Joint Discussion Paper
Series in Economics

by the Universities of

Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 41-2021

Erik Heilmann

The Impact of Transparency Policies on Local Flexibility Markets in Electrical Distribution Networks: A Case Study with Artificial Neural Network Forecasts

The impact of transparency policies on local flexibility markets in electrical distribution networks: A case study with artificial neural network forecasts

Erik Heilmann[a]

[a]*Institute of Economics, University of Kassel, Nora-Platiel-Str. 4, 34109 Kassel, Germany*

Abstract

The energy transition brings various challenges of technical, economic and organizational nature. One major topic, especially in zonal electricity systems, is the organization of future congestion management. Local flexibility market (LFM) is an often discussed concept of market-based congestion management. Similar to the whole energy system, the market transparency of LFMs can influence the individual bidders' behavior. In this context, the predictability of the network status and an LFM's outcome, depending on a given transparency policy, is investigated in this paper. For this, forecast models based on artificial neural networks (ANN) are implemented on synthetical network and LFM data. Three defined transparency policies determine the amount of input data used for the models. The results suggest that the transparency policy can influence the predictability of network status and LFM outcome, but appropriate forecasts are generally feasible. Therefore, the transparency policy should not conceal information but provide a level playing field for all parties involved. The provision of semi-disaggregated data on the network area level can be suitable for bidders' decision making and reduces transaction costs.

Keywords:
Local flexibility markets, Market transparency, Transparency policy, Artificial neural network forecast
JEL classification: L94, L98, Q41, Q47

---

1. Introduction

The energy transition brings various challenges of technical, economic and organizational nature. One major topic, especially in zonal electricity systems, as implemented in the European Union (EU), is the organization of future congestion management. With a growing number of distributed energy sources, such as photovoltaic plants (PV) and wind turbines, but also consumption technologies, such as heat pumps (HP) and electric vehicles (EV), electric networks are increasingly challenged by technical problems, such as line congestion or over- and undervoltage. To solve and avoid these problems in the short term, different congestion management measures are currently under discussion. One of these approaches is the concept of local flexibility market (LFM).[1] LFM is a concept of market-based congestion management in zonal electricity systems as implemented in the EU. Although different approaches to congestion management have been discussed for several years (see, e.g., Kumar et al., 2005), the discussion gained importance due to an increasing share of renewable energy sources and new load technologies such as electric vehicles and heat pumps. An LFM contains trading actions where production, consumption or storage units in a specific network area can provide their flexibility to the network operator to solve technical problems (Ramos et al., 2016). These technical problems can be caused by a local imbalance of production and consumption. In this connection, a high-load situation as well as a high-feed-in situation are thinkable. The concept of LFM is in line with the European directive on common rules for the internal market for electricity (European Commission, 2019), which claims a market based procurement of network-supportive flexibility. Extensive reviews on the topic of flexibility markets and products in general as well as LFM in particular are provided by Villar et al. (2018) and Jin et al. (2020). In the last few years, several pilot projects for the implementation of LFMs have also occurred. Radecke et al. (2019) and Anaya and Pollitt (2020) provide an overview of such pilot implementations and research projects in Europe. Individual examples are discussed in more detail by Schittekatte and Meeus (2020) and Heilmann et al. (2020). Although there is a substantial number of pilot implementations of LFM, the concept is controversial due to the theoretical potential of strategic behavior of flexibility suppliers as well as the flexibility demand side. Hirth and Schlecht (2020) provide a detailed discussion of the possibility of strategic behaviour of flexibility suppliers on an LFM based on the anticipation of congestion situations in connection with LFM prices. Buchmann (2020) discusses the institutional implications of LFM and analyzes three discrimination concerns from the perspective of the network operator as flexibility demander, containing the selection of the flexible assets used in the short term and strategic network investments in connection with information on future flexibility requirements for the network in the long term.

One mostly unexplored issue in the context of LFM is market transparency. Market transparency shall be defined as the availability of information about the market fundamentals, activities and outcome. Such information is the basis for decision making for all market participants, including considerations of strategic bidding. Transparency can in principle be provided by individual market participants, including the market operator or a governmental institution. The type and extent of the information and data provided are referred to as transparency policy. In the case of LFM, it can be expected that there is an information asymmetry with an accumulation of data at the network operator (Buchmann, 2020). For the purpose of this paper, the network oper-

[1] Note, that the terms local/regional flexibility market, network-supportive flexibility market, market-based congestion management or market-based re-dispatch are often used interchangeably.

ator shall be interpreted as both market operator and the demand side of the LFM that provides information in line with a general governmental transparency policy. Based on this assumption, the paper at hand investigates the influence of the chosen transparency policy on the possibility of forecasting network congestion and LFM outcome as the basis for the marketing decisions of flexibility suppliers. The methodological approach is twofold:

i Based on synthetic LFM data, forecast models for the two sequential forecast tasks –forecasting the network status and LFM outcome– are implemented with an artificial neural network (ANN) approach.

ii The influence of different transparency policies on the performance of the forecast models is modeled as a reduction of data input.

The results are used as a basis for suggestions for the design of a general LFM transparency policy.

The paper is structured as follows. Section 2 provides an overview of the theoretical background of (electricity) market transparency in general as well as a discussion of practical examples in the EU and Germany. Based on this, the requirements for a transparency policy for LFMs are discussed briefly. Section 3 contains a description of the data used, the hypothetical transparency policies, the forecast tasks and the forecast models implemented. Section 4 summarizes the main results that are discussed in Section 5. The paper closes with a conclusion and policy implications in Section 6.

2. Market transparency in the context of local flexibility markets

2.1. Theoretical background of electricity markets' transparency

The aim of a market, especially implemented as an auction, is the efficient allocation of resources and the determination of prices based on market participants' bids (McAfee and McMillan, 1987). In general, there is an information asymmetry between the different market participants that leads to individual bidding behavior based on uncertainty (McAfee and McMillan, 1987). The public provision of information, below referred to as transparency policy, can have the following advantages (see Ray and Cashman, 1999; Feltkamp and Musialski, 2013):

- The provision of a level playing field for all market participants.

- Enabling rational decisions and bidding strategies.

- Facilitation of market monitoring and identification of rule violations.

- Reducing market entry barriers.

Therefore, the aims of a transparency policy are strongly connected with the aims of the market itself: economically efficient bidding behavior and the maintenance of operational reliability (Ray and Cashman, 1999).

In the field of electricity markets, information that can influence the decision process of individual market participants can be divided into fundamental and transactional information (Feltkamp and Musialski, 2013). Fundamental information describes the situation of the electricity system in general and contains basic data, such as the time of day, day of week and the weather, but also technical market elements, such as the availability of production units and power line capacity and the amount of load demand (Feltkamp and Musialski, 2013). Transactional information contains data on the market outcome, such as executed transactions and market prices. Both types of information can be considered ex ante (as status quo or forecast) or ex post (Bobinaite et al., 2018).

The specification of the transparency policy contains a selection of the data that are relevant for the decision process and therefore necessary and valuable (Feltkamp and Musialski, 2013; von der Fehr, 2013). Simulation-based studies show that the provision of more information leads to intensified competition (see, e.g., Rosen and Madlener, 2013). Nevertheless, it can be argued that transactional information, especially the price as core information of a market, in connection with information on "major events" (such as outages of big production or consumption units) is sufficient for an efficient bidding process (von der Fehr, 2013). Potential disadvantages of high transparency are the high cost of information procurement and data management, the concealment of private information by individual participants and the facilitation of undesirable behavior such as collusion and the execution of market power (Feltkamp and Musialski, 2013; von der Fehr, 2013). Therefore, any transparency policy must balance different interests and may provide different information for the market participants rather than for the market operator and regulator (von der Fehr, 2013).

2.2. Practical examples of the EU and Germany

In the spectrum of "full information transparency" and a "price only" policy, , the regulation of the European energy market clearly tends toward a high-transparency approach. The EU legislation considers horizontal as well as vertical data exchange. Information is collected and processed by the "European Network of Transmission System Operators for Electricity" (ENTSO-E) and the "Agency for the Cooperation of Energy Regulators" (ACER), which are responsible for data publication as well as market monitoring and reporting to EU institutions and member states (Bobinaite et al., 2018). The most important EU policy is the regulation on the submission and publication of data in electricity markets (European Commission, 2013), which enjoins the ENTSO-E to publish specific data on a transparency platform (ENTSO-E, 2021). The published information contains 49 data items in the fields of load, generation, transmission, balancing, outages and congestion management (ENTSO-E, 2014). The data are mainly aggregated on countries or market area levels with the temporal resolution of the market time units. Although the usability of the platform and the quality of data are under development, the platform is one of the most important collections of energy data in the world (Hirth et al., 2018).

The second important European policy is the regulation on wholesale energy market integrity and transparency (European Commission, 2011), which contains a disclosure obligation toward inside information and the interdiction of market manipulation. Inside information in this context is information that is not available to the public and is capable of affecting the market price. In connection with this regulation, the European Energy Exchange (EEX) provides a transparency platform[2] for the publication of all relevant inside information (European Energy Exchange AG, 2021b). This provided information also contains fundamental data, such as the capacity, usage and availability of generation, storage and loads. While availability considers individual larger-scaled units, data of generation and consumption are in general highly aggregated. In addition to this obligated information, the EEX provides market data in different qualities as an intrinsic service (European Energy Exchange AG, 2021a).

[2]Note, that the EEX transparency platform is totally independent of the entso-e transparency platform, but both may provide overlapping data.

The European regulations are also the basis for the national transparency policies of the member states. In the case of Germany, the four transmission system operators (TSOs) provide collective data of the German energy system on their own platform (50Hertz Transmission GmbH, 2021). In contrast to the European data, this platform provides more locally granular data, such as for the different balancing zones or rough network areas. Still, the provided data are relatively highly aggregated. As a special case of market data, the four TSOs provide relatively detailed information on the German reserve power market (50Hertz Transmission GmbH et al., 2021). The published information, obligated through German regulations (Bundesnetzagentur, 2017a,b), contains the procured amount of reserve power, an anonymized list of bids including information on bid acceptance, reserve energy used and statistical price information for the different reserve products.

In contrast to the high transparency of the discussed market examples, the information availability in distribution networks (including the disaggregated generation and consumption of the connected users) is currently relatively low. This is especially the case in networks with sparsely installed measurement technology, such as smart meters, as is the case in Germany (Bundesnetzagentur, 2021). But even with the presence of such data, the question of data access for different participants has to be answered (Buchmann, 2017).

2.3. Transparency policy for LFM

LFMs are a special form of electricity markets. A Provider of flexibility can be every asset of consumption, production or storage (Heilmann et al., 2020). As discussed in Section 2.1, different information can influence the decision making of bidding on the LFM. On the level of the transmission network, these data are often available (see Section 2.2). Therefore, the focus of this paper is on the applicability of an LFM at the distribution network level. Considering market transparency, an LFM approach at the distribution level can be characterized by the following aspects:

- The participating assets are relatively small and often not monitored in the electricity system's standard processes. Therefore, the (historical) information on schedules of production and consumption are generally not publicly available.
- The market area of LFM is, compared to classical electricity market areas, relatively small. Therefore, the collection of information is in general possible, especially for bigger market participants such as aggregators.
- There is an accumulation of data at the network operator Buchmann (2020).

Against this background, it is necessary to define an appropriate transparency policy for LFM. From a theoretical point of view the provision of information contains different advantages. Still, with a wide spectrum of potential information, the usefulness of individual information has to be considered. This is especially true in small emerging markets where local market power and other strategic bidding behavior could be executed (Ray and Cashman, 1999), as is the case for LFM. Therefore, the theoretical optimum of an LFM's transparency policy lies somewhere between a complete description of the system state with forecast of the economic and physical information and a sole provision of the market price (Ray and Cashman, 1999).

3. Methodological approach

The methodological approach of this paper investigates the relationship between LFM's transparency and the possibility of forecasting relevant information for the decision making of market participants. Therefore, taking the perspective of different bidders on the LFM as potential flexibility suppliers, forecast models for two different tasks are implemented and evaluated. The forecast tasks (see Section 3.3) are on one hand the classification of the network status for every time step and on the other hand a prediction of individual bidders' acceptance at the LFM for time steps with network problems to be solved. Both tasks can be interpreted as sequential and are thus modeled individually. The forecast models are developed on the same data basis that contains synthetic network data for a two-year time horizon and simulated LFM data for every quarter hour with technical problems (see Section 3.1). The limitation of the input data used in three quality levels approximates three different transparency policies from "high transparency" to "low transparency", with a reference case using all available data (see Section 3.2). The evaluation of all models (see Section 4) is based on state-of-the-art performance measures for forecast models and contains a comparison for both forecast tasks with the different transparency policies. Figure 1 summarizes the methodological approach. The individual aspects are discussed in more detail in the following sections.

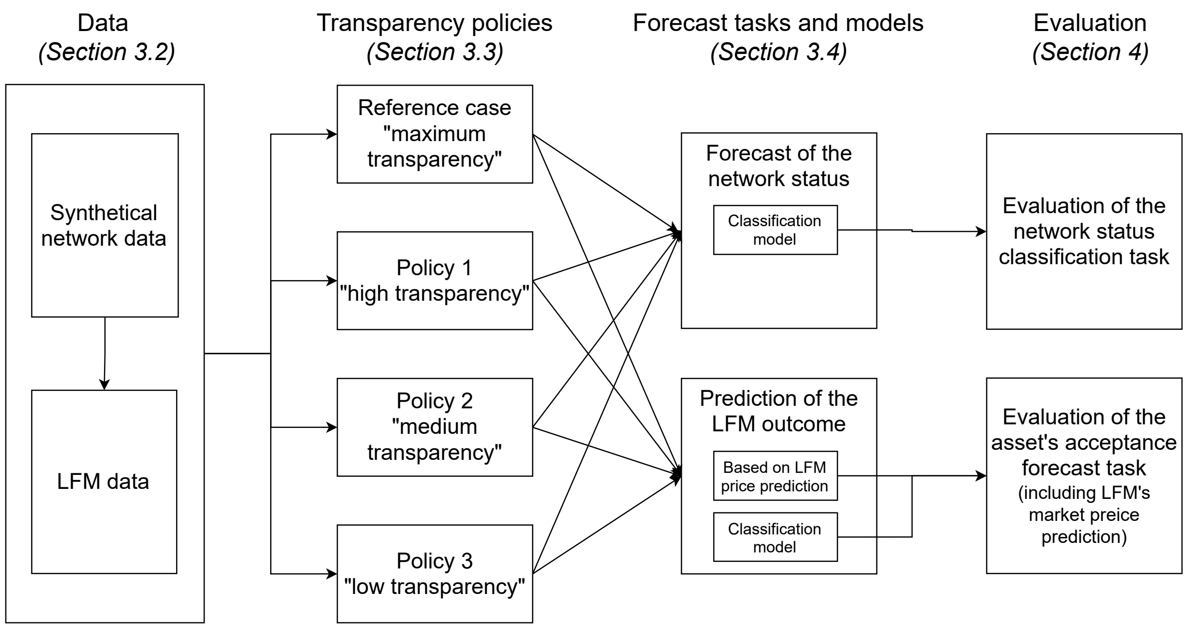

Figure 1: Method overview

3.1. Data

The investigations are based on a synthetic dataset of quarter-hourly production and consumption for two years in a standardized mid-voltage network model. The electrical network is modeled with the Python module "pandapower" (see Thurner et al., 2018), which provides power flow calculations and network analysis tools. It is based on the the CIGRE medium voltage distribution network (see Rudion et al., 2006; CIGRE, 2014) with 14 network nodes. Each of the nodes can contain a residential area, industrial loads, both of them or no laod/production. The connected assets of the network were assumed as follows:

- Ten of the network nodes contain between 100 and 150 households. The behavior of these households is modeled as aggregated load based on standard load profiles (see BDEW, 2017).
- The share of PV is assumed to be 80 percent and the share of HPs to be 75 percent. Each resulting PV plant is modeled as an individual production unit (between two and 40 kW nominal power) and each HP as an individual consumption unit (between 2 and 10 kW nominal power). The behavior of these assets is modeled with synthetic data (see Müller et al., 2019 based on Fünfgeld and Fiebig, 2002).
- • Seven of the nodes contain industrial loads between 700 kW and 1,500 kW maximum consumption, which are modeled as individual loads. The behavior of these loads is modeled based on normalized and randomized real-world data (see Huber et al., 2019).
- In sum, 1972 of the 986 loads and 1014 generation assets are assumed to be able to provide flexibility.

The first part of the data contains the description of the electrical network for all 70,176 quarter hours of the considered two-year period. Based on the time series of loads and productions, a power flow calculation of every quarter hour is calculated. The results especially contain the utilization of lines and transformers. For each of the quarter hours, the network is classified in one of three classes:

- **Network status 1:** There is no technical problem in the network. This situation is the case in 98 percent of the quarter hours (in sum 68,795 data points).
- **Network status 2:** There is a technical problem caused by a high-load situation. This situation is the case in 476 quarter hours.
- **Network status 3:** There is a technical problem caused by a high-production situation. This situation is the case in 941 quarter hours.

As an additional exogenous parameter, an explicit timestamp as well as a temperature time series are connected with the load and demand data.

The second part of the data only considers quarter hours with network status 2 and 3 and contains the description of a simulated LFM:

- As a market input, all bids (flexible power and prices) of the 1972 flexible assets.
- As a market outcome, the flexibility options (accepted flexible assets) used for each problem and a market price are included.

The market simulation is based on a heuristic market algorithm by Heilmann et al. (2021b). The flexibility supply is provided by the assets connected to the network based on the following assumptions:

- PV plants can reduce their current generation.

- HP loads can either reduce their current load or increase their load until their nominal power is reached.

- Industrial loads can either reduce or increase their load by up to 25 % of their current load. An increase in load is only possible if the maximum load has not been exceeded.

Each asset bids its flexibility based on the current operational status with individual marginal cost and does not follow a bidding strategy. The uniform market price is calculated as marginal price of the flexible asset used with the highest cost. Figure 2 illustrates the LFM prices for the quarter hours with technical problems.

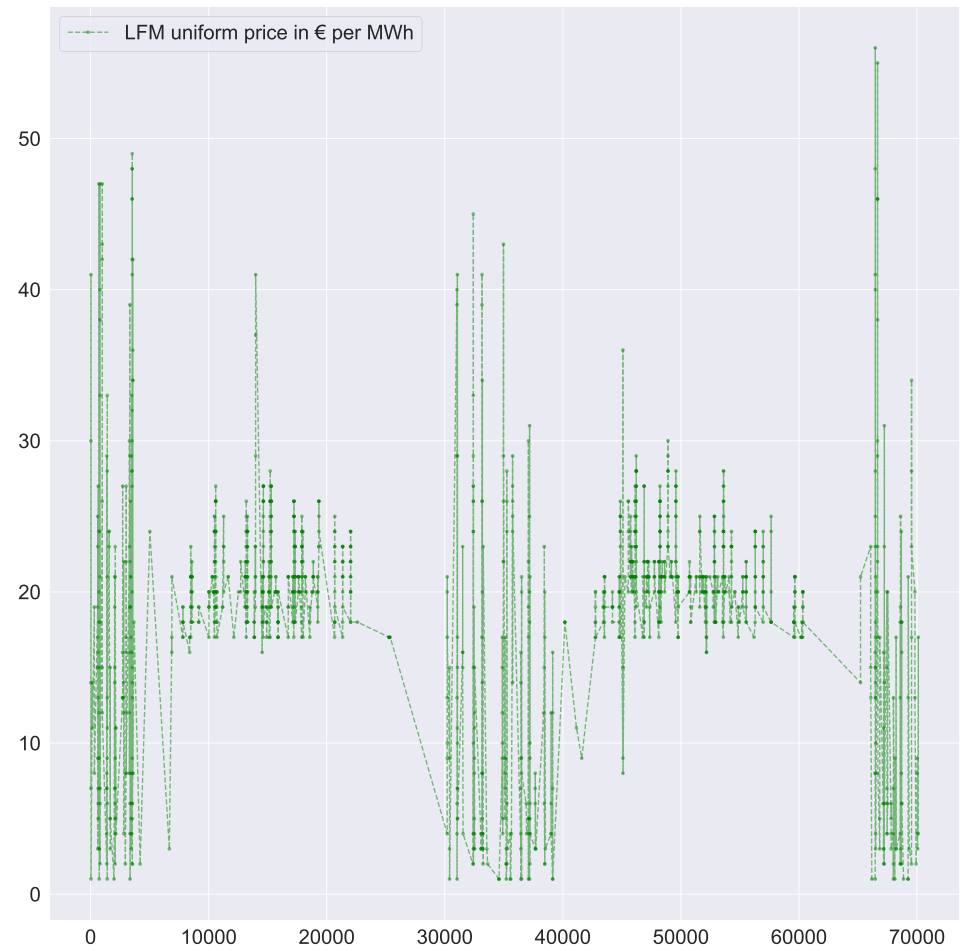

Figure 2: LFM prices in € per MWh (data points only for relevant quarter hours)

The used load and production time series, the results of the power flow calculation, the flexibility bids of all assets and the LFM results are provided as open data (see Heilmann, 2021, file "synthetic network data").

3.2. Transparency policy scenarios

The dataset used provides a very detailed description of the local network status, especially because it contains the disaggregated electrical production and consumption of every connected asset. In combination with information about the network infrastructure, a detailed analysis of every single network status is possible. If technical problems occur, this information can be used in the LFM to determine the market outcome (Heilmann et al., 2021b). This situation of maximal information shall be assumed to be the case for the network operator that can be interpreted as an LFM operator. From an individual bidder's point of view, it is unrealistic to get all this information by own data collection. In particular, information on the network infrastructure shall be assumed to be generally unknown. The remaining data of electricity consumption and production can optionally be provided by the network operator. The provision of network and market data in different qualities is referred to as transparency policy (see Section 2.1). The transparency policy determines the information that can be used for the sequential forecast tasks of the individual bidders.

As discussed in Section 2.1, a transparency policy ranges from revealing full information to giving no additional information except for the market price. In line with this, the following three different transparency policies and one reference case are defined as part of the methodological investigation.

Reference case: maximum information

As a reference case for the different transparency policies, a “maximum transparency” approach is used. This approach contains the full information of the system operator, except the network infrastructure data itself. This includes the electrical production and consumption of every connected asset but also the bids of every flexibility provider in case of a technical problem as well as the accepted flexibility providers with individual price and flexible power. The uniform LFM price is similar to the highest individual price of the accepted providers. As such, a full transparency approach is no real-world option, for example, because of data security issues. It is defined as a reference case but not as a stand-alone transparency policy.

Policy 1: “high transparency” – information on network node level

The first transparency policy provides information on the mid-voltage node level. One mid-voltage node is the connection of a number of households and/or a number of small to medium business locations. Therefore, the provided data of Policy 1 contains the aggregated electricity production and consumption as well as the aggregated flexibility bids (flexible power and weighted flexibility price) for every mid-voltage node. As a market outcome, the uniform LFM price and the aggregated flexible power used are provided.

Policy 2: “medium transparency” – information on network area level

The second transparency policy provides aggregated information on the level of the complete network area. Therefore, the data are aggregated over all individual assets or –in relation with Policy 1– over all network nodes. The kind of information provided is the same as in Policy 1: aggregated electricity production and consumption, aggregated flexibility bids and the uniform LFM in combination with the flexible power used.

Policy 3: "low transparency"

The third transparency policy represents the minimum in the spectrum of transparency policies and only provides the uniform LFM price and the flexible power used. Therefore, no additional information that could be used as explanatory data is revealed.

Summary of the policies

Independent of the revealed information of the different policies, public as well as private information of every single flexibility provider can be used as explanatory data. Public information in the dataset used is the timestamp and the time series of the temperature. Private information is the individual production or consumption of single providers. Table 1 summarizes the transparency policies used. Note that for the different forecast tasks, different data are relevant.

Table 1: Transparency policies overview

Policy	**Production/ consumption and resulting bids**	**LFM outcome**	**Additional information**
Reference	Data of individual assets	Complete historical LFM information	Timestamp and temperature
"high transparency"	Data aggregated on network nodes	Historical uniform LFM prices and flexible power used	Timestamp, temperature and private information
"medium transparency"	Data aggregated on network area		
"low transparency"	No data		

3.3. Forecast tasks and models

The two forecast tasks, (i) the classification of the network status for every time step and (ii) a prediction of individual bidders' acceptance at the LFM are modeled individually, as both tasks can be interpreted as sequential. Below, a brief literature overview for the two tasks is given, followed by the description of the models implemented.

Relevant forecast literature

There is a broad literature basis for the forecast of electricity markets' outcome, especially of electricity price forecasting. Reviews of the topic are, for example, provided by Weron (2014), Lago et al. (2018) and Fraunholz et al. (2021). In general, electricity market prices are influenced by technical, financial and stochastic parameters (Ward et al., 2019). The interdependence between these parameters can be modeled differently using fundamental, gametheoretical, financial mathematical and statistical models, among others (Keles et al., 2016). In the last few years, different approaches of data science (often referred to as machine learning, deep learning or computational learning) have gained importance in the field of energy forecasts. Various studies point out that advanced statistical methods, such as artificial neural networks (ANN), can outperform classical methods of time series analysis (see, e.g., Weron, 2014; Keles et al., 2016; Lago et al., 2018; Kraft et al., 2020).

In contrast to electricity price forecasting, approaches to forecasting the network status are sparsely represented in the literature. He et al. point out that the forecast of a network's status can be an alternative to power flow estimations based on individual forecasts of load and demand. Staudt et al. (2018) provide a study on forecasting the system's re-dispatch demand with different model approaches, including ANN. The demand for re-dispatch can be interpreted as the network status on the transmission network level. In addition, various studies provide approaches for monitoring network status with network equivalent ANNs (see, e.g. Dipp et al., 2019; Menke et al., 2019; Liu et al., 2020). The literature mentioned underlines the fact that for the forecast of the network status, detailed technical network information is not mandatory (if meta information on the network status is provided).

Forecast task 1: Network status classification

In line with the state-of-the-art literature, ANN models for the classification of the network status are applied. The modeling process follows the structured machine learning process by Heilmann et al. (2021a). The target dataset for this forecast task is the classification of all 70,176 quarter hours in one of the three network status "No technical problem", "High load" and "High production". The different network status options are modeled within one multi-class classification approach. The input data are determined with the different transparency policies.

Forecast task 2: LFM's outcome

The second forecast task only concerns the 1417 LFM situations. From an individual flexibility provider's point of view, the relevant aspect of the LFM's outcome is whether one's own bid is accepted or not. In contrast to the first forecast task, the target of the forecast is the individual acceptance of an asset. The first option to reach this target is the prediction of the LFM price in the first step and the comparison of this price with one's own bidding price in the second step. The second option is the modeling of acceptance in a binary (yes or no) classification approach. Such a model provides a direct forecast if an individual asset is accepted, but it does not contain the LFM price (that may is necessary for bidding strategies). Both options are implemented based on the input data, which is determined by the different transparency policies.

3.4. Summary of methodological approach

The two forecast tasks can be interpreted as sequential, dependent tasks: only if a network problem is predicted is the prediction of the LFM outcome relevant. Therefore, both tasks are modeled and evaluated separately. Each forecast model is based on one of 27 manually selected individual asset's[3] point of view, as the data basis is different considering the individual private information of the asset and the individual acceptance at the LFM. The forecast tasks are combined with the information policies introduced in Section 3.2, which determine the input data for every single model. Table 2 provides a summary of the chosen model approaches and the input data used for each forecast task. The variation of the model approaches by the different transparency

[3]The selected assets contain all seven industrial flexibility providers as well as one PV plant and one HP for each of the ten residential network node.

policies and the point of view of the selected assets leads to 82 specified models[4] for the first model task and 108 specified models[5] for the each of the options of the second task.

Table 2: Summary of methodological approach

Forecast task (Model output)	**Model approach**	**Model input** (depending on transparency policy)	**Dataset**[6]	**Model variations**
Forecast task 1: Network status	ANN for multi-class classification of network status	Accessible production/ consumption; public information (time, temperature)	70,176 data points	Point of view of 27 selected assets
Forecast task 2a: assets' acceptance based on LFM price	ANN for price prediction as basis for acceptance evaluation	Accessible production/ consumption and flexibility bids; public information (time, temperature)	1,417 data points	
Forecast task 2b: assets' acceptance	ANN for binary classification of acceptance			

All models are implemented with the Python module "scikit-learn" (Pedregosa et al., 2011). The modeling process follows a standardized approach presented by Heilmann et al. (2021a). An overview on the grid search for the different forecast tasks can be found in the appendix. The detailed Python code of the methodological approach is provided as open data (see Heilmann, 2021, file "Forecast_models"). In this connection, also all input data (as output of the synthetic network model) and results are provided. This contains especially all individual model results with all grid search results, the forecasts of the selected models and a summary file for every forecast task.

4. Results

4.1. Performance measure

As the two forecast tasks contain classification problems, the accuracy of the models can be measured with common classification performance metrics. The straightforward approach is the evaluation of the share of correct predictions as:

$$Accuracy = \frac{\sum True\ predictions}{\sum\ Predictions} \tag{1}$$

However, this measure can lead to a misinterpretation of the model performance, as it does not considers the imbalance between the different classes of the model. This so-called "skewed classes" problem can be observed especially for Forecast task 1, where only 1,417 of the 70,176 data points

[4]One reference model plus 27 individual models for each of the three transparency policies
[5]27 individual models for the reference case and each of the three transparency policies

are not in the class of "no technical problem". To overcome the skewed class problem, the following two metrics can be used (see Rebala et al., 2019):

$$Precision_i = \frac{\sum True\ positive_i}{\sum Predicted\ positive_i} \tag{2}$$

and

$$Recall_i = \frac{\sum True\ positive_i}{\sum Actual\ positive_i} \tag{3}$$

with $\sum True\ positive_i$ as the number of correct predictions of class i; $\sum Predicted\ positive_i$ as the sum of all (true and false) predictions of class i and $\sum Actual\ positive_i$ as the correct number of the class i in the target dataset. To use a single evaluation metric, the F-score combines precision and recall (Rebala et al., 2019):

$$F\text{-}Score_i = \frac{2 * Precision_i * Recall_i}{Precision_i + Recall_i} \tag{4}$$

The value of the the three metrics can be between zero and one. The value of the three metrics can be between zero and one. If there are no true positive predictions, the measure of precision and recalls and in consequence of the F-score is zero. An F-score with the value one is the best possible forecast, as it combines perfect precision and recall. Note that neither precision nor recall should be interpreted separately (Rebala et al., 2019). Note also that for a multi-class problem, as it is given in Forecast task 1, the three metrics must be applied to every single class and then summarized, such as on average over n classes, as a weighted average could lead to the skewed class problem:

$$Metric_{evaluation} = \frac{\sum_{i=1}^{n} Metric_i}{n} \tag{5}$$

In addition to the classification metrics, the performance of the price prediction in Forecast task 2a is measured with the root mean squared error (RMSE) over N data points.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted\ value_i - True\ value_i)^2}{N}} \tag{6}$$

Below, the results of each forecast task are presented separately.

4.2. Results network status classification

The test set of Forecast task 1 contains 25 percent of the two-year data set, in sum 17,544 data points. The assessment of the network status leads to 17,259 data points classified as network status 1 "no technical problem", 115 classified as network status 2 "high load" and 170 classified as network status 3 "high production". Due to this obvious data imbalance, the accuracy of each of the implemented models is nearly one and is therefore not part of the following evaluation of Forecast task 1.[7] As more informative measures, the average precision , recall and F-score over the three classes (see Equations 2 – 6) for each model was evaluated. Figure 3 illustrates the metrics for each of the implemented models. For the reference case, only one model based on the "maximum

[7]The accuracy would be 0.984 for a constant classification of the status "No technical problem".

information" data input represents all 27 considered assets. Therefore, the evaluation is the same for all individual assets. In contrast, for each of the three transparency policies individual models for the 27 considered assets were implemented and evaluated. Table 3 summarizes accuracy and F-score on average for every policy.

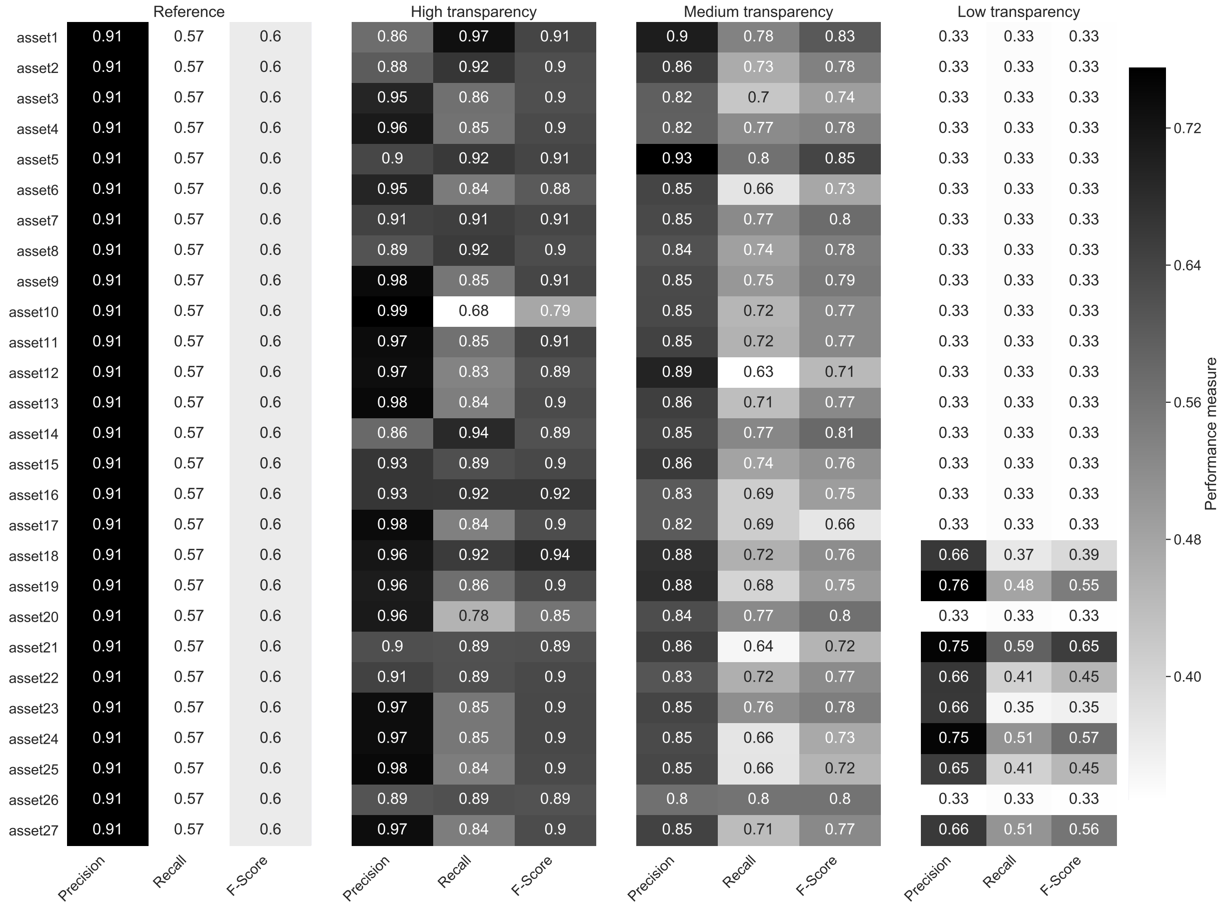

Figure 3: Forecast task 1 - evaluation of precision, recall and F-score of all implemented models

Table 3: Average performance measure of Forecast task 1 for each policy

Measure	**Reference**	**"high transparency"**	**"medium transparency"**	**"low transparency"**
Accuracy	0.988	0.995	0.991	0.985
F-score	0.601	0.896	0.766	0.380

The results, summarized in Table 3 and Figure 3, contain two contrary aspects. The first is the tendency of a decreasing forecast performance with decreasing provision of data in the three transparency policies. In particular, models with low transparency, which only use the private information of the individual assets and the public information, often completely fail to predict the network problem situations.[8]

The second aspect is an underperformance of the reference model that uses the complete data of all individual assets. A deeper analysis of the data shows that network status 2 is particularly underrepresented in the prediction of the reference model. This leads to a relatively low recall and, in consequence the F-score, in contrast to models that use data in line with the high and medium transparency policies.

4.3. Results - assets' acceptance based on LFM price

The test set of Forecast task 2 (a and b) contains 25 percent of all LFM situations, in sum 355 data points. In contrast to Forecast task 1, the classification problem contains only two classes ("no acceptance" = 0, "acceptance" = 1). The distribution of the true values is individual for every considered asset. Seven of the assets (asset 1–7) have no acceptance on the LFM and therefore have only Class 0 as true value. The other assets have between 2 and 240 acceptances that are expressed as true true values in Class 1. In contrast to Forecast task 1, there is no general data imbalance, but still in some cases there is a clear tendency to Class 0.

Forecast task 2a is implemented in two steps. In the first step, the LFM price is predicted. The true LFM prices are between 1 € per MWh and 56 € per MWh, with a mean value of 19 € per MWh. Table 4 summarizes the RMSE of the predictions on average for each policy.

Table 4: Average RMSE of the LFM price prediction of Forecast task 2a for each policy

Measure	**Reference**	**"high transparency"**	**"medium transparency"**	**"low transparency"**
RMSE	7.344	4.662	5.993	7.330

The second step contains a comparison of the predicted LFM price and the individual marginal cost of each asset. If the marginal cost is below the predicted LFM, the acceptance of the asset (Class 1) is expected. The resulting classification for each data point can be evaluated with the measures of Equations 1 – 6. Figure 4 illustrates the performance measure for each of the implemented models of Forecast task 2a. For the first seven assets, a perfect forecast of the acceptance that contains a continuous classification of Class 0 is given. The performance of the other models is in a range between near zero forecast accuracy and F-score (asset 18) and moderate-to-good performance with F-scores between 0.5 and 0.8. Table 5 summarizes the accuracy and F-score on average for every policy.

The accuracy of the different models is on average similar for the different policies on a medium level around 0.75. The two contrary aspects of Forecast task 1, a decreasing performance with decreasing input data and an underperformance of the reference model, are confirmed for the first forecast step (see Table 4) and also for the F-score of the classification in the second step.

4.4. Results - assets' acceptance classification

Forecast task 2b is based on the same dataset as Forecast task 2a, but contains a one-step classification approach. The evaluation of the classification results is equal to the evaluation of the

[8] In the extreme case of only predicting "no technical problem", this leads to a precision and recall and in consequence F-score of zero the network status "high load" and "high production".

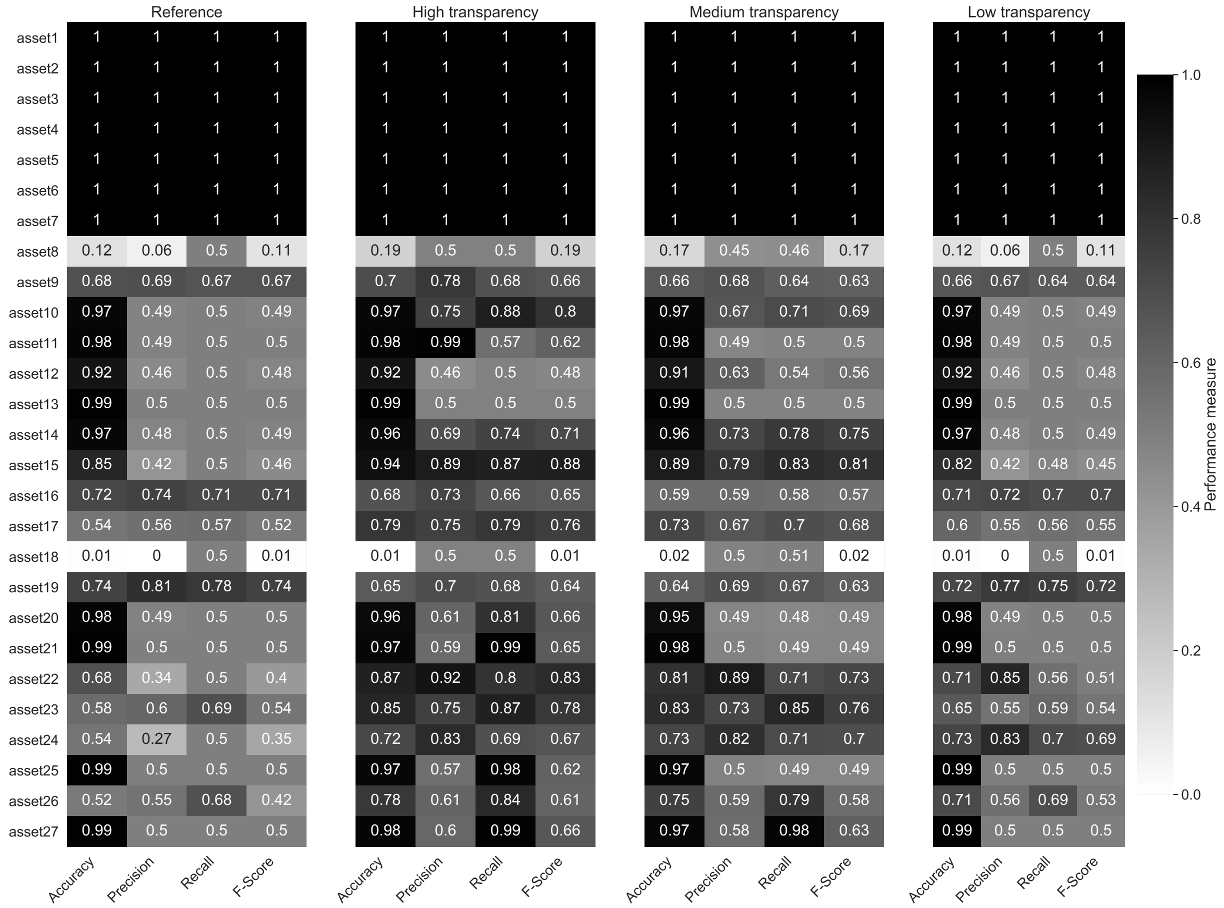

Figure 4: Forecast task 2a - evaluation of accuracy, precision, recall and F-score of all implemented models

Table 5: Average performance measure of Forecast task 2a for each policy

Measure	**Reference**	**“high transparency”**	**“medium transparency”**	**“low transparency”**
Accuracy	0.806	0.847	0.833	0.823
F-score	0.606	0.717	0.681	0.625

second step of Forecast task 2a. Therefore both evaluations can be compared directly. Figure 5 illustrates the performance measure for each of the implemented models of Forecast task 2b. In line with the results of Forecast task 2a, the models of the first seven assets provide a perfect forecast that continuously predicts Class 0 (“no acceptance”). In addition, some other models (asset 22 and asset 20 with medium transparency) provide perfect forecasts that contain every classification of Class 1 and 0 as true prediction. The rest of the models performs in a medium-to-good range with accuracy and F-score between 0.5 and 0.9. Table 5 summarizes the accuracy and F-score on average for every policy.

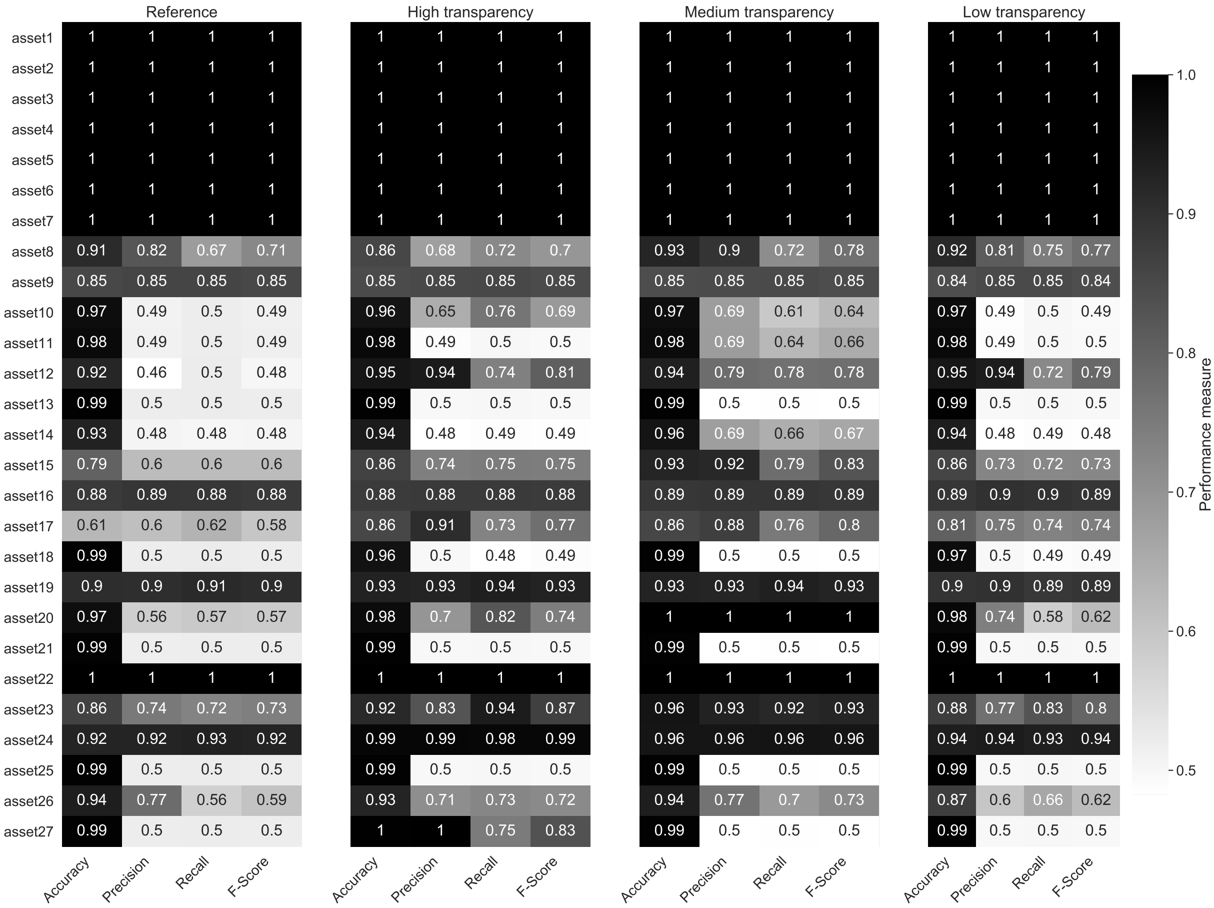

Figure 5: Forecast task 2b - evaluation of accuracy, precision, recall and F-score of all implemented models

Table 6: Average performance measure of Forecast task 2b for each policy

Measure	**Reference**	**“high transparency”**	**“medium transparency”**	**“low transparency”**
Accuracy	0.940	0.956	0.965	0.951
F-score	0.732	0.796	0.812	0.763

The average model performance of the models for Forecast task 2b is considerably higher than for Forecast task 2a. In line with the two previous evaluations, an underperformance of the reference models can be stated. Still, the first aspect, a decreasing model performance with decreasing input data is not generally true for this evaluation. On the contrary, the models with medium transparency on average perform slightly better than models with high transparency.

5. Discussion and outlook

Table 7 compares the average model evaluations, normalized on the reference, for each forecast task and policy. The results underline that the definition of different input data can lead to clear differences in the performance of the forecast models implemented. In particular, the models with low transparency perform considerably lower compared with the models with high-to-medium transparency. The models with high transparency perform best for Forecast tasks 1 and 2a. For Forecast task 2b, the models with high and medium transparency perform similar, showing a small advantage models with medium transparency. The reference models underperform the models of high and medium transparency for every forecast task.

Table 7: Comparison of average model evaluation (normalized on reference score)

Measure	**Reference**	**"high transparency"**	**"medium transparency"**	**"low transparency"**
Forecast task 1: accuracy	1	1.007	1.003	0.997
Forecast task 1: F1-score	1	1.491	1.275	0.632
Forecast task 2a: accuracy	1	1.075	1.050	1.031
Forecast task 2a: F1-score	1	1.320	1.188	1.053
Forecast task 2b: accuracy	1	1.024	1.037	1.016
Forecast task 2b: F1-score	1	1.133	1.167	1.064

Interpreting the numerical results some overall findings can be indicated:

- In general, both forecast tasks are solvable. The majority of the forecast models perform on a medium-to-high level.
- The amount of provided data principally tends to improve the predictability of the network status as well as the LFM outcome.
- The relatively low performance of the reference models could be improved by the application of more advanced model approaches or an additional pre-processing of the input data. As the reference models use all available data, they are in principle able to perform at least as well as the best model with reduced data (by pre-processing the data in the same manner as the transparency policy). This underlines the statement, that the best fitting transparency policy does not necessarily contain all possible information (see Section 2.3).
- The low transparency policy leads to relatively low performance on the Forecast task 1. Few models completely fail to predict problematic network situations. It can be stated that this low transparency approach significantly tends to decrease the predictability of the network status. Nevertheless it is possible that with a nadaption of the model approach or the usage of additional (public or semi-public) data, the performance could be improved.

- The performance in forecasting the individual acceptance strongly depends on the individual asset.

The interpretation must consider some smaller limitations. First, the investigations are based on data of an exemplary (synthetic) network with an exemplary situation of installed load and production assets. Individual network structures as well as the presence of other technologies (e.g., electric vehicles) can strongly influence the data basis and therefore the predictability in general. Second, the input data are only dependent on the chosen transparency policy and assumed to be available as perfect forecasts. Additional public or semi-public information is thinkable to improve the individual forecast performance. On the other hand, inaccuracies of the input data could downgrade the forecast performance.

Concluding the presented results, it can be stated that predictions on the network status as well as the LFM outcome are mostly feasible. In the applied models, only the low transparency policy leads to consistently low forecast performance of the network status' classification. Considering today's real word examples, a clear tendency toward a high-transparency approach can be observed (see Sections 2.2 and 2.3). Available information contains, for example, aggregated information on load and production, especially for renewable energy plants (ENTSO-E, 2014; 50Hertz Transmission GmbH, 2021). A disaggregation of this data would lead to a data quality comparable to the medium transparency policy of the investigations. In addition to the aspect of data availability, an optimization of the forecast models themself must also be considered. The modeling process followed a standardized approach that identifies a best performing model within a pre-defined search grid (see Heilmann et al., 2021a). Still, it is possible (and probable) that a variation of the modeling approach itself or an additional pre-processing of the data could lead to individually better performing models.

As a final remark, possible further developments of the presented investigations shall be discussed. First, the LFM price of the synthetic data used is positive in every market situation. First, the LFM price of the used synthetic data is positive in every market situation. This simplification of the market model (see Heilmann et al., 2021b) is in line with the understanding of flexibility as a service for the network operator. Nevertheless, from an economic point of view, negative prices are thinkable and would influence the decision making of strategic behavior. The methodological approach presented is in principle also applicable to negative prices. Second, no strategic behavior is modeled. All flexibility suppliers are assumed to bid their true marginal cost. This assumption can be stated as valid for uniform pricing markets under perfect competition (see, e.g., Haghighat et al., 2008). Still, individual bidding decisions could influence future network situations and, in consequence, the LFM outcome. A general disadvantage of data-driven forecast models is that changing the behavior of bidders must be modeled with new data and should therefore decrease the short-term model performance (Kraft et al., 2020).

6. Conclusions and policy implications

The present paper contributes to the current debate on local flexibility markets by addressing the topic of market transparency. First, an overview of the theoretical background of electricity markets' transparency was given and discussed in connection with practical examples of the EU and Germany. The theoretical spectrum of transparency policies expands from a full transparency approach that discloses all possible fundamental and transactional information on the energy system to a price-only approach. Particularly in the European energy system, a clear tendency toward a high-transparency approach can be observed. Nevertheless, the availability of information is mostly restricted to highly aggregated data, such as on the country level. Based on this theoretical background, the relationship between LFM's transparency and the possibility of forecasting relevant information for the decision making of market participants is investigated. Therefore, the methodological part of the paper is aimed at the question of how a transparency policy can influence the predictability of the network status and an LFM's outcome. Based on synthetic network and LFM data, ANN forecast models from the point of view of individual bidders are implemented. The data input of these models is varied by three transparency policies and one reference case with full data availability. The models are compared based on common performance measures. The results generally confirm that a decreasing provision of fundamental information leads to a decreasing predictability of network status and LFM outcome. Contrary to this finding, the reference case of full transparency leads to an unexpected low model performance on average. Therefore, it can be expected that the performance of the implemented reference models could be improved by pre-processing the given input data, using new public or semi-public input data or varying the modeling approach.

Although in some cases, particularly the classification of the network status based on a low transparency policy, models fail to predict the desired classes, it can generally be stated that the forecast models for network congestion and LFM outcome are feasible. Nevertheless, the amount and quality of available information influences the performance of these forecasts. It can be expected that some market participants are better able to collect information than others. Therefore, an appropriate transparency policy should be designed as one major step when implementing LFMs, to provide a level playing field. For this, the following policy implication can be formulated:

- In connection with LFMs, the high-transparency approach of the European electricity system should be pursued. This includes the provision of semi-disaggregated forecasts of electricity production and consumption, including on the level of mid-voltage network areas. This information enables market participants to make rational bidding decisions on a level playing field and to minimize the cost of information procurement, particularly for small participants.

- A full transparency approach is, apart from individual data security issues, not desirable considering the transaction cost of administration and processing.

An outstanding issue in this context is the presence of suitable measurement technology and the responsibility for the collection, processing and provision of the data. As a final remark, it should be underlined that the issue of strategic behavior must be kept in mind, apart from transparency issues, before the implementation of an LFM.

Data Availability

Datasets related to this article can be found at http://dx.doi.10.17632/ckhff2yxzy.1, an open-source online data repository hosted at Mendeley Data (Heilmann, 2021).

References

50Hertz Transmission GmbH, 2021. Netztransparenz.de: Informationsplattform der deutschen Übertragungsnetzbetreiber. https://www.netztransparenz.de/Weitere-Veroeffentlichungen/Solarenergie-Prognose.

50Hertz Transmission GmbH, Amprion GmbH, TenneT TSO GmbH, TransnetBW GmbH, 2021. regelleistung.net: Internetplattform zur Vergabe von Regelleistung. https://www.regelleistung.net/ext/tender/.

Anaya, K.L., Pollitt, M.G., 2020. Regulation and policies for local flexibility markets: Current and future developments in seven leading countries: Milestone 3 of the project merlin (modeling the economic reactions linking individual networks).

BDEW, 2017. Standard load profiles for electricity. https://www.bdew.de/energie/standardlastprofile-strom/.

Bobinaite, V., Oleinikova, I., Di Somma, M., Graditi, G., 2018. Market Transparency for the Architecture of Frequency and Voltage Control Under the Web-of-Cells Power Grid Structure, in: Conference proceedings 2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I & CPS Europe), IEEE, Piscataway, NJ. pp. 1–6. doi:10.1109/EEEIC.2018.8494578.

Buchmann, M., 2017. Governance of data and information management in smart distribution grids: Increase efficiency by balancing coordination and competition. Utilities Policy 44, 63–72. doi:10.1016/j.jup.2017.01.003.

Buchmann, M., 2020. How decentralization drives a change of the institutional framework on the distribution grid level in the electricity sector – The case of local congestion markets. Energy Policy 145, 111725. doi:10.1016/j.enpol.2020.111725.

Bundesnetzagentur, 2017a. Festlegung zu den ausschreibungsbedingungen und veröffentlichungspflichten für minutenreserve (bk6-15-159). https://www.bundesnetzagentur.de/DE/Beschlusskammern/1_GZ/BK6-GZ/2015/BK6-15-159/BK6-15-159_download_Beschluss_vom_13_06_2017.pdf?__blob=publicationFile&v=2.

Bundesnetzagentur, 2017b. Festlegung zu den Ausschreibungsbedingungen und Veröffentlichungspflichten für Sekundärregelung (BK6-15-158). https://www.bundesnetzagentur.de/DE/Beschlusskammern/1_GZ/BK6-GZ/2015/BK6-15-158/BK6-15-158_download_Beschluss_vom_13_06_2017.pdf?__blob=publicationFile&v=3.

Bundesnetzagentur, 2021. Bericht zum Zustand und Ausbau der Verteilnetze 2020. https://www.bundesnetzagentur.de/SharedDocs/Downloads/DE/Sachgebiete/Energie/Unternehmen_Institutionen/NetzentwicklungUndSmartGrid/ZustandAusbauVerteilernetze2020.pdf;jsessionid=50C31C4499DC387A2611CB9E4423891B?__blob=publicationFile&v=3.

CIGRE, 2014. Benchmark systems for network integration of renewable and distributed energy resources: Task force C6.04. volume 575 of *[Brochures thématiques]*. CIGRE, [Paris].

Dipp, M., Menke, J.H., Wende von Berg, S., Braun, M., 2019. Training of Artificial Neural Networks Based on Feed-in Time Series of Photovoltaics and Wind Power for Active and Reactive Power Monitoring in Medium-Voltage Grids. INFORMATIK 2019: 50 Jahre Gesellschaft für Informatik – Informatik für Gesellschaft , 545–557doi:10.18420/inf2019_71.

ENTSO-E, 2014. Detailed Data Descriptions: Version 1, Release 4. https://eepublicdownloads.entsoe.eu/clean-documents/mc-documents/transparency-platform/MOP/DetailedDescriptionDocument.pdf.

ENTSO-E, 2021. entso-e transparency platform. https://transparency.entsoe.eu/.

European Commission, 2011. REGULATION (EU) No 1227/2011 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL: of 25 October 2011 on wholesale energy market integrity and transparency. http://data.europa.eu/eli/reg/2011/1227/oj.

European Commission, 2013. COMMISSION REGULATION (EU) No 543/2013: on submission and publication of data in electricity markets and amending Annex I to Regulation (EC) No 714/2009 of the European Parliament and of the Council. http://data.europa.eu/eli/reg/2013/543/oj.

European Commission, 2019. Regulation (EU) 2019/943: of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity. http://data.europa.eu/eli/reg/2019/943/oj.

European Energy Exchange AG, 2021a. EEX Group Data Source. https://www.eex.com/en/market-data/eex-group-datasource.

European Energy Exchange AG, 2021b. EEX Transparency Platform. https://www.eex-transparency.com/power.

von der Fehr, N.H.M., 2013. Transparency in electricity markets. Memorandum No. 13/2013 .

Feltkamp, R., Musialski, C., 2013. Integrity and Transparency in the EU Wholesale Electricity Market: New Rules for a Better Functioning Market? https://www.ogel.org/article.asp?key=3397.

Fraunholz, C., Kraft, E., Keles, D., Fichtner, W., 2021. Advanced price forecasting in agent-based electricity market simulation. Applied Energy 290, 116688. doi:10.1016/j.apenergy.2021.116688.

Fünfgeld, C., Fiebig, C., 2002. Bestimmung von Lastprofilen für unterbrechbare Verbrauchseinrichtungen.

Haghighat, H., Seifi, H., Rahimi Kian, A., 2008. The role of market pricing mechanism under imperfect competition. Decision Support Systems 45, 267–277. doi:10.1016/j.dss.2007.12.011. i.T. and Value Creation.

He, Y., Henze, J., Sick, B., . Forecasting Power Grid States for Regional Energy Markets with Deep Neural Networks, in: 2020 International Joint Conference on Neural Networks (IJCNN), IEEE. pp. 1–8.

Heilmann, E., 2021. "The impact of transparency policies on local flexibility markets in electricaldistribution networks - A case study with artificial neural network forecasts", Mendeley Data, v1. doi:10.17632/ckhff2yxzy.1.

Heilmann, E., Henze, J., Wetzel, H., 2021a. Machine learning in energy forecasts with an application to high frequency electricity consumption data. MAGKS Joint Discussion Paper Series in Economics doi:{https://www.uni-marburg.de/en/fb02/research-groups/economics/macroeconomics/research/magks-joint-discussion-papers-in-economics/papers/2021-papers/35-2021_heilmann.pdf}.

Heilmann, E., Klempp, N., Wetzel, H., 2020. Design of regional flexibility markets for electricity: A product classification framework for and application to German pilot projects. Utilities Policy 67, 101133. doi:10.1016/j.jup.2020.101133.

Heilmann, E., Zeiselmair, A., Estermann, T., 2021b. Matching Supply and Demand of Electricity Network-Supportive Flexibility: A Case Study with Three Comprehensible Matching Algorithms. Smart Energy 4, 100055. doi:10.1016/j.segy.2021.100055.

Hirth, L., Mühlenpfordt, J., Bulkeley, M., 2018. The ENTSO-E Transparency Platform – A review of Europe's most ambitious electricity data platform. Applied Energy 225, 1054–1067. doi:10.1016/j.apenergy.2018.04.048.

Hirth, L., Schlecht, I., 2020. Market-based redispatch in zonal electricity markets: Inc-dec gaming as a consequence of inconsistent power market design. http://hdl.handle.net/10419/194292.

Huber, J., Klempp, N., Becker, J., Weinhardt, C., 2019. Electricity consumption of 28 German companies in 15-min resolution. Karlsruhe. doi:10.5445/IR/1000098027.

Jin, X., Wu, Q., Jia, H., 2020. Local flexibility markets: Literature review on concepts, models and clearing methods. Applied Energy 261, 114387. doi:10.1016/j.apenergy.2019.114387.

Keles, D., Scelle, J., Paraschiv, F., Fichtner, W., 2016. Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. Applied Energy 162, 218–230. doi:10.1016/j.apenergy.2015.09.087.

Kraft, E., Keles, D., Fichtner, W., 2020. Modeling of frequency containment reserve prices with econometrics and artificial intelligence. Journal of Forecasting 39, 1179–1197. doi:10.1002/for.2693.

Kumar, A., Srivastava, S.C., Singh, S.N., 2005. Congestion management in competitive power market: A bibliographical survey. Electric Power Systems Research 76, 153–164. doi:10.1016/j.epsr.2005.05.001.

Lago, J., de Ridder, F., de Schutter, B., 2018. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. Applied Energy 221, 386–405. doi:10.1016/j.apenergy.2018.02.069.

Liu, Z., Bornhorst, N., Wende-von Berg, S., Braun, M., 2020. A Grid Equivalent Based on Artificial Neural Networks in Power Systems with High Penetration of Distributed Generation with Reactive Power Control. NEIS 2020; Conference on Sustainable Energy Supply and Energy Storage Systems , 1–7.

McAfee, R.P., McMillan, J., 1987. Auctions an Bidding. Journal of Economic Literature , 699–738.

Menke, J.H., Bornhorst, N., Braun, M., 2019. Distribution system monitoring for smart power grids with distributed generation using artificial neural networks. International Journal of Electrical Power & Energy Systems 113, 472–480. doi:10.1016/j.ijepes.2019.05.057.

Müller, M., Zeiselmair, A., Pedraza Gómez, J., 2019. Tapping flexibility potential of decentralized controllable loads for smart markets through aggregation.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research 12, 2825–2830.

Radecke, J., Hefele, J., Hirth, L., 2019. Markets for local flexibility in distribution networks. http://hdl.handle.net/10419/204559.

Ramos, A., de Jonghe, C., Gómez, V., Belmans, R., 2016. Realizing the smart grid's potential: Defining local markets for flexibility. Utilities Policy 40, 26–35. doi:10.1016/j.jup.2016.03.006.

Ray, D., Cashman, E., 1999. Operational risks, bidding strategies and information policies in restructured power markets. Decision Support Systems 24, 175–182. doi:10.1016/S0167-9236(98)00081-5.

Rebala, G., Ravi, A., Churiwala, S., 2019. An Introduction to Machine Learning. Springer International Publishing, Cham. doi:10.1007/978-3-030-15729-6.

Rosen, C., Madlener, R., 2013. An auction design for local reserve energy markets. Decision Support Systems 56, 168–179. doi:10.1016/j.dss.2013.05.022.

Rudion, K., Orths, A., Styczynski, Z.A., Strunz, K., 2006. Design of benchmark of medium voltage distribution network for investigation of DG integration, in: 2006 IEEE Power Engineering Society general meeting, 18 - 22 June 2006, Montreal, Canada, IEEE Operations Center, Piscataway, NJ. p. 6 pp. doi:10.1109/PES.2006.1709447.

Schittekatte, T., Meeus, L., 2020. Flexibility markets: Q&A with project pioneers. Utilities Policy 63. doi:10.1016/j.jup.2020.101017.

Staudt, P., Träris, Y., Rausch, B., Weinhardt, C., 2018. Predicting Redispatch in the German Electricity Market using Information Systems based on Machine Learning. ICIS 2018 Proceedings .

Thurner, L., Scheidler, A., Schafer, F., Menke, J.H., Dollichon, J., Meier, F., Meinecke, S., Braun, M., 2018. Pandapower—An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems. IEEE Transactions on Power Systems 33, 6510–6521. doi:10.1109/TPWRS.2018.2829021.

Villar, J., Bessa, R., Matos, M., 2018. Flexibility products and markets: Literature review 154, 329–340. doi:10.1016/j.epsr.2017.09.005.

Ward, K.R., Green, R., Staffell, I., 2019. Getting prices right in structural electricity market models. Energy Policy 129, 1190–1206. doi:10.1016/j.enpol.2019.01.077.

Weron, R., 2014. Electricity price forecasting: A review of the state-of-the-art with a look into the future. International Journal of Forecasting 30, 1030–1081. doi:10.1016/j.ijforecast.2014.08.008.

Appendix – Additional information on the methodological approach and results

The following appendix contains additional information on the model selection of the implemented forecast models, discussed in Section 3.3 and some additional results that are not part of the presentation in Section 4:

- Table A.1 summarizes the grid search for the different forecast tasks.
- Tables A.2 and A.3 contain the average performance measure of Forecast task 2a and 2b for each policy. In contrast to the tables 5 and 6, the average doues not take into account the perfect forecasts of assets 1 to 7.
- Figures A.1 - A.4, illustrate the comparison between the price predictions of the different policies and the true values of the LFM price in the test set.

Table A.1: ANN grid search parameters for different forecast tasks.

Parameter	Forecast task 1	Forecast task 2a (prediction)	Forecast task 2b (classification)
Network structure	[(10,10,10), (10,25,10), (10,50,10), (25,50,25), (25,25,25), (50,50,50), (50,100,50), (100,100,100)]	[(5,5,5), (10,10,10), (10,25,10), (10,50,10), (25,50,25), (25,25,25), (50,50,50), (100,100,100), (250, 500, 250), (500,500,500)]	[(10,10,10), (10,25,10), (10,50,10), (25,50,25), (25,25,25), (50,50,50), (50,100,50), (100,100,100)]
Regularization parameter	[0.1, 0.01, 0.001]	[0.1, 0.01, 0.001]	[0.1, 0.01, 0.001]
Activation function	[tanh, logistic]	[relu, logistic]	[tanh, logistic]
Initial learning rate	[0.01, 0.001]	[0.01, 0.001]	[, 0.01, 0.001]

Table A.2: Average performance measure of Forecast task 2a for each policy – without assets 1 to 7

Measure	**Reference**	**'high transparency'**	**'medium transparency'**	**'low transparency'**
Accuracy	0.738	0.793	0.775	0.761
F-score	0.469	0.619	0.557	0.494

Table A.3: Average performance measure of Forecast task 2b for each policy – without assets 1 to 7

Measure	**Reference**	**'high transparency'**	**'medium transparency'**	**'low transparency'**
Accuracy	0.919	0.941	0.953	0.934
F-score	0.639	0.724	0.746	0.680

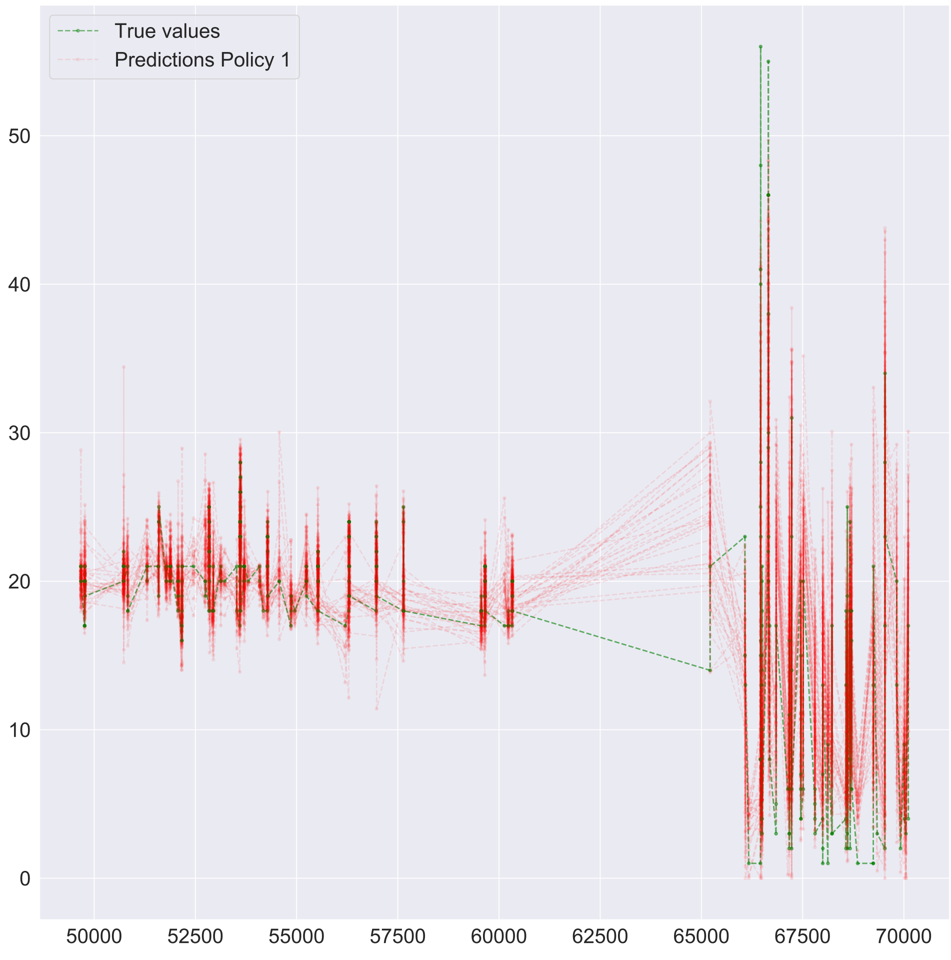

Figure A.1: Price prediction of high transparency policy vs. true value of LFM price

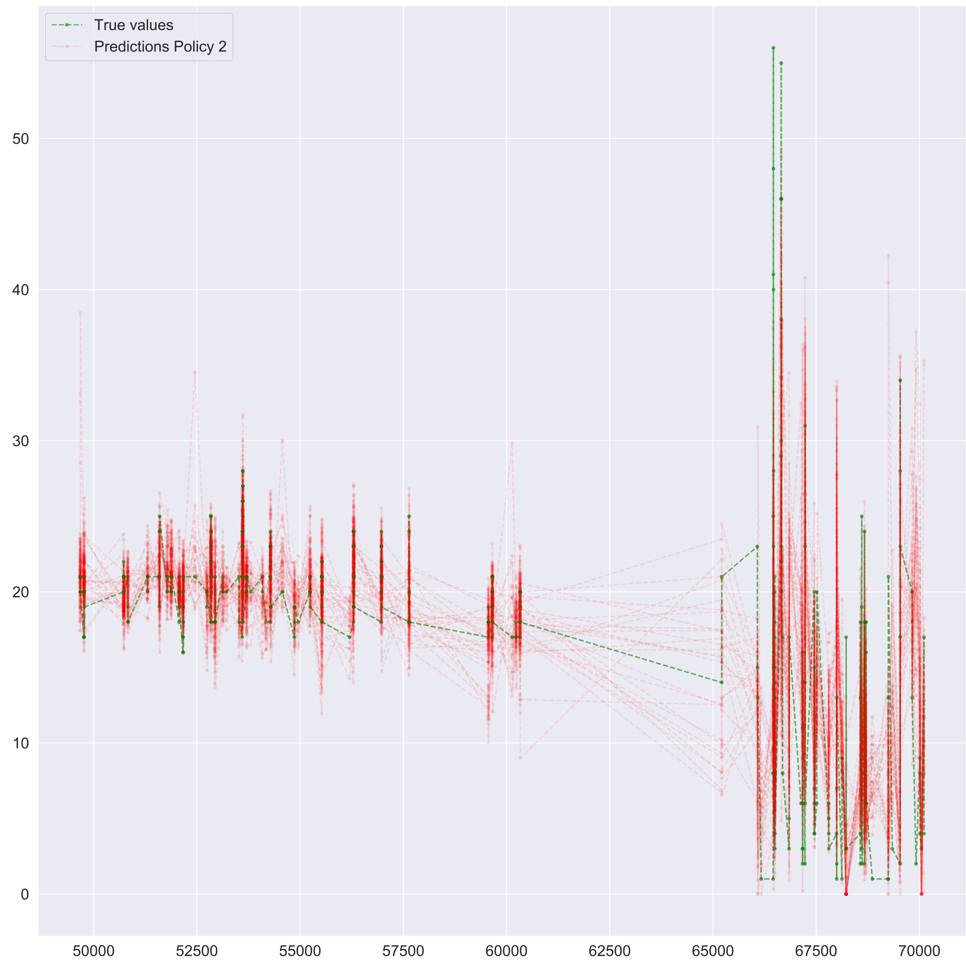

Figure A.2: Price prediction of medium transparency policy vs. true value of LFM price

Figure A.3: Price prediction of low transparency policy vs. true value of LFM price

Figure A.4: Price prediction of reference case vs. true value of LFM price