Adaptive change in national markets of electricity as benchmark for microgrids: the case study of Poland and the UK

Krzysztof Wasniewski   
Department of Management  
The Andrzej Frycz – Modrzewski Krakow UniversityKrakow, Poland  
[kwasniewski@afm.edu.pl](mailto:kwasniewski@afm.edu.pl), <https://orcid.org/0000-0003-0076-4804>

*Abstract:*

*This article studies national markets of electricity as benchmark for predicting the behavior of microgrids. The market of electricity is assumed to be a system of collective decision-making, where some phenomena are stressors and trigger adaptive change. Empirical data pertinent to the national markets of electricity in Poland and the UK is studied with a random forest algorithm to determine the likelihood of particular variables to become roots of computationally plausible decision trees. The working hypothesis of this research is that energy markets are stressed (i.e. provoked into adaptive change) by observable changes in prices of electricity, and by the relative prevalence of assets relative to renewable energy sources. Empirical research only partially confirms that hypothesis. The markets studied seem to be stressed into adaptive change by fluctuations in demand and supply of capacity more than by anything else. Collective behavior in the participants of a microgrid is likely to be focused on adjusting the balance between supply and demand, thus, among others, between investment in RES-based generation assets.*

Keywords: Electricity market; microgrids; decision forest;

# Introduction and review of literature

Microgrids are a promising solution for the deployment of renewable energy sources (RES), and yet they are idiosyncratic, as they adapt to their local markets and communities of stakeholders. Available literature tends to model and predict the behaviour of microgrids by pure simulation, where the actual characteristics of the market (load, supply, storage, interconnective flows to and from other markets etc.) are parametrized a priori, and generation from RES is predicted based on geophysical variables, including weather, without clear reference to the actual assets (solar, wind, hydro etc.) present in the market.

Optimally energy-efficient market of electricity differs from a sub-optimally energy-efficient one mostly with respect to the possible losses, which appear when energy is intermittently generated from renewable sources, mostly PV solar, and, to a lesser extent, wind installations. Modern markets of electricity face a paradox: whilst renewable sources are the cleanest, they are the most intermittent, and their output is the most likely to be partially lost in the moments of peak generation. Microgrids do not have the buffer of non-intermittent power plants, and therefore they are even more exposed to losses of energy due to the intermittence of RES. Empirical material used in this research refers precisely to such a situation, mostly in the Polish case, less in the British one. The spectacular take-off in the capacities available in PV solar installations coincides with episodes of temporary disconnection between solar farms and the national grid, even if the former are officially registered suppliers.

Business practitioners do not realistically expect predicting the exact future state of the market, nevertheless they value the understanding of the path to such future uncertain states. Markets of energy are marked by significant technological change, manifest as investment in new types of assets. Microgrids obey to the same rule, as they emerge only because and under the condition of significant local investment in new energy assets. The faster the technological change, the faster the moral depreciation in the corresponding assets, and the more substantial such stay-in-the-game investment becomes. Economic success attracts new investment in a snowball effect, whilst economic failure discourages further development of productive assets. Local microgrids which yield good financial results in their operations are likely to swell, whilst those marked by poor performance will probably shrink (i.e. lose prosumers).

Price incentives, such as the feed-in-tariff, are frequently used in policies pertinent to the deployment of RES. The first-sight logic is simple: the higher the price, the higher the gross margin over the Levelized Cost of Energy (LCOE), and the greater the freedom of financial movement in the operators of RES-based assets. Still, a different logic can be applied. Investment in energy assets is generally long-term, with the expected technological lifecycle, implied in the calculation of LCOE, ranging from 10 to 20 years. No one can predict prices in that temporal horizon, and investment is made in order to be in the game, in the first place.

Microgrids are small grids, quite simply, and therefore they are small markets of electricity. In their fundamental mechanics, until the proof of the contrary, they should work similarly to the big, national markets. This article presents a chain of reasoning where data regarding big, national markets of electricity is used to emulate the way a market of electricity works, and the results are transposed to model a microgrid with prevalent sourcing from RES. The ‘way a market works’ is studied here with a decision forest algorithm, where a set of variables forms an ensemble of classifiers and allow constructing a random forest of sequences, where the choice of an option within one classifier modifies the likelihood of a specific choice in other classifiers. Therefore, change in observable variables pertinent to the market of electricity is a quantitative estimation of decisions being made by market participants. ‘The way a market works’ is understood as a process of collective decision making. The interest of such an approach is both practical and theoretical.

The working hypothesis of the here-presented research is that energy markets are stressed (i.e. provoked into adaptive change) by observable changes in prices of electricity, and by the relative prevalence of assets relative to renewable energy sources. Many national energy markets are connected to other national energy markets: energy is a commodity in trade. Local microgrids can be, although not always are, in the similar situation. Besides balancing internally their supply of energy and demand for it, they can be connected to broader networks, possibly to the national one. The working hypothesis, such as stated above, reflects the interplay of two stressors: technological change embodied in new assets, on the one hand, and interconnection with other power grids, on the other hand.

National markets of electricity are surprisingly difficult to study quantitatively in a rigorous manner. They are abundantly regulated, and apparently predictable, and yet it is hard to conduct an econometrically robust analysis of actual data [15]. Algorithmic combination of data coming from different sources is a practical problem. Disparities in the procedures of reporting, as well as in the underlying phenomenology of the variables reported is a significant source of errors in scientific simulations [7]. Robust and reproductible prediction requires comparable empirical material, with periods of time sufficiently long to draw robust conclusions, especially with the increasing popularity of machine learning and deep learning algorithms [10]. There are known, complex models of electricity markets, such as PLEXOS. Yet, these models are constrained by their linearity [2]. On the other hand, in the modelling of microgrids, the more complex the modelling becomes, the more problematic it is to use real empirical data [5][13]. Empirical material of the type used in the here-presented research (i.e. load, capacity, generation, interconnexions) usually serves to calculate fixed parameters, and is not really a variable in the modelling of microgrids [1] [11] [3] [17]. Therefore, the modelling of microgrids seems to be largely theoretical, with parametric assumptions linking the corresponding models to real-life markets of electricity.

Non-linearity and autoregression seem to be the most promising direction to follow in the modelling of electricity markets, especially to capture long-term seasonal swings [12]. Electricity markets rigorously balance their quantities, and their pricing is largely based on local equilibriums. Classical approach is tempting here, where prices contain all information necessary for optimal decision-making by individual economic units [9]. Still, taking the memory of the market into account can give robust predictions, and the memory can be apprehended via autoregression or LSTM-type algorithms [16]. At the methodological level, spikes and outliers are less-than-it-appears informative about the future state of the market. Multi-step smoothing of data and the averaging of predictions generated by different models brings good predictability [4].

From the theoretical perspective, a quantitatively robust, decision-forest-based model of the market is something comparable to Marshallian equilibrium: it gives solid theoretical basis to simulations.

# Material and method

## The conceptual framework and the method

A market can be studied as a system of collective decision making, observable through a vector *V= {h1, h2, …, hk}*, where phenomena denoted by individual variables can be both stressors pushing to adaptation, and component adaptive changes. Each variable *hi* in *V* can be characterized with the probability *PT(hi)* that observable change in that characteristic triggers a chain of adaptive changes in other characteristics.

There is a function *fT(V)*, which produces a vector *PT(hi)* of probabilities out of a given set *V= {h1, h2, …, hk}*,, i.e. *fT(V) = {PT(h1), PT(h2), …, PT(hk)}*. The distribution of *PT(hi)* across *V* informs whether some observables *hi* are obvious stressors, i.e. their specific *PT(hi)* is significantly higher than that of other variables.

Random forest classifications allow defining plausible chains of adaptive changes empirically, with weak assumptions. They define the capacity of variables *{h1, h2, …, hk}* to form an ensemble of classifiers and allow constructing a random forest of sequences, where the choice of an option within one classifier modifies the likelihood of a specific choice in other classifiers. When a random forest algorithm produces a constant number *D* of decision trees, each variable *hi* gets a score *d(hi)* corresponding to the number of trees where *hi* is the root. The proportion *d(hi)/D* is a plausible approximation of the probability *PT(hi)*, and therefore such a random forest algorithm can be an empirical approximation of *fT(V)*.

Empirical material used in the present research and described in further sections allows studying three temporal windows: time of the day (1 hour in Poland, ½ hour in the UK), day, and month. Two perspectives on decision-making emerge: the short and immediate one (time of the day and day), as opposed to a longer one (months). Changes observable over hours are balancing ones and are essentially decisions of the grid operator. On the other hand, changes observable between months, especially the non-neighbouring ones, involve strategizing in all the market participants. Stressors trigger internal adjustments in those entities.

Within the short perspective, entailing hours and days, a subtle distinction is to notice. Changes from day to day are de facto interactions between the intraday market of electricity and the day-ahead one these two markets, whilst changes from hour to hour are strictly intraday. Therefore, time-of-the-day cycle of change is mostly in focus here as regards the short, immediate perspective on the market. When months are selected as labels of classification with a random-forest algorithm, other variables are possible classifiers along the ‘month-to-month’ vector of change.

The algorithm used in this research was based on ‘random\_forest\_model\_1’ in the TensorFlow Decision Forests library, thus essentially coded in Python. The model is a classifier, which builds and tests 300 decision trees built by the procedure of random forest. The classification built with that algorithm typically yields two general metrics and 4 feature-specific ones. Accuracy and logloss inform about the robustness of the model in general. The split of empirical material into training and testing is always 70% for training and 30% for testing.

## Empirical material

National markets of electricity are studied in two countries: Poland, and the UK. That entails some differences in the logical structure of data reported by national grid operators. In the Polish case, data on the average transactional price of electricity is accessible and possible to merge with other variables informative about the market, whilst it is absent from the British data. On the other hand, British datasets allow studying both capacity standing in and generation from solar assets and wind assets, whilst Polish datasets allow analysing just the generation in MWh (data on capacities is too contaminated with string-type entries to be computable). Polish datasets allow studying both the intraday market and the day-ahead one in real time and according to the same logical structure of variables. In the British case, data from the day-ahead market is fragmented, essentially unavailable in annual bulk bases for 2022 and 2023.

Datasets pertinent to Poland have been compiled by the author on the basis of downloads from the website of Polskie Sieci Elektroenergetyczne (PSE), the Polish operator of the national power grid. Four annual datasets have been compiled, respectively for 2022 and 2023, as well as in distinction into the day-ahead market and the intraday one. Data informative about the UK market comes from the website o National Grid ESO, section ‘Historic Demand Data’, and consists in datasets ‘DemandData\_2022’ and ‘DemandData\_2021’. According to the author’s best knowledge, these datasets represent the intraday market.

Discrepancy in the timeframe of data - {2022; 2023} for Poland and {2021; 2022} in the UK case – is caused partly by limitations in availability, and partly by methodological reasons. In the UK, data pertinent to 2023 is simply not available at the moment of writing this article. In Poland, PSE reshaped the format of reporting in 2021, and 2022 seems to be the first year when the new structure of variables is robust. Besides, 2022 in Poland was a special year. On the one hand, the deployment in RES truly kickstarted, and, on the other hand, 2022 was unusually turbulent as regards the prices of electricity, which reached all-time highs in June 2022.

The Polish annual datasets are structured into 17 variables: Temporal label T, which is either ‘Month’, coded as an integer “YYYYMM” or ‘Hour’ (PL: ‘Godzina’), coded as object; *Load* - National Demand for Capacity/Total load [MW]; *CapT* - Total capacity standing in the system [MW]; *CapG* - Total capacity of the scheduled generating units [MW]; *CapS* - Total capacity of the scheduled storage units [MW]; *GenT* - Total generation from all the scheduled units [MWh]; *GenG* - Total generation from the scheduled generation units [MWh]; *GenS* - Total generation from the scheduled storage units [MWh]; *GenNB* - Total generation from non-balancing generation units [MWh]; *GenWind* - Total generation from wind units [MWh]; *GenSolar*- Total generation from solar units [MWh]; *BSync* - National balance on synchronous exchange [MWh], i.e. exchange with other national systems, synchronized with the Polish system; *BAsync* - National balance on asynchronous exchange [MWh], i.e. exchange with other national systems, non-synchronized with the Polish system; *RCapA* - Reserve of capacity above demand [MW]; *RCapB* - Reserve of capacity below demand [MW]; *LR* - Total capacity from the offers of load reduction [MW]; *P* - Market price of electricity [PLN/MWh].

The UK data is structured slightly differently, into 18 variables: 1) Temporal label T: Day; Month; Settlement period (1/2 hour); *ND* – National demand for capacity [MW]; *TSD* - Transmission System Demand [MW]; *EWD* – England and Wales demand [MW]; *GenWind* – Embedded wind generation [MWh]; *WindCap* – Embedded wind capacity [MW]; *GenSolar* – Embedded solar generation [MWh]; *SolarCap* – Embedded solar capacity [MW]; *NON\_BM\_STOR* - Non-Balancing Short-Term Operating Reserve; *PUMP* - [MW] The demand due to pumping at hydro pump storage units; *IFA\_FLOW* – flow in the IFA 1 interconnector between France and the UK [MWh]; *IFA2\_FLOW* - flow in the IFA 2 interconnector between France and the UK [MWh]; *BRITNED\_FLOW* - flow in the Britned interconnector between the UK and the Netherlands [MWh]; *MOYLE\_FLOW* – flow in the Moyle interconnector between Northern Ireland and Scotland [MWh]; *EAST\_WEST\_FLOW* – flow in the East – West interconnector between the Irish and British electricity markets [MWh]; *NEMO\_FLOW* – flow in the Nemo interconnector between the UK and Belgium [MWh]; *NSL\_FLOW* – flow in the North-Sea-Interconnector between the UK and Norway [MWh]; *ELECLINK\_FLOW* – flow in the ElecLink interconnector between the UK and France [MWh].

Full data used in this research, as well as detailed training logs and model summaries for each decision forest are available on demand with the author of this article.

# calculations and results

Twelve robust models (accuracy > 0,8) have been created, corresponding to different structures of empirical data: UK 2021 time of the day, UK 2022 time of the day, UK 2021 month, UK 2022 month, Poland 2022 intraday time of the day, Poland 2023 intraday time of the day, Poland 2022 intraday month, Poland 2023 intraday month, Poland 2022 day-ahead time of the day, Poland 2023 day ahead time of the day, Poland 2022 day ahead month, Poland 2023 day ahead month.

Fig. 1 to Fig. 5, further below, document the most salient properties of those models as regards the substance of the here-presented research. As those models are decision trees, their relative complexity matters and is measured by the number of nodes (Fig.1).Poland day-ahead-time-of-the-day-type models, as well as Poland intraday-month-type ones are the most complex in terms of the number of nodes. Three models are on the opposite end of the complexity spectrum: UK 2021 month, UK 2022 month, and Poland 2023 day-ahead month.

As regards the relative prevalence of GenRES-type variables as roots in decision trees (Fig. 2), one model clearly sticks out of the ordinary: UK 2022 month, with the probability *PT(GenRES) = 0,51*. Only one other model - Poland 2022 intraday time of the day – displays *PT(GenRES)* in the same order of magnitude (0,10), and all the others show one-digit probabilities. Probability *PT(Price)* (Fig. 3) is observable only in models based on Polish data, and appears only in month-periodized ones - Poland 2022 intraday month, Poland 2023 intraday month, Poland 2022 day ahead month, Poland 2023 day ahead month – and remains fairly predictable across these, between 0,1 and 0,2. Price seems not to be a significant stressor at all in the models based on time-of-the-day data. Variables pertinent to interconnections to other markets seem (Fig. 4) to be significant stressors in month-periodized models, rather than those based on the time of the day. One model – UK 2021 month – clearly sticks out, with *PT(Interconnections) = 0,98*.

The most systematically prevalent stressors in the models studied are variables relative to aggregate quantities in the market: load, capacity, and overall generation (Fig. 5). In 8 models out of 12, *PT(Load, Cap, Gen) > 0,5*, it is just below 0,5 in other two, and only two models are truly idiosyncratic in that respect: UK 2021 month, and UK 2022 month. These two models have their decision trees based either on *GenRES*-type variables, or those relative to interconnections.

![A graph of numbers and a number of nodes

Description automatically generated with medium confidence]()

Fig. 1. Complexity of the models generated, as measured by the number of nodes



Fig. 2. Probability of GenRES-type variables as roots in decision trees



Fig. 3. Probability of price as root in decision trees



Fig. 4. Probability of interconnections-related variables as roots in decision trees



Fig. 5. Probability of load-storage-capacity variables as roots in decision trees

# Discussion and conclusion

This article presents a method of using publicly available data pertinent to national markets of electricity in order to deconstruct patterns applicable to microgrids and their possible behaviour as markets of electricity. National markets of electricity are much more abundantly described than local microgrids, in terms of quantitative data: many possible states of the market are described in a nationally standardized manner. One among the possible ways of studying markets is to assume they are collective decision-making systems, and to predict how decisions made in a given state of the market are conducive to other, different states. This is an important distinction.

The method of the here-presented research begs the question of applicability to microgrids. Solutions such as Blockchain-based settlement systems in real time could make microgrids inherently different from national markets of electricity. Such as studied here, the market of electricity is composed of assets with a given capacity, operational generation from those assets (or, in the case of storage assets, into and from them), interconnexions to other markets, and a settlement system. Blockchain-based settlement systems in microgrids are a good idea to increase the financial liquidity of those microgrids, yet it is to keep in mind that current liquidity does not translate per se into investment in productive assets, and therefore into installed capacity. Whilst there are cryptocurrencies which facilitate investment, the technological state of the microgrid (assets, capacity, generation, storage) is determined by access to capital measured in fiat currencies, not in Blockchain-based tokens.

Real-time energy trading is a notion to approach with caution. Real-time suggests simultaneity, and simultaneity is essentially an illusion. Everything that happens in any market of electricity, regardless its physical size, is a sequence, and that sequence always involves a time lag. In the here-presented research the window of settlement is 1 hour in Poland and ½ hour in the UK. Those windows get split at times. The Polish system knows, for example, the 2 a.m. time, the 2A a.m. time, and the 2B a.m. one., which produces 26 settlement windows in a 24-hour cycle. The British grid, although half-an-hour-based in principle, has 50 settlement periods in a 24-hour cycle, thus, once again, two of them are shorter than ½ hour.

Both of the national grids studied here are doctrinally and technologically targeting 15-minute settlement periods. Let’s compare it now to a microgrid, e.g. a 200-chimney (figuratively speaking) local energy community, equipped with the latest state-of-the-art transmission, metering and balancing technology. With the realistic assumption that owners of installations want to control both the distribution of their locally produced energy, and the intake of power from others, a window of settlement neighbouring 3 minutes is hard to beat in practical terms. Besides, energy communities need a connection to national grids, at least for the sake of energy security. In such case, they need to adapt their cycle of settlement to that of a broader grid. With all the above in mind, microgrids can realistically achieve slightly smoother settlement and balancing, as compared to national grids, but this is a difference of degree, not of order of magnitude.

Predicting how future states of the market are generated is different from predicting the exact future states, and a random forest algorithm has been used here as regards the former, on empirical data from the operators of national grids in Poland and in the UK. Each of the variables reported in the corresponding national datasets is prone to become the root of a computationally plausible decision tree, and therefore a stressor, observable change in which triggers a chain of adaptive changes in other variables.

The working hypothesis is that energy markets are stressed (i.e. provoked into adaptive change) by observable changes in prices of electricity, and by the relative prevalence of assets relative to renewable energy sources. The most general observation to derive from the results of calculations is idiosyncrasy of the decision forests generated. The same algorithm, applied to different datasets, yields decision forests robust in their accuracy and yet disparate in the distribution of root variables in decision trees, and therefore disparate as regards stressors which trigger adjustment.

The working hypothesis is just partly true in the light of empirical results. Among the 12 models studied, just one, based on British data for 2022 and periodized over months, yields a truly high probability of the market being stressed by variables relative to wind and solar generation, and therefore to technological change. Adaptive change triggered by the deployment of renewable energy sources seems to be a singularity, and not the rule. Price makes a noticeable stressor, and yet never the dominant one. Although the type of prices used as empirical data in Polish datasets is a de facto intraday price averaged over 1-hour windows, its importance as stressor becomes apparent only in models periodized over months.

Market price of electricity, such as observed in models based on Polish datasets, gives root to decision trees only in month-periodized models. Does it contradict all the research on electricity pricing on the day-ahead and the intraday basis? Not necessarily. Variables which give root to decision trees are stressors rather that adapters. When price is a stressor on an hourly basis, market participants are in permanent stress. It is more rational to assume that adjustments in price within a day or within the day-ahead window are adaptive changes, subservient to longer-reaching strategies. Results obtained in the above-presented models suggest that observable change in prices starts being a stressor in a monthly step of decision-making. Capacities committed to the grid and actual generation are adaptive changes triggered by prices from last month.

That result entails a caveat. In the datasets studied, a month covers {30 ÷ 31}\*24 = 720 ÷ 744 hourly instances of the market. Two consecutive nodes in a decision tree, spread over two consecutive months, can be the 699th hour of the month t0 and 2nd hour of the month t1, and the algorithm does not provide a reliable way of singling out such occurrences. Still, as hour-based models do not yield at all decision trees rooted in ‘Price’. It seems we are really talking about monthly strides in the decision-making process.

The same month-oriented edge (with the same caveat) is visible in stressors resulting from interconnections to other markets, and it seems making sense with respect to prices. Exports and imports of electricity are simply services supplied by assets located beyond the official delimitation of the national grid. Decisions pertinent to interconnections are decisions about commitment of capacity and about actual generation, just in a different spatial arrangement.

Some provisional conclusions for microgrids emerge. The type of adaptive change that prevails in the above-presented models is arbitrage between respective variances in demand and supply, in the presence of quick deployment in RES-based assets. The substantive difference between the national markets studied and typical microgrids is that the former can disconnect RES-based assets in moments of abundance and compensate their intermittence by other sources in the times of scarcity (e.g. night-time). Microgrids based on RES cannot do that. Balancing a microgrid requires capacity in energy storage to curtail intermittence. In that context, adaptive pattern focused on balancing capacity translates in two different strategies. Either investment in storage assets essentially goes in step with that in RES-based generation assets, or the microgrid develops a backup connection to a broader grid endowed with non-intermittent generation assets. Should microgrids behave the way the national markets studied behave, they would develop a month-long adjustment process to prices from last month and to imports/exports of energy from last month.

The initial thought of the here-presented research follows the logic of energy policies relative to green transformation: technological change, including RES, is the major stressor of adaptive change in the markets of electricity. The findings of this research, however, show a different picture. Markets of electricity seem to make collective decisions oriented on optimizing the balance between demand and supply and therefore on minimizing the overhead of lost surpluses in the energy generated. In other words, markets stress themselves into curtailing intermittence of generation. Technological change, in the form of new, RES-based assets connected to the grid, appears as a smooth-out problem. Should microgrids behave in a similar way, it means that each case of investment in new assets connected to a microgrid is followed by a period (how long exactly?) of consecutive attempts at equilibrium between supply and demand. Further inference suggests that microgrids might be prone to functional overinvestment: too much capacity connected at once may lead to so long a period of adaptive balancing that significant chunks of that capacity will remain effectively unused for a time roughly equivalent to moral depreciation of the corresponding assets.

Three models based on month-long periodization – UK 2021, UK 2022, and Poland 2023 day ahead – generate much shorter decision trees as compared to those between settlement periods in one day. Their relatively low complexity is a singularity. Shorter decision trees mean less adaptive steps, and thus more decisiveness, once adaptation has been triggered by change in the root variable. The theory cited earlier allows hypothesising (as it is to early to assume) that the two electricity markets studied – the UK and Poland - are collectively experimenting with speeding up and simplifying their decision-making amidst rapid deployment of new assets in RES-based generation. The same hypothetical explanation can be applied to other singularities observed among month-periodized models: the unusual importance of SolarCap and WindCap in the UK 2022 model or that of interconnections in UK 2021 model are manifest of experimentation amidst technological change.

##### References

1. Bahramara, S., Shahrokhi, S., Sheikhahmadi, P., Khezri, R., & Muyeen, S. M. (2022). Modeling the risk-based decisions of the microgrid in day-ahead energy and reserve markets considering stochastic dispatching of electrical and thermal energy storages. Energy Conversion and Management: X, 14, 100201. https://doi.org/10.1016/j.ecmx.2022.100201
2. Brinkerink, M., Gallach√≥ir, B. √ì., & Deane, P. (2021). Building and calibrating a country-level detailed global electricity model based on public data. Energy Strategy Reviews, 33, 100592. https://doi.org/10.1016/j.esr.2020.100592
3. Castellanos, J., Correa-Fl√≥rez, C. A., Garc√©s, A., Ord√≥√±ez-Plata, G., Uribe, C. A., & Patino, D. (2023). An energy management system model with power quality constraints for unbalanced multi-microgrids interacting in a local energy market. Applied Energy, 343, 121149. https://doi.org/10.1016/j.apenergy.2023.121149
4. Cornell, C., Dinh, N. T., & Pourmousavi, S. A. (2024). A probabilistic forecast methodology for volatile electricity prices in the Australian National Electricity Market. International Journal of Forecasting. Article in press. https://doi.org/10.1016/j.ijforecast.2023.12.003
5. Dai, L., Sun, S., Li, T., & Farkoush, S. G. (2021). Probabilistic model for nondispatchable power resource integration with microgrid and participation in the power market. Energy Strategy Reviews, 33, 100611. https://doi.org/10.1016/j.esr.2020.100611
6. Evangelopoulos, V. A., & Georgilakis, P. S. (2022). Probabilistic spatial load forecasting for assessing the impact of electric load growth in power distribution networks. Electric Power Systems Research, 207, 107847. https://doi.org/10.1016/j.epsr.2022.107847
7. Gotzens F., H. Heinrichs, J. H√∂rsch, and F. Hofmann, Performing energy modelling exercises in a transparent way - The issue of data quality in power plant databases, Energy Strategy Reviews, vol. 23, pp. 1-12, Jan. 2019. https://doi.org/10.1016/j.esr.2018.11.004
8. Iqteit, N. A., Arsoy, A. B., & √áakƒ±r, B. (2022). The random varying loads and their impacts on the performance of smart grids. Electric Power Systems Research, 209, 107960. https://doi.org/10.1016/j.epsr.2022.107960
9. Kihlstrom, R. E., & Mirman, L. J. (1975). Information and Market Equilibrium. The Bell Journal of Economics, 6(1), 357-376. https://doi.org/10.2307/3003230
10. Lago, J., Marcjasz, G., De Schutter, B., & Weron, R. (2021). Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark. Applied Energy, 293, 116983. https://doi.org/10.1016/j.apenergy.2021.116983
11. Manjunatha, H. M., Supritha, M. R., HK, N. P., & Santhoshkumar, G. M. (2023). Auction-based single buyer energy trading framework in grid-tied microgrid with distributed energy storage and demand response using a multi-agent approach. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 6, 100367. https://doi.org/10.1016/j.prime.2023.100367
12. Marcjasz, G., Uniejewski, B., & Weron, R. (2019). On the importance of the long-term seasonal component in day-ahead electricity price forecasting with NARX neural networks. International Journal of Forecasting, 35(4), 1520-1532. https://doi.org/10.1016/j.ijforecast.2017.11.009
13. Mattsson, N., Verendel, V., Hedenus, F., & Reichenberg, L. (2021). An autopilot for energy models-Automatic generation of renewable supply curves, hourly capacity factors and hourly synthetic electricity demand for arbitrary world regions. Energy Strategy Reviews, 33, 100606. https://doi.org/10.1016/j.esr.2020.100606
14. Myers, J. H., & Tauber, E. (2011). Market structure analysis. Marketing Classics Press.
15. Pollitt, M. G. (2018). The European Single Market in Electricity: An Economic Assessment. Energy Policy Research Group, University of Cambridge. http://www.jstor.org/stable/resrep30310
16. Saranj, A., & Zolfaghari, M. (2022). The electricity consumption forecast: Adopting a hybrid approach by deep learning and ARIMAX-GARCH models. Energy Reports, 8, 7657-7679. https://doi.org/10.1016/j.egyr.2022.06.007
17. Wang, Y., Wang, B., & Farjam, H. (2024). Multi-objective scheduling and optimization for smart energy systems with energy hubs and microgrids. Engineering Science and Technology, an International Journal, 51, 101649. https://doi.org/10.1016/j.jestch.2024.101649