
\end{aligned} \tag{4}$$

where $Cons_w(t)$ stands for the actual water consumption of the house.

Power is a signed value. $P_w(t)$ is negative (consumption) when the heater is on ($Reg_w(t)$):

$$P_w(t) = -Cons_w(t). \tag{5}$$

The calculated flexibility can be defined for both the up and down direction between current power consumption and the maximum power capacity (down) or 0 (up) using (Equation (6)) below.

$$\begin{aligned}
F_w^{up}(t) &= Cons_w(t) \\
F_w^{down}(t) &= Cons_w(t) - P_w^{max}
\end{aligned} \tag{6}$$

A separate thermal model calculates the power consumption of the heating system that keeps the indoor temperature around a defined setpoint. The heating system is equipped with a thermostat and an electric heater. Similar to the water heater, the thermostat switches the heater on and off when the temperature drops below and above the setpoint by a predefined threshold. An air-to-air heat pump supplies warm air for the house, operating at an average COP ratio. Total thermal resistance is calculated from the geometry and the material properties of the house. A thermal model calculates the indoor air temperature dynamics of the house. Its two main inputs are the heat provided by the heating system and heat losses. Heat loss is proportional to the temperature difference between the room and outdoor temperature. The available flexibility quantity of the heating subsystem is calculated in the same way as for the hot water tank.

Storage provides the flexibility of shifting energy over time. A conventional greedy algorithm was implemented to control the storage operation when no external flexibility regulation was applied in order to prefer self-consumption and reduce feed-in power. If there is a higher consumption by the household than generation by the PV, the storage is discharged until a minimum charge level. When generation surplus occurs, the storage is charged until it is full.

PV generation depends only on solar radiation. When no flexibility control is applied, it is assumed that the panels always generates the maximum power, and no upward regulation is available. The PV can offer downward flexibility between 0 and its current generation.

The energy model of the house implemented in Matlab calculates the total energy consumption/generation and the available flexibility that it could provide. Four simulations were performed to analyze the flexibility under different weather conditions and patterns for a 24-hour period: sunny-winter / cloudy-winter / sunny-summer / cloudy - summer.

Figure 6 shows the power consumption and generation of the simulated devices for a sunny winter day. Supply from the grid and PV generation is the primary sources of energy. Net power is the balance of the house; it is the volume of power consumption from or fed to the grid. When the PV generates sufficient power to feed all consumption units, the energy surplus charges the battery. The greedy battery control method discharges the storage when the PV is low. After 8 p.m., the house is supplied from the grid again, after the battery becomes empty.

The upward and downward flexibility capabilities of each device are added, resulting in the building's maximum flexible power (Figure 7). The band of flexibility is not symmetric: although the house is a prosumer, generation and storage capacity is limited, and consumption is intermittent. There are more occasions when a consumption device could be turned on than off, so the downward flexibility is higher. PV generation increases the upward flexibility by charging the battery: the battery consumption can always be switched to production.

The quantification of the flexibility provides instant volumes of the up and down regulation capabilities. Instantaneous values are not valuable for flexibility buyers such as system operators or aggregators, so forecasts need to be calculated. It was not a primary objective to study the prediction methods and evaluate the results; however, a linear (Ridge Regression [7])

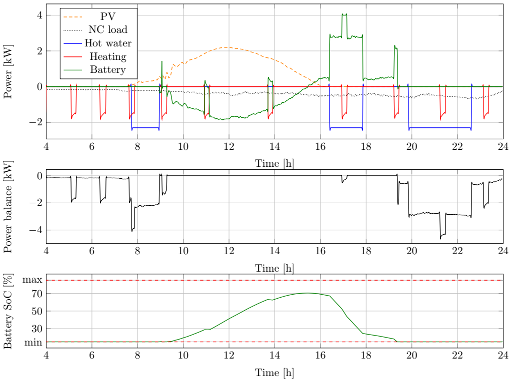

Figure 6: Power consumption/generation of devices for the winter sunny day scenario.

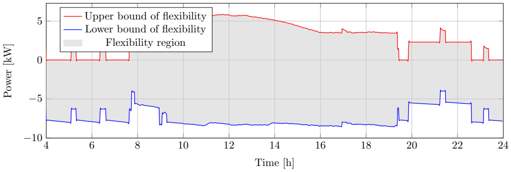

Figure 7: Available upward and downward flexibility for the winter sunny day scenario.

and a non-linear forecast model (Extra Trees Regression) was built to show the short-term prediction opportunities.

All the predictive models were trained on the same data, i.e. one month of one-minute resolution simulated results. The simulation of flexibility represents the true value of the target variable. The 1-minute simulation of the target and the explanatory variables were resampled to 15-minute and a single period forecast was made for the flexibility in up and down direction. The prediction results and the target value for one day are shown in Figure 8 for upward direction. Ridge regression follows the shape of the target variable in both upward and downward directions, but in a naive manner, it reflects the previous period's value in the predictions. This occurs because despite the L2 regularization, the lagged variable of our target variable received the highest coefficient. The linear model perceives the autoregressive effect as much stronger than the explanatory power of the explanatory variables.

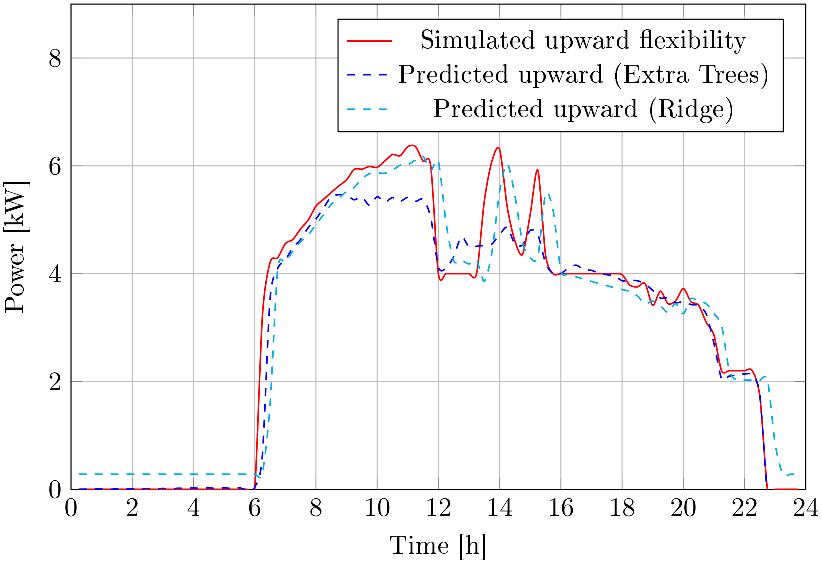

Figure 8: Sample from the upward flexibility prediction for a day.

In the case of ETR, it can be observed that overfitting of the target variable does not occur. However, peaks in flexibility capability are typically underestimated in absolute value in both directions.

Table 2 contains the metrics for both predictions. Despite the incorrect estimates of the outliers, the ETR produced more accurate forecasts in both directions and by both metrics. There is potential to improve the accuracy of the predictions by increasing the size of the training set and by testing additional prediction algorithms.

Table 2: Prediction results

Metric	Direction	ETR	Ridge
CVRMSE	Up	16%	22%
	Down	8%	10%
R_2	Up	0.95	0.91
	Down	0.76	0.6

3 New scientific results

3.1 Theses

Thesis I *Short-term system imbalance forecast of the power grid using autoregressive distributed lag method* ([8], [9])

I have conceived and constructed a data acquisition, processing, and prediction tool tailored for the short-term forecast of system imbalance within the electrical grid. I have formulated the forecasting problem, which aims to generate forecasts from publicly available time series data for the power system at a quarter-hourly resolution for 2 hours after the system imbalance forecast moment. I formulated the problem in such a way that it could be handled by an Autoregressive Distributed Lag (ARDL)-based method, then parameterized it, partially modifying the basic ARDL for the prediction purpose. To evaluate the accuracy of the estimates, I developed a custom metric (Sign Accuracy Percentage - SAP) to measure the accuracy and usability of the results. I checked the results with 10 months of test data. The procedure I developed and proposed is capable of performing the 1-hour forecasting task with a conditional predictive accuracy above 88%. I compared the results with the methods (ARIMA, LSTM, ETR) commonly used in the literature on the subject and determined that the efficacy of the devised ARDL-based approach is found to be commensurate with that of a significantly more complex neural network and decision tree-based prediction. I have developed a data collection framework that collects model input data in real time and continuously performs predictions according to time dependencies, demonstrating that the efficiency of the method does not come from a violation of causality, the short-term prediction method indeed only uses existing and available time stamps for prediction.

Thesis II. *Time series simulation of the operation and trading activity of aggregated power generation and consumption portfolios in a multi-market environment* ([10], [11])

I have developed a method to manage the power generation of a diverse array of assets, including producers and consumers. The proposed method is based on a discrete-time predictive model that relies on power flow equations of the underlying dynamical system. These equations are formulated to incorporate the technical parameters and economic characteristics of the assets, while adhering to the regulatory constraints and operational rules of the market. A key innovation of this work is the ability to optimize profit maximization within a heterogeneous portfolio of assets, effectively navigating and leveraging the opportunities in a multi-market energy environment. This approach also utilizes short-term system imbalance forecasting, over a one-year simulation period, comprehensive validation demonstrates that the imbalance predictions achieve satisfactory accuracy. The results of a scenario analysis also showed that the portfolio achieved a surplus with the participation in the balancing market using the model.

Thesis III. *Model-based quantification of the power flexibility of a household with residential solar panels and energy storage* ([12])

I have developed a discrete-time nonlinear thermodynamic simulation model of a modern residential building based on first engineering principles. The model is equipped with solar panels and energy storage, where individual dynamic models for consumers, producers, and storage devices are developed to interact in response to external disturbances. A novel aspect of this work is the integration of the thermodynamic model with the flexibility calculation of the building's electricity consumption. I have proposed a method to calculate the flexibility of each device, enabling the aggregation of the building's overall up and down flexibility. Using real-time weather data and consumption patterns, I applied the thermodynamic model in four scenarios representing real conditions to quantify flexibility potential across different time periods. Additionally, I incorporated forecasting techniques, including ridge regression and extra trees regression, to predict short-term flexibility. The results demonstrate that the developed model effectively quantifies and forecasts the flexibility potential of the system.

3.2 Areas of application

In recent publications, the forecast of the volume of imbalances has usually been considered as a preliminary step to the price forecast. I believe that the joint prediction of imbalance volume and price provides market participants with the information they need to take the most advantageous market position by trading on intraday markets or by controlling their assets. The direction of the system imbalance is most important from a market position perspective. However, the forecasted volume helps to judge how accurate the sign prediction is. On the other hand, TSOs publish anonymous balancing bids in near real time, so that the resulting price of balancing energy can be approximated from the balancing energy demand and the merit order of the bids, based on knowing the settlement rules. For a portfolio of gas engines, it is worth controlling up for negative imbalance and down for positive imbalance if its short-run marginal cost is between the negative and positive balancing energy prices. A solar portfolio with a short run marginal cost around 0 should not be controlled downward in any case in case of positive system imbalance. When there is a surplus in the system, PVs may be controlled downward only if the downward balancing energy price is negative. Thus, for a given BRP position, the prediction of the imbalance direction is of great importance, because the positive and negative direction require completely different reactions.

A necessary element of integrating renewable technologies and increasing the flexibility of the electricity system is to create portfolios that together effectively exploit the benefits of different technologies and eliminate operational disadvantages. I have shown that, based on extensive data collection and knowledge of the current state of the market and the portfolio, it is possible to influence the market and control activities of a complex portfolio through automated decision logics in a way that serves both the economic interests of the BRP and the interests of the system. This techno-market model provides an opportunity to study and compare portfolios of different composition and size and different scenarios. The modeling also enables the effectiveness of different market strategies and the consequences of their application to be considered, in addition to the technical composition.

The initial development of data collection and control functions for large central power plants was driven by the need to optimize the generation side with a limited number of plants. However, the decentralization trend has rendered this approach inadequate in the context of the present distributed energy system. The involvement of end-consumers is essential to resolve local grid issues. However, the emergence of a small players represents a significant challenge for market players. My work demonstrates the intervals within which the time-series energy balance of a modern residential building can be influenced and the constraints under which it can be predicted.

Future work regarding system imbalance forecast should focus on further refining the ARDL model by incorporating additional predictors and exploring advanced ensemble techniques to improve both accuracy and reliability under varying system conditions. Additionally, extending the evaluation to include more diverse datasets and operational scenarios will help generalize the model's applicability and robustness across different grid environments. This research provides a solid foundation for advancing forecasting methodologies in power system operations, contributing significantly to the field's knowledge and practice.

In the area of complex portfolios, the addition of the tools presented in my work with residential households and the management of the uncertainties arising from their control can significantly increase the economic performance of the portfolio and leads to a difficult optimization problem. It is necessary to generalize the method to a higher number of households, for example a local transformer area, in order to give an estimate of the flexibility of a group of prosumers. Another step in the development of the proposed method is to use novel prediction methods from the field of data science to enhance the short-term prediction performance for flexibility. In the market dimension, the inclusion of instantaneous price information can further increase the complexity of the model.

Publications related to theses

[1] A. Basit, A. D. Hansen, P. E. Soerensen, and G. Giannopoulos, "Real-time impact of power balancing on power system operation with large scale integration of wind power," *Journal of Modern Power Systems and Clean Energy*, vol. 5, no. 2, pp. 202–210, 2017.

[2] M. H. Pesaran, Y. Shin, and R. J. Smith, "Bounds testing approaches to the analysis of level relationships," *Journal of applied econometrics*, vol. 16, no. 3, pp. 289–326, 2001, Publisher: Wiley Online Library.

[3] P. Geurts, D. Ernst, and L. Wehenkel, “Extremely randomized trees,” *Machine Learning*, vol. 63, no. 1, pp. 3–42, 2006.

[4] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997, Publisher: MIT Press.

[5] H Husin, M Zaki, and others, “A critical review of the integration of renewable energy sources with various technologies,” *Protection and control of modern power systems*, vol. 6, no. 1, pp. 1–18, 2021, Publisher: PSPC.

[6] R. A. Lopes, A. Chambel, J. Neves, D. Aelenei, and J. Martins, “A literature review of methodologies used to assess the energy flexibility of buildings,” *Energy Procedia*, vol. 91, pp. 1053–1058, 2016.

[7] G. C. McDonald, “Ridge regression,” *Wiley Interdisciplinary Reviews: Computational Statistics*, vol. 1, no. 1, pp. 93–100, 2009, Publisher: Wiley Online Library.

[8] I. Balázs, A. Fodor, and A. Magyar, “Short-Term System Imbalance Forecast Using Autoregressive Distributed Lag Method,” in *2023 IEEE 6th International Conference and Workshop Óbuda on Electrical and Power Engineering (CANDO-EPE)*, 2023, pp. 000 083–000 088.

[9] I. Balázs, A. Fodor, and A. Magyar, “Short-term system imbalance forecast using linear and non-linear methods,” *Energy Systems*, pp. 1–22, Mar. 2024, ISSN: 1868-3975.

[10] I. Balázs, G. Oláh, I. Pácsonyi, A. Fodor, and A. Magyar, “[ACCEPTED] Simulating Operation and Trading of Aggregated Energy Portfolios in Multi-Market Environments.,” in *IEEE Power Electronics and Motion Control 2024 conference*, 2024.

[11] I. Balázs, A. Fodor, and A. Magyar, “Aggregation of Heterogeneous Flexibility Resources Providing Services for System Operators and the Market Participants,” *Hungarian Journal of Industry and Chemistry*, vol. 47, no. 1, pp. 65–70, 2019, Publisher: Pannon Egyetem.

[12] I. G. Balázs, A. Fodor, and A. Magyar, “Quantification of the flexibility of residential prosumers,” *Energies*, vol. 14, no. 16, p. 4860, 2021, Publisher: MDPI.