Increasing Price Granuality in Electricity System Models

Carla Mendes[1], Iain Staffell[2], Richard Green[3]

[1] Centre for Environmental Policy, Imperial College London, SW7 1NE, UK, c.tavares-mendes@imperial.ac.uk
[2] Centre for Environmental Policy, Imperial College London, SW7 1NE, UK, i.staffell@imperial.ac.uk
[3]Imperial College Business School, Imperial College London, SW7 1AZ, UK, r.green@imperial.ac.uk

***Abstract*— Electricity system models are widely used to study future designs for power markets. They are commonly used to represent electricity dispatch decisions but struggle to reproduce realistic variation in prices. We show that current assumptions of generators bidding short-run marginal cost underestimates the spread and volatility of hourly wholesale prices. Imperfect competition makes market prices differ from the theoretical optimum. Therefore, a simple modification to the short-run marginal cost approach is considered in a way that allows generators to make a spread of bids. Additionally, we add volatility into the model by making a post-optimizer transformation in the cost function. The objective is to propose a model to simulate prices on day-ahead markets that accounts for generators' ability to bid below marginal costs for their first megawatts of capacity and above for their last, as well as to consider other variables that have an impact on power prices and that cannot be captured by the typical approaches. Using this method, we show the impacts of price volatility and price spreads in the power market.**

***Index Terms*-- Day-ahead markets, Electricity Prices, Electricity Market Model, Power System Model, Price Volatility**

INTRODUCTION

Modelling electricity markets has been a fundamental tool used by policymakers and participants to guide their decisions in terms of shaping future power markets or investing in emerging technologies. However, all too often models lack transparency and validation ([1], [2]).

Current electricity system models easily optimize expected supply and demand in order to minimize the total power system cost. These models are able to represent dispatch decisions by incumbent generators, but they struggle to reproduce realistic daily variation and spreads of prices [3]. Literature on the validation of time-dependent variations of price outputs produced by these models is still scarce.

The relevance of replicating realistic power prices in terms of their volatility and spread creates good investment signals for new investors. In the coming years, electricity markets will undergo extensive reforms to decarbonize demand and supply, in ways that will increase price volatility. Demand profiles will become more volatile as the use of electric vehicles and electricity for both space-heating and cooling increase. The generation mix is also changing rapidly, with weather-driven renewable technologies increasing their participation in the electricity market, and consequently, increasing the impacts of price variation on generation.

Many of the solutions to help accommodate these changes rely on arbitrage for their business case (e.g., over space for transmission, or over time for storage). Therefore, an inadequate representation of price volatility in current models can lead to an underestimation of the revenue available to storage technologies and transmission grids, and thus the optimal amount of investment in them. The homogenous price signals that result from these modelling tools will also misrepresent the size of price cannibalization on renewables, the value of flexible peak capacity, and so on.

In this work we extend a classic linear dispatch electricity model to create a tool where historic price time-series can be better replicated. By changing the total system cost function to a quadratic form and by applying a post-optimizer transformation, we were able to develop more realistic supply and price curves that significantly improve the model's skill at representing daily price variation. External effects on prices derived by European interconnectors were also considered. These new model features make it a suitable tool for exploring the impacts of price volatility within the market as well as to investigate the importance of price spreads on arbitrage earnings and price cannibalization of different technologies.

MODEL APPROACHES FOR ELECTRICITY PRICES ASSESSMENT

Several methods have been explored in the literature to determine which factors influence energy prices. Time series models, artificial neural networks and regression trees are often used to simulate power prices, where prices are defined as a function of exogenous regressors. However, these statistical models imply that correlation between variables can be observed and that forecast methods are accurate [4]. Additionally, they are not able to reflect structural changes in the power market [5].

To overcome this drawback, equilibrium models are often used. These models are usually modelled as an economic dispatch or unit commitment approach. They determine the most cost-efficient dispatch decision of generation assets to meet electricity demand. The optimal solution provides the optimal dispatch of power plants and market prices for a given period. However, as these models seek the global optimum, they implicitly take the view of the central operator and do not take into account the strategic behaviour of generators.

To include agents' strategic behaviour, equilibrium models can also be studied using a multi-agent perspective. Bayesian approaches or inverse optimization methods are commonly used to explore variables that have influence on generators' bids ([6]–[8]). By considering only simulated test cases this analysis is only suitable to study qualitative problems rather than long-time series of market prices ([5], [9]).

Following a more market-oriented perspective, supply curves aggregate market bids that depend both on the merit order and bidding strategies by market participants. In [3] the model creates supply curves for each technology using the definition of short-run marginal costs. To reflect must-run constraints, prices are reduced in case of low output, while scarcity rents are considered by increasing prices in periods of high demand. Supply curve modelling can also result from statistical models, where the curve is derived as a function of normalized load and market prices, and it is adjusted to account for the evolution of fuel and emission costs [10]. However, these models do not include the effects of technology availability and production costs.

A combination of optimization and statistical methods to simulate long-term power prices is still scarce in the literature. Previous work developed by [5] states that this approach captures the main characteristics of price dynamics but underestimates the price spikes observed in historical data. Electricity prices are dependent of a wide range of factors such as: volatility in demand and supply, transmission network physical limits, ramping constraints, strategic bidding practices and volatility in fuel prices [3]. In order to simulate electricity prices as closely as possible to historic data, we develop a zonal European model with one node per country that mimics the market clearing mechanism, taking into account power system and network constraints. The model connects 27 European countries using net transfer capacities (Figure 1).

The link between technical constraints and electricity prices is modelled using an economic dispatch model. Additionally, a quadratic function is used to introduce non-linear price increases in case of limited supply margins. Finally, a post-optimizer transformation was applied in order to bring volatility into the modelled prices. A more detailed explanation of the model is described in the following section.

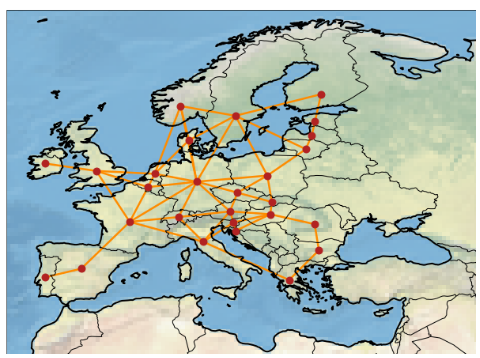

Figure 1. Spatial dimension used in EuroMod with grid connections

LINEAR MODEL

For our analysis, we employ the electricity market model Euromod. The model includes generation of thermal power plants p ∈ P, natural inflow and pumped storage plants h ∈ H, and renewable sources w ∈ W. Generation of the different technologies are aggregated as power blocks to each zone.

The objective of this model is to minimize the total system operating costs for a specific time horizon T (eq. 1), considering power plant and network restrictions. Generation of thermal power plants in period t ∈ T is denoted by $Q_{p,t}$. Their generation is limited upwards by their installed capacity corrected by power plants' availability, $q_{t,p}^{max} \times avail_{t,p}$, and downwards by their minimum chp requirements, $chp_{t,p}$ (eq. 3). The generation from hydro plants is denoted by $Q_{t,n,h}^{TURB}$, and pumping or withdrawal from the market is given by $Q_{t,n,h}^{PUMP}$. Generation and pumping from hydro units are upper bounded by the turbine and pump capacity, $q_{n,h}^{maxT}$ and $q_{n,h}^{maxP}$, respectively (eq. 5-6). The efficiency of the pumping process is given by $\mu \in [0,1]$. Each hydro generator is connected to a reservoir that is limited upwards by their maximum capacity, $q_{n,h}^{maxSTOR}$, (eq. 7). Additionally, a law of motion for hydro units is introduced to track the amount of water that is available in the reservoir, $STOR_{t,n,h}$, in period t ∈ T. Equation 8 shows us that the level of water a reservoir has at the end of period t is equal to the level of water in the reservoir at the end of period *t-1*, plus the water that is introduced by the water inflows and pumping in period *t*, minus the generation from hydro power plants in period *t*. A spillage variable is introduced to solve possible model infeasibilities, due to excess of water in the reservoir, $SPILL_{t,n,h}$.

Renewable generation is introduced in the model as an infeed. Therefore, for each renewable generator, a time-series of maximum infeed is specified as this is exogenous based on weather conditions, although it may be reduced by the amount of renewable supply that is curtailed, $C_{w,t}$. In this case, it is assumed that the marginal generation costs are zero, but the curtailment of RES is penalized by a payment of $c_w^{curtail}$. The use of this penalty reflects the prioritization of renewable generation in the merit order.

Load and generation are connected to a set of zones n ∈ N that represent 27 European countries (Figure 1). Power plants are associated to zones by the set Θ ⊂ (P ∪ H ∪ W) × N. Load at zone n in period t is denoted by $d_{n,t}$. Electricity demand is assumed to be fixed and price inelastic, which needs to be satisfied by generation technologies and net-imports from other countries (eq. 2). Additionally, load can be also curtailed in case of lost load, $VOLL_{n,t}$, which incurs the cost of curtailing load, $c^{LostLoad}$. Furthermore, the model includes limits on the transmission flows between countries that are given by the Net Transmission Capacities (NTC), $q_{t,n,nn}^{NTC}$, (eq. 4).

Euromod is calibrated for the period of 2017 to 2020. Data on historic load, prices, capacities and NTC are provided by ENTSO-E ([11], [12]). The hydrological inflow data we employ is derived from the ENTSO-E hydrological model PECD ([13], [14]).

Euromod runs on an hourly basis and generates country-specific hourly generation mix, zonal electricity prices and trade flows. The mathematical formation of the linear model is the following:

$$\begin{aligned} COST \geq & \sum_{t,p} a_{t,p} Q_{t,p} \\ & + \sum_{w,t} c_w^{curtail} C_{w,t} \\ & + \sum_{n,t} c^{LostLoad} VOLL_{n,t} \qquad \forall p,w,t \end{aligned} \tag{1}$$

Subject to:

$$\begin{aligned} d_{n,t} = & \sum_{p} map_{n,p}^{pl} Q_{t,n,p} + res_{t,n} \\ & + \sum_{h} map_{n,h}^{hydro} (Q_{t,n,h}^{TURB} - Q_{t,n,h}^{PUMP}) \\ & + \sum_{nn} (1 - ntc_{nn,n}^{loss}) NTCFLOW_{t,nn,n} - NTCFLOW_{t,n,nn} \\ & + VOLL_{n,t} - C_{w,t} \qquad \forall n,t \end{aligned} \tag{2}$$

$$chp_{t,p} \leq Q_{t,n,p} \leq q_{t,p}^{max} \times avail_{t,p} \qquad \forall p,t \tag{3}$$

$$NTCFLOW_{t,n,nn} \leq q_{t,n,nn}^{NTC} \qquad \forall n,nn,t \tag{4}$$

$$Q_{t,n,h}^{TURB} \leq q_{n,h}^{maxT} \qquad \forall t,h,n \tag{5}$$

$$Q_{t,n,h}^{PUMP} \leq q_{n,h}^{maxP} \qquad \forall t,h,n \tag{6}$$

$$STOR_{t,n,h} \leq q_{n,h}^{maxSTOR} \qquad \forall t,h,n \tag{7}$$

$$STOR_{t,n,h} = STOR_{t--1,n,h} + inflow_{t,n,h} + \mu Q_{t,n,h}^{PUMP} - Q_{t,n,h}^{TURB} - SPILL_{t,n,h} \qquad \forall t,h,n \tag{8}$$

QUADRATIC MODEL

To better represent electricity prices, we changed the total system cost function from the standard linear formulation (eq. 1) to a quadratic form (eq. 9).

$$
\begin{aligned}
COST &= \sum_{t,p}(a_{t,p} + b_{t,p}Q_{t,p})Q_{t,p} + \sum_{w,t} c_w^{curtail}\, C_{w,t} \\
&\qquad + \sum_{n,t} c^{LostLoad}\, VOLL_{n,t} \\
&= \sum_{t,p}\left[mc_{t,p} - \delta mc_{t,p} + \frac{\delta mc_{t,p}}{q_p^{max}} Q_{t,p}\right] Q_{t,p} \\
&\quad + \sum_{w,t} c_w^{curtail}\, C_{w,t} \\
&\quad + \sum_{n,t} c^{LostLoad}\, VOLL_{n,t}
\end{aligned} \qquad (9)
$$

The linear model formulation takes the view of a central operator where perfect competition is on its basis. However, generators have typically an imperfect behaviour. Following the approach developed by [3], we allow power plants to place bids that deviate from the short-run marginal cost (SRMC). The SRMC of a generator is given by the first derivative of the cost function (eq. 9) and given by:

$$
SRMC_{t,p} = mc_{t,p} - \delta mc_{t,p} + \frac{2\delta mc_{t,p}}{q_p^{max}} Q_{t,p} \qquad (10)
$$

The price that each generator bids includes the marginal cost $mc_{p,t}$ minus a parameter δ that specifies the size of deviation from the SRMC, $\delta mc_{t,p}$. Therefore, if a δ of 30% is used, the generator will bid 30% below its SRMC for the 1st MW that is introduced into the market, and 30% above its SRMC when the full capacity is bided into the market. Additionally, we add a slope to the cost function, $\frac{2\delta mc_{t,p}}{q_p^{max}}$, that increases the cost of generation from a technology as a function of what proportion of that technology's fleet is being deployed within a given country. The parameter δ is uniform across all technologies and countries, and relative to total capacity. The Euromod price in each country in each period, $r_{n,t}$, is the shadow price on constraint (2).

In order to choose the parameter δ, we perform a series of different model runs from $\delta = 0$ (linear case) to $\delta = 100\%$ and for the different modelled years (2017-2020). The mean absolute (MAE) of errors in prices and generation were then compared (Figure 2). As modelling prices is the main objective of this paper a δ of 30% was chosen as being the one that minimizes the MAE of price errors. Regarding generation, Figure 2 shows that for a δ of 30% the MAE is lower than in the linear case, except for the years 2017 and 2018.

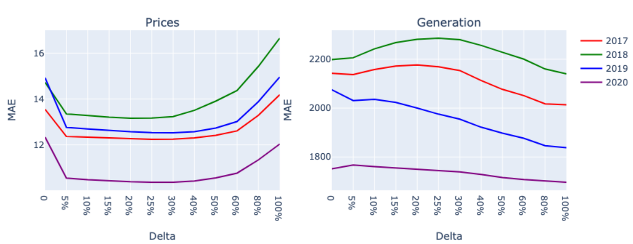

Figure 2. Mean absolute errors in Prices and Generation

MODIFIED QUADRATIC MODEL

Finally, a post-optimizer transformation is introduced to account for other factors that might have an impact on prices. After performing an evaluation on the impacts of net-demand on prices for the different countries, we verified that there is a correlation between these two variables. Therefore, errors on modelled prices for the different countries were plotted against the net-demand normalized around its mean, and a linear regression model was applied (Figure 3).

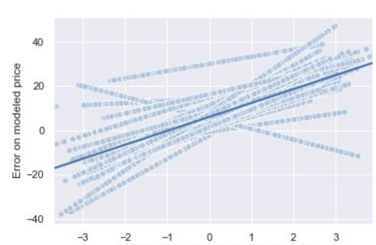

Figure 3. Linear Regression Curve of Errors on Modeled Prices

The best fit equation of this linear regression model is given by Equation 10.

$$6.30 \times \frac{\text{netdemand}_{t,n} - \mu_n}{\sigma_n} + 6.04 \quad (11)$$

By applying Equation 10 to the cost function of the model (eq. 9), we adjust the Euromod price, $r_{n,t}$, depending on the relation between net demand and its mean. Therefore, if net-demand is below its mean, there is more electricity coming from renewable sources, which decreases the electricity price. If net-demand equals the mean, then the wholesale price is given by Euromod. Finally, if net-demand is higher than the mean, an increase in the electricity price will occur, justifying the need for more conventional generation in the market.

RESULTS

To evaluate the performance of the model, we compare the
the Euromod results with the historic data provided by ENTSO-E. Table 1 shows the mean absolute error on prices between the different model approaches, where the linear model presents the worst results in terms of MAE. With the introduction of a quadratic function in the model, the MAE is improved by 13% when compared to the linear model, while the QCP modified model improves the model performance in terms of MAE in 22%.

Prices	*LP*	*QCP*	*QCP Modified*
2017	13.54	12.25	11.41
2018	14.93	13.24	11.94
2019	14.69	12.53	10.78
2020	12.25	10.37	8.85

Table 1: Mean Absolute Error on Prices between Models

In terms of generation, the different models were compared to the ENTSO-E data. Figure 4 and Figure 5 present the mean, 10th percentile and 90th percentile of the deviations between historic data and Euromod results for the different technologies in the UK between 2019 and 2020. Larger deviations are presented by the linear model, especially for coal and gas. In contrast, the QCP modified model allows the Euromod to have a better performance but a further calibration process is still needed.

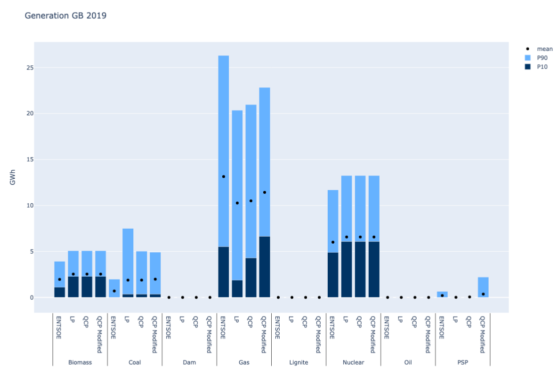

Figure 4. Mean, 10th and 90th Percentile in Generation for GB in 2019

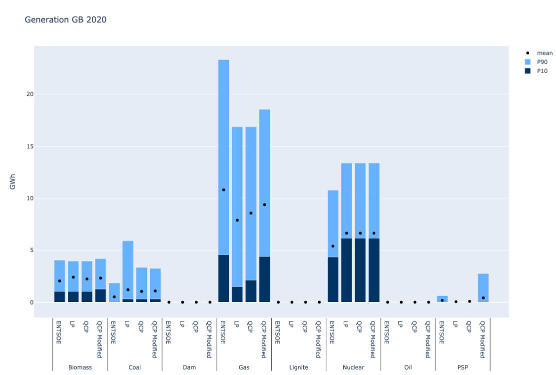

Figure 5. Mean, 10th and 90th Percentile in Generation for GB in 2020

Regarding electricity prices, Figures 3, 4 and 5 show the electricity price comparison between ENTSO-E prices and the modelled prices for the hourly, monthly and 24 hours average, as well as the price range for the different model approaches.

The linear model follows the general shape of the average prices over the four years. However, the model still cannot fully match the amplitude and variability of power prices and underestimates them (Figure 6).

Figure 6. Prices Comparison for GB in the Linear Model

By using a non-linear form for system costs, we were able to develop more realistic supply and price curves that significantly improve the model's skill at representing daily price variation, as well as at representing the generation dispatch (e.g., the balance between coal and gas) without the need for detailed country-by-country calibration. On average, hourly and monthly electricity prices are still underestimated but 24 hours average and the price range present a better (Figure 7).

Figure 7. Prices Comparison for GB in the Quadratic Model

The modified quadratic model improves even further the price results in terms of volatility. This feature allows Euromod to increase the volatility of prices by two times when compared to the other models. The monthly average prices closely match the historic ENTSO-E real prices, the 24 hours average follow the same pattern of the historic data, and the range of prices shows a strong increase, which improves the model performance in modelling volatility of power prices (Figure 8).

Figure 8. Prices Comparison for GB in the Quadratic Modified Model

We conclude that prices not only vary more when generators' bids deviate from their initial marginal costs, but there are other relations that can have a bigger impact on prices, such as net-demand. This is of particular relevance as it plays a central role in guiding the decisions of both market participants and policy makers. It also provides better market signals regarding future revenues to support investment decision on key technologies to support the current energy transition.

CONCLUSION

The decarbonisation of electricity markets is disturbing demand and supply in ways that increase price volatility. Structural models of day-ahead markets account for price formation mechanisms and techno-economic constraints, allowing us to find the optimal price to minimize total system costs. They usually predict quite well yearly average prices but, typically, misrepresent the volatility and amplitude of price spikes. Solutions that help to accommodate the current energy transition rely on arbitrage opportunities. Therefore, an inadequate representation of electricity prices volatility can lead to an underestimation of the revenues available for storage and transmission grids. Having a bottom-up model with a representation of supply technical characteristics, the value of interconnectors and storage units, as well as a non-linear cost function, allows us to develop fairly good supply and price curves. The introduction of imperfect competition behaviour from generators and the influence of net-demand on prices improved the model performance in modelling more realistic supply and price curves that improve the daily and yearly price volatility.

These new model features make it a suitable tool for exploring the impacts of price volatility and price spreads within the market as well as to investigate the importance of price variation on arbitrage earnings and price cannibalisation of different technologies.

REFERENCES

[1] S. Pfenninger, J. DeCarolis, L. Hirth, S. Quoilin, and I. Staffell, "The importance of open data and software: Is energy research lagging behind?," *Energy Policy*, vol. 101, pp. 211–215, Feb. 2017, doi: 10.1016/j.enpol.2016.11.046.

[2] H. K. Ringkjøb, P. M. Haugan, and I. M. Solbrekke, "A review of modelling tools for energy and electricity systems with large shares of variable renewables," *Renewable and Sustainable Energy Reviews*, vol. 96. Elsevier Ltd, pp. 440–459, Nov. 01, 2018. doi: 10.1016/j.rser.2018.08.002.

[3] K. R. Ward, R. Green, and I. Staffell, "Getting prices right in structural electricity market models," *Energy Policy*, vol. 129, pp. 1190–1206, Jun. 2019, doi: 10.1016/j.enpol.2019.01.077.

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

[5] V. Mahler, R. Girard, and G. Kariniotakis, "Data-driven structural modeling of electricity price dynamics," *Energy Economics*, vol. 107, p. 105811, Mar. 2022, doi: 10.1016/j.eneco.2022.105811.

[6] C. Ruiz, A. J. Conejo, and D. J. Bertsimas, "Revealing rival marginal offer prices via inverse optimization," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3056–3064, 2013, doi: 10.1109/TPWRS.2012.2234144.

[7] R. Chen, I. Ch. Paschalidis, M. C. Caramanis, and P. Andrianesis, "Learning From Past Bids to Participate Strategically in Day-Ahead Electricity Markets," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5794–5806, Jan. 2019, doi: 10.1109/tsg.2019.2891747.

[8] L. Mitridati and P. Pinson, "A Bayesian Inference Approach to Unveil Supply Curves in Electricity Markets," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 2610–2620, May 2018, doi: 10.1109/TPWRS.2017.2757980.

[9] R. Weron, "Electricity price forecasting: A review of the state-of-the-art with a look into the future," *International Journal of Forecasting*, vol. 30, no. 4. Elsevier B.V., pp. 1030–1081, Oct. 01, 2014. doi: 10.1016/j.ijforecast.2014.08.008.

[10] Yang He, Marcus Hildmann, Florian Herzog, and Göran Andersson, "Modeling the Merit Order Curve of the European Energy Exchange Power Market in Germany," *IEEE TRANSACTIONS ON POWER SYSTEMS*, vol. 28, no. 3, 2013.

[11] ENTSOE, "Indicative values for Net Transfer Capacities (NTC) in Continental Europe," 2020.

[12] ENTSOE, "ENTSOE Transparency Platform," 2020.

[13] ENTSOG and ENTSOE, "TYNDP 2020 Scenarios Report," 2021.

[14] M. de Felice, "ENTSO-E Hydropower modelling data (PECD)," 2020. Accessed: Feb. 17, 2022. [Online]. Available: https://zenodo.org/record/3985078#.Yg4g7i-l1pQ