Performance Comparison of two Market Algorithms for Providing Support Services to Distribution Systems

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Performance comparison of two market algorithms for providing support services to distribution systems

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Abstract: Several market algorithms, such as Fast Locational Marginal Pricing (FLMP) and Receding Horizon Control (RHC), have shown the ability to cope with grid congestion. The RHC algorithm can cope with fluctuations in power consumption and generation but is computationally intensive due to the larger search space within the time horizon. The FLMP algorithm is not complex but does not utilise a horizon with information on future consumption and generation. This study demonstrates a performance comparison between the FLMP and Horizon Marginal Pricing (HMP) algorithm. HMP is an algorithm that combines the simplicity of the FLMP algorithm with the time horizon possibilities of the RHC algorithm. The HMP algorithm uses the predicted generation profile to adjust the bid curves, such that consumption shifts to moments with more renewable generation available. Simulations are carried out to compare the performance between the HMP and FLMP algorithms. The results show comparable performance between the FLMP and HMP, whereas the FLMP computes the simulation faster and requires less bandwidth.

1 Introduction

Distribution system operators and transmission system operators are facing technical issues, such as congestion of lines and overloading of the distribution transformers, as a result of a significant increase in electricity consumption and renewable generation. A significant amount of studies into finding possible solutions to resolve grid congestion with new market-based models have already been conducted, for instance, in [1, 2]. Currently, the focus is on the properties of two market algorithms for future local market settings in electricity distribution grids: Receding Horizon Control (RHC) and Fast Locational Marginal Pricing (FLMP). The RHC algorithm shows it can cope with sudden fluctuations and plans power consumption of consumers involved [3]. The FLMP is based on local marginal pricing that is simple and effective for congestion management [4]. One disadvantage of the RHC algorithm is that, due to optimising within the horizon, it is expected that once the number of involved connections is increased, the computation time becomes too significant. Therefore, there is an interest in developing a horizon method that combines the simple and effective FLMP bid curves with the information of future generation/consumption. This paper focusses on a performance comparison between two market algorithms: FLMP and Horizon Marginal Pricing (HMP). The HMP is a horizon algorithm that uses identical bid curves to the FLMP but can shift generation and load based on circumstances within the horizon. Both algorithms are tested by simulation on a distribution grid consisting of a low-voltage (LV) and a medium-voltage (MV) grid. The LV section of the simulation consists of households that have an electric vehicle (EV), photovoltaic (PV) panels and a baseload. The MV part is simulated with equivalent sources to represent conventional and wind generation. The performance comparison of the HMP and FLMP is based on the ability to shift load to match renewable generation, in this study wind and PV generation. Also, a discussion on the scalability and bandwidth requirements of both algorithms is given. This paper is organised as follows: first, in Section 2, an elaboration on the methodology is given, followed in Section 3 by the results and discussion, and finally, in Section 4, a conclusion is given.

2 Methodology

2.1 Fast locational marginal pricing

The FLMP algorithm [3] uses the marginal pricing concept, where each consumer and producer submit a bid curve. These bid curves are then aggregated to determine the clearing price and clearing volume. Marginal pricing is used to determine the electricity price in most electricity markets. The difference between conventional electricity markets, such as the day-ahead and intraday markets, is that the FLMP algorithm is locational and allows devices to communicate a bid curve. All households and generators submit a bid curve to a root node, in this study the root node is located at the distribution transformer. Knowing both the load and generation bid curves, the root node can determine the clearing volume and price.

The bid curves of all households follow the same guidelines shown in Fig. 1. The baseload (green circled) is not flexible and is constant for all prices. For low prices, the EV (blue crossed) charges with maximum power and sloping slowly to the minimum charging power for higher prices. The PV panel (red asterisked) curtails to zero for negative prices, slopes for prices between zero and three, and supplies the maximum generatable power for prices higher than three. Each household supplies the aggregated bid (purple) to the root node. The price λ does not have a financial motive and is purely used as a steering signal.

2.2 Horizon marginal pricing

HMP is an iterative method, where price and load are negotiated several times. Owing to this negotiation process, the HMP can be split into two instances. The first changes an array of prices in

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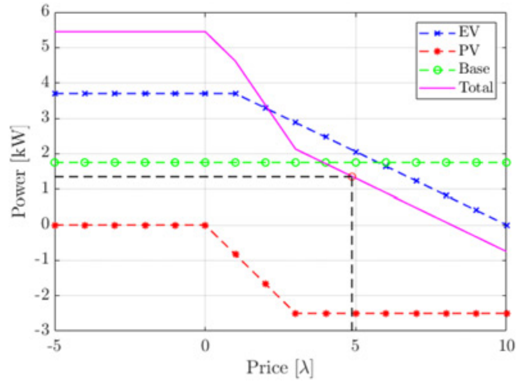

Fig. 1 *Bid curves of a household and energy consumption determination based on price (HMP only)*

load profiles, whereas the second changes load profiles into updated prices.

2.2.1 Price into load profiles: Turning price into load profiles is based on bid curves. Each household receives an array of prices and generation, one for each fifteen-minute block or programmable time unit (PTU) on the horizon. The window size of the horizon t determines the length of the price and generation array and therefore determines the amount of information about the future the households receive. To have an equal comparison, each household creates a bid curve for each PTU for the EV, PV, and baseload identical to the FLMP bid curves shown in Fig. 1. The difference between the FLMP and HMP algorithms is that the FLMP only receives information on current consumption and generation, whereas the HMP receives the forecasted wind and PV generation within the horizon. Using this forecast, a generation factor (GF) that biases the bid curves is created:

$$P_{\text{gen}} = P_{\text{wind}} + P_{\text{pv}}$$

$$\text{GF}(t) = k \cdot (P_{\text{gen},t} - \min(P_{\text{gen}}))/(\max(P_{\text{gen}}) - \min(P_{\text{gen}}))$$

P_{gen} is an array of all generated power within the horizon length t. The GF biases the bid curves of the EV and PV, such that houses are inclined to use more energy when more renewable generation is available. When there is more generation the EV will charge with more power at lower prices, and the PV supplies more power at lower prices. The extent of the bid curve alteration is determined by k. Fig. 2 shows the biasing of the EV and PV bid curves with $k = 10$. As with the FLMP algorithm, the bid curves of the EV, PV, and baseload are added together to create the total bid curve (purple line in Fig. 1). With the total bid curve and the price known, the power consumption of the household during the PTUs on the horizon is determined. For the PTU example in Fig. 1 the price is $\lambda = 4.87$, meaning that the household consumes 1.35 kW during this PTU. For each PTU or timestep t, a bid curve is created, and the process is repeated until the power consumption for all timesteps within the horizon is determined to produce a t-sized load profile.

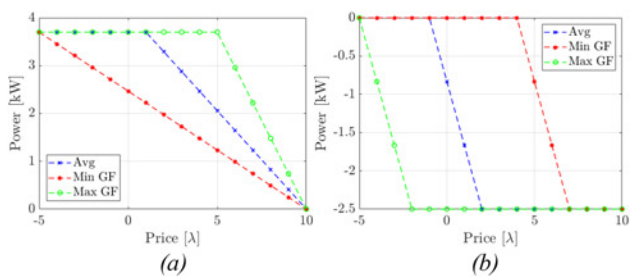

Fig. 2 *Biasing*

a EV bid curves
b PV bid curves. Average (blue crossed), minimum GF (red asterisked) and maximum GF (green), based on the GF

2.2.2 Updating prices: Once the load profiles of each household are determined, an aggregated load profile of all the households can be created. This aggregated load profile is then used to update the prices. For each PTU a generation bid curve is created and the aggregated load is then compared to the generation bid curve and the price λ is then adjusted accordingly. Fig. 3 illustrates how an aggregated load of 140 kW updates the price λ to 7.

The generation bid curve depends on the wind generation and the number of households h in the simulation. For negative prices, the generation bid curve is a linear line from zero to the available wind generation, and for positive prices, it is a linear line from the available wind generation to the maximum available power. To ensure that consumption can match generation but is not too high such that electricity becomes too cheap, the maximum generation possible is determined by:

$$P_{\max} = P_{\text{wind}} + 2 \cdot h$$

Fig. 3 shows a generation bid curve where the wind generation equals 50 kW and the number of households h equals 200. With the updated prices, the households update the load profiles based on the updated prices. This process is repeated for i iterations.

2.3 Grid layout

In this study, only congestion management is considered, and cable impedances are neglected. Therefore, the layout of the households is disregarded and can be added to determine the total load in the distribution grid. The number of households h depends on the executed test. Each household has a baseload, an EV and a PV panel. The EVs and PV panels are used for flexibility in power consumption, and the baseload is fixed. The maximum charging power of the EVs is 3.7 kW. The baseload and PV production is based on consumer data from a DSO. Behind the distribution transformer, a conventional power plant and wind turbines are placed. The conventional power plant produces the energy the wind turbines and PV panels are not producing. Fig. 4 shows an overview.

2.4 Simulation

Two scenarios are simulated, a winter and a summer scenario. The summer scenario has more PV generation available, and the winter scenario has a higher baseload consumption. Also, wind generation varies in both scenarios. The EVs arrival and leave times and charging energy are the same for both scenarios. Both simulations are in increments of 15 min and are run for seven

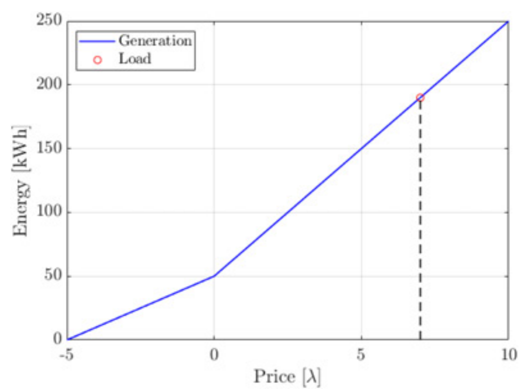

Fig. 3 *Updating the price, using the (blue) generation bid curve and (red dot) aggregated load during a PTU*

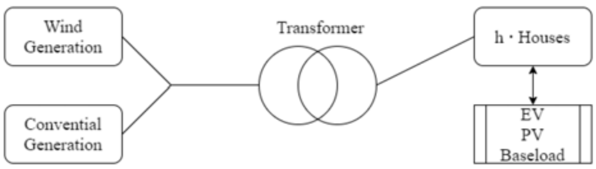

Fig. 4 *Overview of the system topology used in this study*

days, of which the first and the last day are omitted from the results because these days are used for starting the simulation (all EVs arrive at the same time) and closing the simulation (all EVs need to be fully charged at the same time).

2.5 Data

The load profiles of the connected households and generators are obtained from several data references. The wind generation is determined by the total Dutch wind energy production [5] and scaled to the number of households *h* in the simulation. The PV generation and the baseloads are load profiles obtained from actual data of consumers of a DSO, where the PV generation is in W/m^2 and the baseloads are in *kW*. The baseload and PV data vary between customers. The arrival and leave times of the EVs are determined from data obtained from a research institute [6]. The institute provides data for private, public and workplace chargers and in this study, the public chargers are chosen because the arrival and leave times are more evenly distributed. The amount of energy charged for each session is randomised for each EV between 5 and 40 kWh.

The dates used for the winter scenario are from the 24 January to the 1 February and for the summer scenario from the 23 to 31 of May. The years may vary between the devices and consumers.

2.6 Testing

2.6.1 Performance: The performance of these algorithms is tested by how well the methods can shift the consumption to match the renewable generation. The best performing method utilises the wind energy behind the transformer and the PV generation at each connection better. After running the simulations, the coal, combined renewable, wind and PV energy used by the algorithms are compared.

2.6.2 Scalability: Since the HMP is an iterative algorithm that moves through a horizon, this method requires more computational time per scenario. Therefore, it is important to understand how the method scales when the grid size, or the number of households, increases. To test this, the number of households is varied to see how both algorithms scale when the number of households is increased.

2.6.3 Bandwidth: Bandwidth does not have an impact on the capability of utilising renewable generation but requiring fewer data and communications makes an algorithm more resilient to outside interruptions such as package losses or data errors. After testing, the used parameters will tell more about the data and communication requirements and remarks can be made.

3 Results and discussion

3.1 Simulation results

With sensitivity analysis, it was found that the horizon length $t = 8$ and for GF $k = 4$ would give the HMP the best performance. The conventional, renewable, wind and PV energy usage/generation in Wh for the algorithms in both the winter and summer scenario can be found in Table 1. The power consumption (blue), renewable energy consumption (red) and conventional energy consumption (green) of both algorithms in both scenarios can be found in Fig. 5.

Table 1 Results algorithms for both scenarios in Wh

	Conv.	DG.	Wind	PV
FLMP winter	9195	9672	9284	389
HMP winter	9222	9632	9146	486
FLMP summer	8979	8555	6354	2201
HMP summer	9177	8308	5727	3144

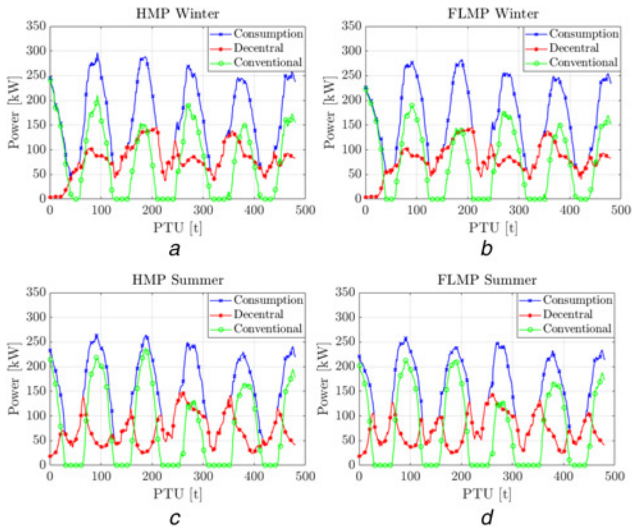

Fig. 5 *Overview of simulation results, power consumption (blue crossed), renewable energy consumption (red asterisked) and conventional energy consumption (green circled) of*

a, b Winter scenarios of both algorithms
c, d Summer scenarios of both algorithms

The results show that FLMP utilises 1.0% more wind energy in the winter and 5.3% more wind in the summer scenario compared to the HMP. Whilst the HMP utilises 1.0% more PV energy in the winter and 12.1% more PV energy in the summer scenario compared to the FLMP. In total, the FLMP algorithm has a larger percentage of the total power consumption come from renewable energy, 0.17% in the winter and 1.2% in the summer scenario compared to HMP.

The FLMP is better in utilising the wind energy available while the HMP better utilises the PV generation. This result might be due to the GF added to the bid curves of the HMP, where for lower prices PV energy is curtailed less than the PV bid curves in the FLMP algorithm. Although the results show that the FLMP makes better use of the available renewable energy, the differences for both scenarios are not significant and for the winter scenario, it is even within the margin of error.

The results show that the HMP, an algorithm in between the RHC algorithm and the FLMP algorithm, gives similar results to the FLMP algorithm. A reason that the results of the HMP are similar to the FLMP algorithm, might be due to the loss of independence between timesteps. In the HMP algorithm, future timesteps depend on the results of previous timesteps, whilst with the RHC algorithm, the timesteps are independent.

3.2 Scalability and data requirements

The computational time of varying the number of households *h* can be found in Table 2 and is determined on a laptop with 16 GB of RAM and an i7 8750 h. Both algorithms show a linear increase in computational time when the number of households *h* is increased. However, due to the significant amount of extra iterations, the HMP algorithm takes about two to five times longer to complete the simulation. The difference becomes more significant if the number of households becomes larger.

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Table 2 Results of increasing the number of houses

Households *h*	10	50	100	500
FLMP	2.7s	9.3s	17s	82s
HMP	9.3s	17s	86s	426s

Also, the HMP has a higher bandwidth, since the algorithm communicates more between negotiating the price and load profiles back and forth. More data, such as future wind and PV generation, is required as well since the HMP requires the expected wind and PV generation for all timesteps t within the horizon. This extra data requirement increases the implementation complexity of the algorithm.

4 Conclusion

This paper demonstrated a performance comparison between the FLMP and HMP algorithms. The HMP, a horizon algorithm based on bid curves, showed a comparable capability to shift consumption to generation to the non-horizon FLMP algorithm. Even though the results where comparable, the HMP takes longer to compute and requires more data and bandwidth to operate, increasing the implementation complexity.

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