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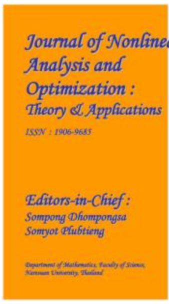

GRAPH THEORY IN ELECTRICITY PRICEFORECASTING

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ABSTRACT:

Graph theory is a mathematical study of objects and their pair wise relations, known as nodes and edges respectively. This paper explores the electricity price forecasting, the price depends on a large set of fundamental drivers, including systems loads (demands, consumption figure), weather variables (temperature, wind speed, precipitation, solar radiation), fuel costs (oil and natural gas). The feature selection can be done by empirical expert knowledge in the respective fields, this approach can be loaded with time-consuming manual work and uncertainty when discriminating the importance of different features. Background on the electricity and roles in the market are explained in this paper. The price will be forecasted by various methods and the methods are expressed here. The feature selection of the forecasting of the price are mentioned in this paper.

INTRODUCTION:

Societies are currently undergoing a transition towards a low-carbon energy system. The main drivers of this change, electric utility companies are digitalized and innovating on new products to stay or become more competitive. The technological advancements with respect to the energy and information technology sectors provide new opportunities for utilities to optimize their operations or find new revenues streams. Graph theory appears as a potentially helpful technology to support such endeavours. It has been used in the contexts of internet of things for routing, fraud detection, customer analysis, advanced search, scheduling and much more.

Roles in the market:

TSO (Transmission System Operator)

The operator of the national power system. Oftentimes the grid owner, it is responsible for the physical balance between supply and demand and the development of the network.

Generators

Market participants responsible for the supply of electricity.

Power exchange

The marketplace where the electricity is traded between the market players through an auction system.

BRP (Balance responsible party)

A market participant, or the chosen representative, which is responsible for its power imbalances in the system. A power imbalance refers to the difference between their bid and their actual production or consumption. The BRP is financially responsible for these imbalances and is incurred a cost proportional to its imbalance.

Imbalance settlement administrator

Market participant settling the imbalances between the scheduled quantity of power supply or consumption and the actual values exchanged on the market. It is responsible for setting the price of the imbalance and dispatches the costs or incomes to the BRPs. In most markets, the imbalance settlement administrator is the TSO itself.

Traders

Also called retailers, these market participants buy electricity from the producers, either bilaterally or on the power exchange, to sell it to their customers.

The day-ahead spot-market:

The spot market is organised through auctions: each working day, a market player makes a bid to buy or sell electricity on the power exchange for the following day. The TSO is responsible for settling the selling and buying bids, thus creating a dispatching schedule for the generators and establishing the market-clearing price for each power period (generally an hour) for the following day.

In their most generic form, the bids consist in a power quantity and a pricefor each power period. If the bid is accepted, the market player engages in selling or buying the quantity from the bid for each power period auctioned. Sellers bid the lowest price at which they are willing to be paid for a certain quantity of power (in other words, the marginal cost) and buyers state the highest price at which they are willing to consume a certain quantity of power (the marginal utility).

Upon market closure (generally 12:00 the day before), the TSO constructs the buying and selling curves, in other words, sorts the selling and buying bids by price and quantity for each period. The bids are accepted in order of increasing price until the total demand is met, according to Figure.

As per fundamental microeconomics rules, the intersection of the supply and demand curves determine the price, called the market clearing price. This way, marketequilibrium is reached and social welfare is maximized. All supply bids at a price point lower than the clearing price are accepted, so are all purchasing bids at a price point higher than the clearing price. This process is called the generation dispatch, asit dictates the production schedules of each generator.

Because each bid is based on forecasts (of either generation or consumption), it is logical that there is some margin of error and the actual values will look different.These variations are remedied in various ways in the balancing market.

It is worthwhile mentioning that the biggest portion of power sales is still generated by bilateral contracts with large customers, also called futures. Suppliers and buyers agree on a future delivery of electricity at a pre-determined rate, hedging against the risk caused by the daily price volatility.

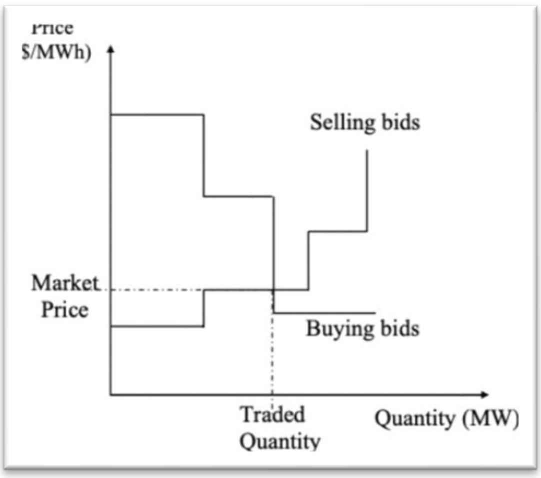

Figure : Formation of electricity prices

The balancing market:

During the day of delivery, continuous adjustments in production and consumption need to be made continuously in order to keep the physical balance of the grid. For this reason, it is also referred to as the real-time market, where suppliers and bidders continuously place bids on the power exchange. The market clearing takes place during the hour of operation: the TSO selects the relevant bids and call theentities in real time. The TSO uses this real-time auction mechanism for the delivery of energy for tertiary regulation and for the management of network congestions in real time. If the regulation is upward (the system needs more power), generally the TSO must pay the entity that generates power, while if the regulation is downward (the system needs less power), generally the entity that consumes power must pay the TSO.

This market has two economic consequences for traders. Firstly, it is rare that generators produce exactly the quantity from their bid in their day-ahead market. The TSO incurs a cost for this imbalance, either an upward-regulation if the system needs more electricity or a downward-regulation in the opposite scenario. Secondly, market participants can choose to trade on this market instead of the day-ahead market, if they predict that it would be more beneficial to them.

As soon as buy- and sell-orders are matched, the trade is executed. Electricity can be traded up to 5 minutes before delivery and through 1 hour, half an hour or quarter hour contracts. As this allows for a high level of flexibility, market participants can also make last minute adjustments to balance their positions closer to real time to reduce their imbalance.

Electricity price forecasting:

Forecasting methods:

As earlier indicated, electricity price forecasting (EPF) is not trivial and there is a rapidly growing literature on electricity price forecasting. Most research report similar challenges in their respective studies, namely the non-linear dynamics, strong self-correlation, time varying means and deviations as well as spikes and seasonality. The integration of more volatile renewable energy in the system adds to the complexity of accurately predicting prices.

The following taxonomy of the different types of models:

Multi-agent models simulate the behaviour of agents in a system, in other words, the interaction between the various market players is analysed. This approach is justified by the fact that the electricity price is determined through a bidding process, where market participants can adopt various strategies to maximise their revenues (e.g. by exerting market power). They can be used for qualitative studies in the market.

Structural models take into account the fundamental relationship between the elements of the electrical system. Parameters affecting the electricity price in the physical sense to create a realistic electricity price representation.

For instance the capacities of the transmission and distribution lines, the geographical representation of the generators, the feed in from renewables, the load sources, weather variables.

Reduced form models, or stochastic models, are inspired from the financial markets and do not aim at forecasting the electricity price per se, but rather seek to replicate their main characteristics to capture the price dynamics (e.g. marginal distributions, correlations). They are commonly used for derivatives valuation and risk analysis. Several approaches including jump-diffusion models or Markov regime-switching models have been proposed.

Graphs can help capture the dynamics between prices in the stock market. In fact, there is a type of graph usually employed for such modeling, the market graph. It has been used on various occasions for modeling the correlations between stocks and between energy commodities. As the markets of natural gas and crude oil are becoming more financialized and are known to impact the electricity price, a combination of graphical and financial insights in characteristics such as causality, centrality, degree distribution and impact of exchange rates can be of interest. Although the simplicity of this type of models can be a serious limitation and few attempts are being made, it performs reasonably well to capture the volatility or price spike forecasts.

Statistical models build upon the seasonality of electricity prices and capture their auto-regression at the same time as exogenous factors can be considered. They have been exhaustively applied to EPF thanks to their simplicity and satisfying accuracy.

Computational intelligence (CI) models aim at overcoming the aforementioned weakness of statistical models as they are effective for capturing the non-linearbehaviour of electricity prices.

Artificial neural networks Support Vector Machines, Fuzzy inference systemshave often been suggested, but a vast set of models is being tried (e.g., genetic algorithms, regression trees). Their ability to handle complexity and non-linearity make them a promising approach for short-term predictions and author shave reported excellent performance.

They can furthermore accept much larger amounts of data than traditional statistical regression models. However, this can also be their very drawback, as a risk is to overfit the model to the training set and incorrectly forecast the point forecasts. The accuracy of the models is dependent on the calibration of the hyper parameters, the initial conditions, which is to a large extent made by computationally intensive exploratory means and through trial and error, which reduces their replicability. Also, they can suffer from a low level of explain ability as they generally adopt a black-box model, i.e. what happens in the neural networks is not fully understood.

Feature selection in electricity price forecasting:

The overall goal of feature selection is three-fold:

- Model simplification, to make them more easily interpretable.
- Reduce the curse of dimensionality, which refers to the increase in computation time as we go toward very large data sets.
- Reduce over fitting, namely the risk of models to correspondtoo closelyor exactly to a particular set of data and potentially failing to fit additional data or predict future observations reliably.

There are three families of feature selection, filter, wrapper and embedded methods.

Filter methods use statistical metrics to evaluate the key characteristics. Their primary drawback is that they could choose unnecessary information or omit certain crucial features as the performance of the particular model is not assessed and the relationships between features are not taken into account. Their primary benefit is that they are incredibly quick because no model needs to be approximated.

On the other hand, wrapper techniques **search over several feature sets, assessing a set's performance by first estimating the prediction model and then utilising the model's predictive accuracy as a performance metric.Their primary benefit is that they take into account a more accurate assessment of the functionality and relationships between the features; their disadvantage is a lengthy computation time.**

Embedded techniques**, like regularisation, pick up the feature selection knowledge when estimating the model. Their benefit is that they take into account the underlying model even if they are less computationally demanding than wrapper techniques. Nevertheless, their specificity to a learning method is a disadvantage.**

Conclusion:

To summarise the discussion above, feature selection is key to increase the accuracy and speed of any electricity price forecasting models and more specificallyin the case computational intelligence models. To approach this, researchers have tried filter, wrapper and embedded methods, each having their advantages and drawbacks. Whereas filter methods such as mutual information are model-free, scalable and can be apply non-linear dimensionality reduction, they have a lower accuracy level. Embedded and wrapper methods, on the other hand, can contribute to more accurate predictions, but can become too computationally intensive. To cope with large dimensions of data, sparse regularisation methods have been employed successfully, particularly LASSO and elastic nets. However, they can still lack in performance for non-linear mappings. Hybrid models are receiving increasing attention for their ability to aggregate the inherent benefits of each method, forinstance filter-wrapper methods.

Feature selection is particularly important in the context of intra-day trading, given the large amounts of data available, the higher volatility of prices and the impact of fundamental factors such as line congestions. As trade volumes are being shifted to the intra-day market, research on the mechanisms in this market are still lagging and the varying conclusions inferred by the models proposed in literature suggest that there is a need to better understand the price dynamics.

Graphs have a reported value for enriching computational intelligence models, either by modelling neural networks through graphs or by pre-processing the high amounts of chaotic data for feature selection purposes through graph embeddings. Graph embeddings are able to reduce the dimension of data sets. They can be applied directly on graph structures, but can also be employed on regular data sets after they have been converted into a graph.

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