Report on New Clustering Algorithms with Simulation Results

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1 Introduction

In the conventional power systems, balancing between the supply and demand sides is usually performed by changing the output of the centralized generation units. When the consumption rises, the generation has to be increased to meet the consumption. Similarly, the generated output must be lowered when the demand reduces [1]. However, in recent years, the power system is facing significant changes due to the high penetration of distributed generation (DG). Unlike the centralized generators, the DG units are mostly weather-dependent and thus offer limited controllability to follow the demand. They also introduce a higher uncertainty in the overall operation due to their varying size and the network levels they are connected to [2]. Emerging concepts, such as virtual power plants (VPPs) and micro-grid, have been introduced to facilitate a higher integration of DG and as well as to balance the supply and demand in the energy transition [3], [4].

In the liberalized electricity markets, a BRP is responsible for balancing the supply and demand for its portfolio of producers and consumers. The BRP forecasts the required energy supply and demand of its portfolio and seeks the most economical solution to maintain the balance. If the BRP does not fulfil this task, the transmission system operator (TSO) could charge an imbalance penalty cost based on the amount of imbalance of the BRP and the amount of imbalance in the system [5]. To avoid this problem, flexibility can be procured from micro-grids using real-time market-based demand response (DR) methods. The aggregator can efficiently coordinate the process, since it is responsible for managing the supply and demand of the prosumers in a micro-grid.

A large body of literature has been developed in recent years for dealing with local supply and demand balancing in the micro-grids [6], [7]. In its basic form, a micro-grid is usually defined as a group of physically interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the network [8]. Depending on the configurations, such physical micro-grids can be operated in grid-connected or islanded modes. However, a physical micro-grid is limited in a certain geographical location, and hence limits the use of flexibility for real-time support of the imbalance market [9]. To compensate for the lack of flexibility, the concept of dynamic micro-grid is introduced in [10]. Unlike the fixed topology of a physical micro-grid, a dynamic micro-grid changes its configuration according to demand fluctuations due to unforeseen reasons. The dynamic changes have been reported to be able to keep the mismatch between the forecasted and real-time demand under 6.6\%. However, the computational time of such a system exceeds 15 minutes, when at least 50 consumers are connected in the micro-grid. Another major drawback of the dynamic micro-grid is the additional investment required for the alteration of the micro-grid configuration.

In a complementary development, virtual or commercial micro-grids have been growing in popularity for energy management and market integration of smart micro-grids [9], [11], [12]. Virtual micro-grids represent a group of prosumers coordinated by a single aggregator who are not limited to geographical locations. Since the prosumers connected in a virtual micro-grid are not limited by network topologies, the configuration of such micro-grids can be easily altered. In other words, different clusters of prosumers can be formed depending on the need of the aggregator. In this context, a clustering approach for balancing supply and demand for real-time operation is introduced in [9]. A distributed information exchange algorithm (gossiping) is used to form virtual clusters of end-users. The objective of the work has been building as many balanced virtual clusters as possible. However, no active actions are taken in the algorithm to minimize the net imbalance, resulting in at least one unbalanced cluster at all times. Consequently, the net imbalance of the whole system remains the same with and without the clustering algorithm. Several clustering techniques, namely spectral clustering algorithm, genetic algorithm, and real-time clustering have been investigated in [11] in order to minimize the imbalance cost. However, like [9], the clustering techniques merely regroup the end-users, without affecting their total consumption or generation, and consequently the total imbalance of the system. To this end, suitable market-based DR methods can efficiently circumvent this problem by clustering the prosumers according to their demand. In this paper, a dynamic clustering mechanism is proposed in order to provide flexibility for minimizing the imbalance cost during real-time operation. The remainder of the report is organized as follows: Section 2 presents the background of the market-based supply and demand balancing, including the agent based DR platform; Section 3 elaborates on the clustering techniques for imbalance management; Section 4 discusses the simulation case study, before concluding with Section 5.

2 Market-based Local Balancing and DR

Market-based approaches have been drawing an extensive attention of late with the growing sources of flexibility in the forms of household appliances and small-scale generation units [13]–[15]. Utilization of demand flexibility has been investigated for diversified applications ranging from balancing services [5], [16] to network support [17], [18]. In this regard, different types of price-based and incentive-based DR programs have been proposed to procure flexibility from the small-scale end-users. Due to the scalability issues of the DR programs, local flexibility markets have shown to have immense potential to facilitate a seamless interaction among the involved actors [19].

2.1 Agent-based local balancing framework

Multi Agent System (MAS) based distributed intelligence has been widely implemented for power system applications for its ability of managing complex and interconnected systems [18]. In this work, the MAS-based hierarchical architecture, as discussed in [18], has been employed as the DR platform. As shown in Figure 1, in this platform, residential DERs are represented by software agents with main objective being the optimal operation of respective devices. An internal control signal, expressed in per unit values ranging from 0 to 1 is used to coordinate the agents.

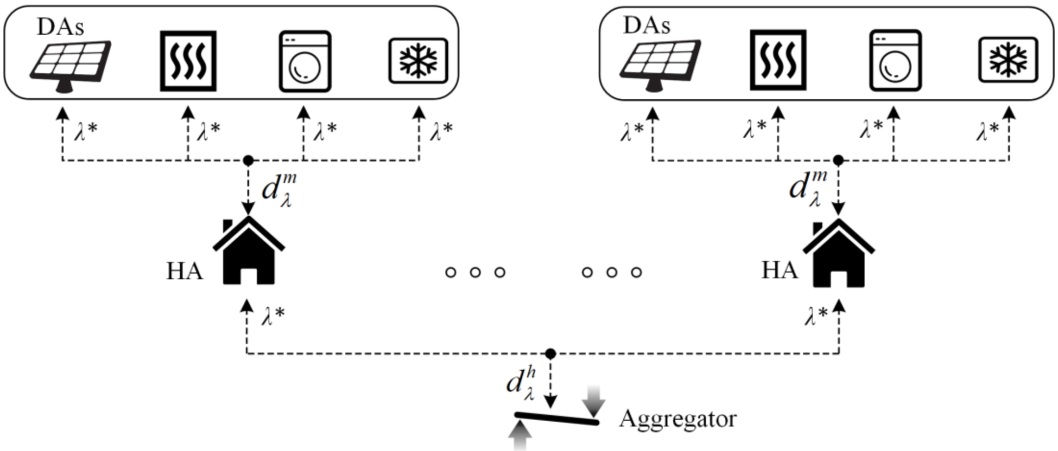

Figure 1. Distributed system architecture [20].

In this bottom-up approach, device agents (DAs) represent the appliances and DG units in each household. Each DA determines the priority of the respective device, m in each time step, t as a function of the control price signal, λ. The priority is expressed in terms of a bid (d_t^m) of expected levels of power consumption/generation in the next time interval. A House Agent (HA) collects the device bids and combines them in a house bid, $d_{t\lambda}^h$ such that,

$$d_{t\lambda}^h = \sum_{m=1}^{N_m} d_{t\lambda}^m \tag{1}$$

where, N_m denotes the number of devices available at house h. The house bids are sent to the aggregator for the development of the aggregated bid, $d_{t\lambda}^a$.

$$d_{t\lambda}^{a} = \sum_{h=1}^{N_h^a} d_{t\lambda}^{h} \tag{2}$$

where, N_h^a is the number of households present in aggregator's portfolio. For the scalability purposes, the aggregator can classify their prosumers in separate clusters.

The aggregator calculates the equilibrium point as the control signal, λ^* by matching the supply and demand of its prosumers (eq. (3)) and returns it to the DAs via respective HAs.

$$\lambda_t^* = \arg\min \left| d_{t\lambda}^{a} \right| \tag{3}$$

The DAs govern the actions of the corresponding devices based on the received signal. Thus, the net power consumption of each household, P_t^h is given by,

$$P_t^h = d_{t\lambda_t^*}^{h} \tag{4}$$

Since the equilibrium control signal replicates the dynamic price signal, it will henceforth be termed as the local price for the prosumers. A more detailed discussion of the coordination mechanism can be found in [18].

The above mentioned methodology aims to maximize the social benefit by matching the local supply and demand. This platform can be essentially utilized for procuring flexibility from the prosumers. A methodology has been proposed in [18] to make use of the aggregated flexibility for congestion management of distribution transformers. In this paper, the prosumers will be dynamically clustered in groups for procuring adequate flexibility in order to minimize the imbalance cost of the aggregator.

2.2 Sourcing the Flexibility

The aggregated bid, $d_{t\lambda}^{a}$ depicts the priority of all the prosumers in the portfolio of the aggregator at time t. The available flexibility of the aggregator at that time can thus be calculated from the aggregated bid and the equilibrium price, λ_t^*. This is done by taking the respective shifts in power from the aggregated bid for the shifts from equilibrium price. Thus, the available flexibility offers of the aggregator at each time step are given by,

$$F_t^a = d_{t\lambda}^{a} - d_{t\lambda_a^*}^{a} \tag{5}$$

where F_t^a denotes the flexibility offers of the aggregator at time t.

3 Clustering for Imbalance Management

In every time step, the procurable flexibility can be used by the aggregator to balance the mismatch owing to the uncertainty of the local generation (forecasting error) or the deviation from the predicted demand. Let us define the power mismatch occurred at each time step t, ϵ_t as follows:

$$\epsilon_t = P_t^f - P_t^r \tag{6}$$

where, P_t^f and P_t^r denote the forecasted and actual load at time, t respectively.

Corresponding imbalance cost, c_t^{im} is then given by,

$$c_t^{im} = p_t^{im} \epsilon_t \Delta t \tag{7}$$

where p_t^{im} and Δt depict the imbalance price at time, t and the length of the time interval in hours respectively.

The aggregator can minimize the imbalance cost by procuring flexibility from the contracted prosumers. A negative mismatch implies that the forecasted demand is less than the real-time load (underestimation), which can be rectified by selecting flexibility offers with a lower load representing an increased equilibrium price. Similarly, the overestimation or positive mismatch resulting from a higher forecasted demand can be minimized by selecting a flexibility offer with an increased load, i.e. by lowering the equilibrium price.

Since the process of minimizing the imbalance requires a shift from the equilibrium price, an incentive is paid to the prosumers for the shift. In reality, calculating the incentive involves complex market dynamics and diverse business models of the aggregator. In this work, a simplified approach is adopted by using the day-ahead price as per unit cost of the procured flexibility. Thus, the total payable incentive, c_t^{in} is given by,

$$c_t^{in} = p_t^{DA} F_t^{*} \Delta t \tag{8}$$

where p_t^{DA} and F_t^{*} denote the day-ahead price and the selected flexibility offer at time, t respectively.

The total cost at each time step, c_t^{total} is thus determined by the summation of the imbalance cost and the payable incentive.

$$c_t^{total} = c_t^{im} + c_t^{in} \tag{9}$$

However, the procured flexibility following the aforementioned scheme involves all the prosumers of the aggregator's portfolio. Consequently, the procured flexibility may be significantly higher than the required amount. A more convenient approach would be to select the prosumers in an optimal way or by clustering the prosumers based on their flexibility and select suitable clusters in a more dynamic way.

3.1 Optimized Selection of Prosumers

Instead of considering the aggregated flexibility of all the prosumers, in this case, flexibility will be procured from some selected prosumers of the aggregator. The selection is performed with an objective of minimizing the total incurred cost. The cost minimization problem, as shown in eq.(10), selects flexibility offers from the prosumers and is constrained by the new mismatch following the procurement of flexibility, ϵ_t^{new}.

$$\min_{x_i^h} \sum_{h=1}^{H} \sum_{i=1}^{n(F_t^h)} \left(\left| x_i^h F_i^h t p_t^{DA} \right| + \left| \epsilon_t^{new} p_t^{im} \right| \right) \Delta t \tag{10}$$

subject to,

$$\sum_{i=1}^{n(F^h)} x_i^h \leq 1 \tag{11}$$

$$\sum_{h=1}^{H} \sum_{i=1}^{n(F_t^h)} \left(\left| x_i^h F_i^h t \right| + \left| \epsilon_t^{new} \right| \right) = \left| \epsilon_t \right| \tag{12}$$

$$\sum_{h=1}^{H} \sum_{i=1}^{n(F_t^h)} \left(\left| x_i^h F_i^h t p_t^{DA} \right| + \left| \epsilon_t^{new} p_t^{im} \right| \right) \leq \left| \epsilon_t p_t^{im} \right| \tag{13}$$

where, x_i^h is the binary decision variable that selects i -th flexibility offer of house, h. $F_i^h t$ denotes the flexibility offers available at each household, while $n(F_t^h)$ gives the total number of available flexibility offer of house, h at time, t. Constraint in eq. (13) restricts from selecting multiple flexibility offers from one house. Eq. (13) maintains the balance between the mismatch and offered flexibility, while constraint in eq. (13) is imposed to limit the total cost within a value lower than the original imbalance cost.

For the selected households, the net consumption is calculated by the consumption as depicted in eq.(4) , plus the amount of procured flexibility. Thus, eq. (4) can be rewritten as,

$$P_t^h = d_{t\lambda^*}^h + x_i^h F_i^h t \tag{14}$$

3.2 Dynamic clustering

The optimized selection approach requires an extensive calculation involving many integer variables. The dynamic clustering approach is introduced in order to circumvent the computational burden by clustering the houses according to their flexibility offers. The house bids of each cluster are then aggregated to obtain the flexibility offers of the respective cluster. First, a clustering method is discussed considering a fixed number of clusters. Next, a simplified approach of adaptive clustering is also proposed.

3.2.1 Fixed number of clusters

The main objective of the clustering is to reduce the computational burden of selecting suitable flexibility offers. In order to do so with a reasonable degree of accuracy, the clustering algorithm needs to ensure that the optimization problem still has as many options as possible for the optimization algorithm, i.e. evading as many clusters with zero flexibility offer as possible. Thus, the first step of the proposed clustering algorithm is to calculate the number of HAs with nonzero flexibility offers, NZ_t^{flex}. A uniform number of members is assumed for each cluster, which is determined by,

$$M = \left\lceil \frac{NZ_t^{flex}}{K} \right\rceil \tag{15}$$

where, K and M denote the number of clusters and number of households in each cluster respectively. M households are assigned to each cluster based on the descending order of flexibility offers. The cluster of the households are then considered for procuring the flexibility. Thus, the optimization problem in eq.(10) – (13) can be rewritten as,

$$\min_{x_i^k} \sum_{k=1}^{K} \sum_{i=1}^{n(F_t^k)} \left(\left| x_i^k F_i^k t p_t^{DA} \right| + \left| \epsilon_t^{new} p_t^{im} \right| \right) \Delta t \tag{16}$$

subject to,

$$\sum_{i=1}^{n(F_t^k)} x_i^k \leq 1 \tag{17}$$

$$\sum_{k=1}^{K} \sum_{i=1}^{n(F_t^k)} \left(\left| x_i^k F_i^k t \right| + \left| \epsilon_t^{new} \right| \right) = \left| \epsilon_t \right| \tag{18}$$

$$\sum_{k=1}^{K} \sum_{i=1}^{n(F_t^k)} \left(\left| x_i^k F_i^k t p_t^{DA} \right| + \left| \epsilon_t^{new} p_t^{im} \right| \right) \leq \left| \epsilon_t p_t^{im} \right| \tag{19}$$

where, x_i^k is the binary decision variable that selects i -th flexibility offer of cluster, k . $F_i^k t$ denotes the flexibility offers available at each cluster, while $n(F_t^k)$ gives the total number of available flexibility offer of k -th cluster at time, t . The optimization problem defined by eq.(16) – (19) represents a simplified version of the optimized selection approach. Evidently, the required computation has been reduced by using the clusters instead of the households. Since the number of clusters can be considerably less than the number of households ($K << H$), the number of integer variables will be reduced significantly.

3.2.2 Adaptive clustering

The number of required clusters can be varied in each time step according to the observed mismatch. When the number of clusters, K is high, each cluster can have flexibility offers with high granularity. Thus, smaller mismatches are intuitively easier to be minimized with large number of clusters. Similarly, using a low value of K leads to clusters with high flexibility offers. An empirical first-order relation is therefore assumed between the mismatch and number of clusters as,

$$K \approx a\epsilon_t + b \tag{20}$$

where a and b can be approximated by observing the maximum and minimum values of mismatch error resulting from a certain range of K . Thus, the number of required clusters can be altered based on the mismatch for later time steps.

4 Case Study

4.1 Simulation setup

A simulation case study is performed with a time step of 15 minutes considering one aggregator controlling 600 houses and one wind farm. The equilibrium price is expressed in discrete per unit values between 0 and 1 with a step size of 0.05.

Each household is equipped with freezers, solar PV systems, heating devices, and uncontrollable base loads. In order to satisfy the heating demand, 90% of the households are equipped with heat pumps, while the rest is µCHPs for the purpose. The uncontrollable base loads have been modelled using normalized profiles of Dutch households [21]. Typical rated values of other devices and parameters are shown in Table 1. Outdoor temperature, solar irradiation and wind speed data are obtained from Royal Dutch Meteorological Institute (KNMI) [22].

In this work, the wind power is considered as the only uncertainty source. The forecast errors are realized using a Gaussian distribution with statistical requirement shown in Table 1 [23].

Table 1. Simulation parameters

Property	Values
Installed PV capacity	1.5 to 6 kWp
Rated power of the freezer	150 W to 400 W
Temperature range of freezer	-15° to -30°C
Rated pump power of HP	1.5 kW to 2 kW
Rated resistive heating of HP	3 kW to 3.5 kW
Household temperature range	17° to $23°C
COP of HP	2.5 to 3.5
Rated power of µCHP	800 W to 1200 W

Wind turbine cut in velocity	0.5 m/s
Wind turbine rated velocity	12 m/s
Wind turbine cut out velocity	50 m/s
Wind turbine rated power	31 kVA
Wind turbine diameter	11.2 m
Installed wind capacity	1560 kVA
Wind forecast error deviation	0.01 p.u. (normalized by installed wind capacity)
Wind forecast error mean	0
Number of wind farms	1
Number of wind turbine	50

The simulation is conducted in Matlab R2015a environment with an Intel core i7 processor and 8 GB of RAM. The optimization process uses MILP optimization solver of Matlab optimization toolbox.

4.2 Numerical results

Overall performances of the proposed approaches are assessed in terms of net energy mismatch, total savings, and associated computation time for a typical spring week in April. Three proposed approaches, as discussed in Section 3, are termed as-

- Case 1 - Basic shift considering all the households
- Case 2 - Optimized selection of households, and
- Case 3 - Dynamic clustering.

First, a comparative analysis among three cases is presented considering $K = 80$ followed by a more in-depth discussion on the efficiency of the dynamic clustering method.

4.2.1 Comparative analysis

Table 2 illustrates the simulation results in percentages of the case without any control. As expected, Case 1 takes significantly less time than the other two approaches. This is because, virtually no computation is required to determine the change in price signal in this case. However, Case 2 and Case 3 outperform Case 1 by a large margin in terms of minimized imbalance and subsequent savings in cost.

Although the gain in mismatch and cost saving are similar for Case 2 and Case 3, the latter shows a considerably higher efficiency in terms of simulation time. This is expected since, 80 clusters are taken into consideration for Case 3 compared to 600 houses in Case 2.

Table 2. Comparative performance of the cases

Total mismatch = 2119.7 kWh Total cost = EUR 99.77			
Cases	**Net mismatch (%)**	**Cost saving (%)**	**Time (s)**
Case 1	41.81	52.24	0.57
Case 2	9.44	84.67	25387
Case 3	9.25	85.44	1532.34

4.2.2 Effect of number of clusters

The effects of different number of clusters have been summarized in Table 3 keeping the forecast error and associated cost fixed. The number of clusters, K has been varied between 5 and 120. The savings in cost and net mismatch have been expressed as percentages of corresponding values with no control applied. It can be observed that as K increases, the net mismatch decreases while the savings and computational time increase. Availability of more clusters ensures more options to choose from, leading to better results at the expense of a higher computation time.

However, it is worth noting that, the reduction in mismatch and gain in total savings tend to stop as K becomes higher than 40 and becomes constant when K is 80. Therefore, 40 and 80 will be used as the values of K for the approximation of a and b of adaptive clustering.

Table 3. Effects of different number of clusters

Total mismatch = 2119.7 kWh Total cost = EUR 99.77			
K	**Net mismatch (%)**	**Cost saving (%)**	**Time (s)**
5	25.75	78.49	35.31
10	16.92	82.2	57.09
20	11.59	84.29	161.22
30	10.26	84.78	366.6
40	9.65	85.2	551.43
50	9.39	85.33	760.02
60	9.33	85.38	931.11
80	9.25	85.44	1532.34
100	9.25	85.44	1882.05
120	9.25	85.44	2412.00

4.2.3 Performance of the adaptive clustering

The performance of the adaptive clustering has been assessed compared to the dynamic clustering method with $K = 80$. In order to estimate the values of a and b, maximum and minimum forecast error is observed with K being 40 and 80. In each time steps, the number of cluster is then altered based on the realized mismatch. As shown in Table 4, the resulting energy mismatch and cost saving are similar between the two methods. However, the time required by the adaptive clustering is considerably lower than the non-adaptive counterpart.

Table 4. Performance of the adaptive clustering

Total mismatch = 2119.7 kWh Total cost = EUR 99.77			
Cases	**Net mismatch (%)**	**Cost saving (%)**	**Time (s)**
Non-adaptive	9.25	85.44	1532.34
Adaptive	9.25	82.45	128.68

4.2.4 Effects of installed wind capacity

The adaptive clustering method has been evaluated for varying degree of installed wind capacity. The number of wind turbine used by the wind farm is varied from 20 to 200. The resulting energy mismatch, total savings and computation time have been tabulated in Table 5. While the net mismatch and cost savings vary within 2%, the computation time is limited within ±200s for different penetration levels of wind. The adaptive clustering is shown to be quite robust, as the performance indicators do not vary much for different levels of wind generation.

Table 5. Effects of installed wind capacity

Installed wind capacity (kVA)	Uncontrolled mismatch (kWh)	Net mismatch (%)	Cost saving (%)	Time (s)
624	834.75	10.17	84.73	1348.74
1560	2119.7	9.24	85.45	1228.68
3120	4313.9	10.16	84.29	1505.64
4680	6199.2	11.23	84.78	1605.42
6240	8692.7	11.89	83.88	1488.18

4.2.5 Impact on the prosumers

Since the approaches inherently aim to influence the demand through the changes in prices, an impact is expected on the attributes of each flexible device. In this section, the effect of price shift on the heating devices and freezers are analysed. The histogram of the probability of the daily average temperature of the households and the freezers are shown in Figure 2.

It is evident that in the controlled case, the working temperatures of the heating devices tend to shift to the lower allowable limits while the inside temperature of the freezers shift towards the higher acceptable margin. It is important to note that, the temperature set points are not violated, i.e. the household interior temperature stays above 17°C and the freezer temperature stays below -17°C.

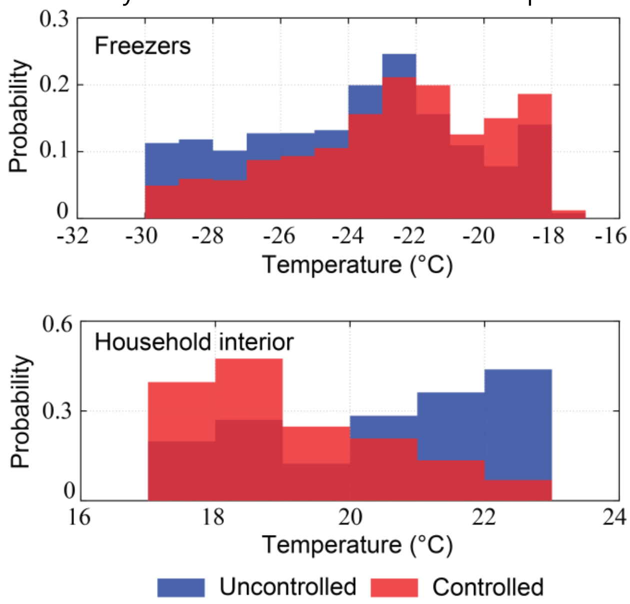

Figure 2. Probability of the daily average temperature for the controlled and uncontrolled case.

5 Conclusion

The focus of this work has been to propose a suitable mechanism for real-time dynamic clustering of the prosumers in commercial micro-grids for imbalance management through local supply and demand balancing. An agent-based platform has been used to implement the DR methodology combining with the local balancing scheme. Three flexibility-procurement methodologies have been investigated through simulations for 600 households.

Simulation results indicate a high efficiency of the proposed dynamic clustering approaches in terms of cost saving and computational time. Significant savings in imbalance cost have been achieved by utilizing the flexibility offers from the demand side clusters. Furthermore, the adaptive clustering method has shown promising results for varying levels of wind generation.

Future research will be directed towards modifying the adaptive clustering mechanism for solving simultaneous issues of the electricity market and distribution networks. In order to represent a more realistic scenario, more uncertainty sources, such as solar irradiation and base load demand need to be included. Moreover, the coordination mechanism needs to be improved facilitating multiple market actors in the process.

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