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Dynamic, self-organized clusters as a means to supply and demand matching in large-scale energy systems

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Centralized management of power systems is becoming more challenging due to the increased introduction of distributed renewable energy resources, along with demand increase and aging infrastructures. To address these challenges, this paper proposes new mechanisms for decentralized energy management. Based on *self-organization* of consumers, prosumers and producers into virtual groups, called *clusters*, supply and demand of electricity is locally matched. Distributed multi-agent systems are used as a way to represent virtual cluster members. The mechanisms are illustrated, and static and dynamic virtual clusters are compared. Dynamic reconfiguration is achieved by varying the time periods for which clustering is performed. The proposed clustering mechanisms demonstrate that large-scale centralized energy systems can operate in a decentralized fashion when only local information is available.

1 Introduction

Power systems are large scale, complex socio-technical systems that provide society with one of its most valuable assets: electricity. Electricity is not only an irreplaceable asset in households, but is also vital for day-to-day operations of today's critical infrastructures. The main objective of power systems [3] is to constantly ensure that there is enough electricity supply to meet the demand of consumers. This is also known as supply and demand matching or balancing. In a traditional power system, this matching is centrally controlled, with big power plants with centralized generation still as the main electricity suppliers [19]. As power systems increase in size and complexity, centralized control becomes more challenging [3]. This is particularly the case due to the increased introduction of distributed renewable energy resources (DER) [9]. As a consequence of increased flexibility of the demand-side for choosing supply sources, traditional, centrally controlled nature of energy systems management is changing to coordination among a large number of supply sources and responsive loads [19]. Thus, the complexity of an already highly complex system is increasing.

To handle this complexity, different types of decentralized organization of power systems that enhance local control with respect to power supply and demand [4, 5, 15] have been proposed. Methods for minimizing centralized control are proposed in [4, 5, 9]. These methods use complex adaptive systems to represent power systems, and intelligent agents as their components. The potential of a multi-agent approach to manage distributed energy resources is assessed in [19,20,28], where residential combined heat and power units are represented by individual groups acting as a type of a virtual power plant. While these papers envision power systems as decentralized, they do not propose mechanisms for enabling this decentralization.

Key concepts such as microgrids and virtual power plants (VPPs) have been introduced in the past to facilitate decentralized power system organization, and to support the increased introduction of distributed renewable energy resources into power systems [7, 16]. Microgrids are subsets of existing power systems that can operate together with the main power system, or run independently in an *islanded* mode. The latter is considered one of the main beneficial characteristics of microgrids. However, microgrids require sophisticated physical infrastructure for their operation and are tied to specific geographic regions, making them static (non-reconfigurable) [7,24]. Future microgrids are envisioned as being able to dynamically meet changing objectives in real-time. This requires the change in power systems management, as well as the change in system infrastructure. One of the main motives for enabling real-time, dynamic reconfiguration is to improve system resilience and quality of service for consumers [27].

Unlike microgrids, virtual power plants do not require a dedicated infrastructure. Their main aim is to group several types of power sources, and allow them access to the energy market as a group for economic and other reasons [7]. VPPs are typically organized as fixed groups. As such, the composition of a VPP does not change over time. In contrast with microgrids, VPPs are not designed for islanding during outage periods, thus they are always grid-tied. However, an advantage of VPPs is that they are not geographically limited and do not require new, sophisticated infrastructures [7].

Both microgrids and VPPs are promising developments in the move towards a more decentralized power system. However, both typically assume prior full knowledge of a power system, focus on long term relationships with their members and lack the flexibility required for near real-time dynamic supply and demand matching in changing group compositions, see e.g. [10].

The rest of the paper is organized as follows: Section 2 gives an overview of clustering and explains the concept in context of this paper, Section 3 explains the proposed decentralized clustering mechanism in detail, Section 4 describes the conducted experiments, and Section 5 discusses the obtained results. Finally, Section 6 summarizes the main conclusions and gives suggestions for future work.

2 Clustering as the enabling mechanism of decentralization

In this paper, the concepts of microgrids and VPPs are further extended with clustering techniques for enabling the formation of dynamic, virtual groups in power systems. These virtual groups locally perform electricity provisioning and are able to adapt to changes in supply and demand.

Clustering is a technique used to organize objects into groups according to a specified criteria [14,17]. Depending on its operation, clustering can be distributed or centralized. In centralized clustering methods, such as K-means, a central repository contains the information about the entire system and performs clustering. In contrast, in a distributed approach, nodes have only local information and obtain aggregate information about other nodes by communicating [22, 23, 26]. Depending on the changes in their composition, clustering can be static or dynamic. In dynamic clustering, clusters adapt to changes in the environment by changing their composition, whereas in static clustering, clusters are initially formed and do not change during their lifetime [12].

In this paper, consumers, prosumers and producers organize themselves into local communities [4, 5, 15], which are referred to as *virtual clusters*. Geographical distance, and load and production profiles are the main clustering criteria, whereas the main objective is to locally, i.e. within a cluster, minimize supply and demand mismatch. Autonomous organization into clusters based on local information is referred to as *self-organization*. Self-organized clusters enable more flexibility in matching local demand and supply [8]. Clusters reconfigure to adapt to changes in the dynamic environment. This paper proposes mechanisms that do not assume full knowledge of a power system and rely only on local information of every system member.

The main objective of developing the mechanism for dynamic self-organization is twofold, namely (i) to demonstrate that large-scale centralized systems can operate in a decentralized fashion when only local information is available, and (ii) to study the effects of changing the time period for which clusters stay the same, thus, to observe the differences in outcomes of static and dynamic clustering.

3 Clustering algorithm for decentralized supply and demand balancing

The proposed mechanisms abstract from the physical layer of power systems. Clustering is performed on the virtual level, relying on external communication, e.g., using telecommunication networks, to create the grouping.

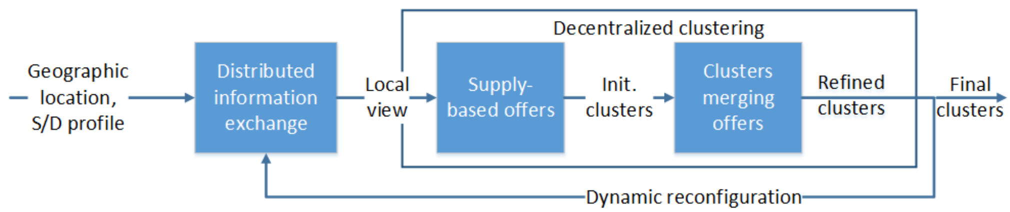


Figure 1: The proposed clustering mechanism

Cluster members are represented by autonomous agents with a local view of the system that exchange information with other agents. This paper assumes that every consumer, prosumer and producer in a power system has a computational device on which an autonomous agent (a software component) is installed that acts on their behalf. Thus, a consumer is represented by a *consumer agent (CA)*, a prosumer by a *prosumer agent (PSA)*, and a producer by a *producer agent (PDA)*. Devices which agents are installed on are distributed across the network and can communicate with each other, regardless of the geographical distance. Every agent contains information such as its own geographic location, load and production profile for a period of time (usually a daily profile), energy type produced, and the cluster which it belongs to. Load and production profiles of every agent are sampled every hour, and these sampled profiles are then used to match supply and demand with other agents or clusters. Agents are reconfigurable, enabling individuals they represent to change their settings at any time. They negotiate membership in clusters, and can send and receive membership offers. Each agent can belong to only one cluster and each cluster has a coordinator which monitors it, and manages and facilitates the negotiation. Agents can accept or reject cluster membership offers. Negotiation results in a formed service level agreement (SLA), that specifies the terms and conditions of electricity service provisioning [11]. Negotiation can be performed using one of the standard negotiation protocols for SLAs, such as Web Services Agreement [6, 21]. In this paper, SLAs contain information about the membership offer, and are as such used as a means to fix cluster boundaries.

As seen on Fig. 1, the process starts by building a local view containing the geographically closest neighboring agents of every agent. In this work, geographic proximity is taken as the distance measure, more advanced distance measures are left for future research. To build this local view, a distributed information exchange algorithm (gossiping) is used. This algorithm assumes that every agent is reachable by any other agent in the system, either directly or through alternative paths (via other nodes) [13,18]. After building the local view, the distributed clustering phase begins. Each agent has a local objective function, which differs based on the agent's type. For *PSA*s and *PDA*s, the initial objective is to provision electricity to those *CA*s whose demand is the highest. *PSA*s and *PDA*s ask *CA*s which match their objective function to join their clusters. This step results in membership offers sent to *CA*s. *CA*s assess every offer received, and choose the best one. In this case, the best offer is the one which minimizes *CA*'s mismatch. The process is repeated until all the *CA*s are clustered. This phase results in initial clusters, formed by local objectives of its members. Cluster coordinators of the generated clusters are the *PSA* or the *PDA* that initially sent the offers.

The next phase refines the clusters by letting the coordinators communicate and send offers to merge clusters. In this stage, the objective of every cluster is to minimize its supply and demand mismatch. Coordinators (*PSA*s or *PDA*s) send offers for merging to neighboring (geographically closest) clusters (see Algorithm 1). Offers are sent only to those clusters whose mismatch, when combined with that of the cluster sending the offer, is closest to zero. The number of offers sent is parametrized. Clusters that receive an offer can either accept or reject it, depending on how good it is. In this case, a good offer means that the mismatch will be decreased. The output of this phase are the final clusters. The number of rounds for which this process is repeated is controlled by parameters such as maximum cluster size, and maximum number of iterations. Clustering is performed for different time periods, observing the changes in cluster numbers, sizes and composition in dynamic environments.

Algorithm 1 Decentralized supply and demand matching

```
procedure REFINE CLUSTERS
    for all Clusters do
        C_N ← N best neighboring clusters
        for all C_N do
            Send membership offer O_n
        end for
        for all Clusters do
            if received offers ≥ 0 then
                O_b ← best offer
                if O_b mismatch < cluster mismatch then
                    Accept O_b
                end if
                Reject pending offers
                Send Accept/Reject to clusters
            end if
        end for
        for all Clusters do
            if accepted offers ≥ 0 then
                O_b ← best accepted offer
                Add the agent A(O_b) to the cluster
                Recalculate cluster mismatch
            end if
        end for
    end for
end procedure
```

The main objective is to minimize the supply and demand mismatch on the local level (i.e. on the cluster level). The mismatch of an agent a at time t is calculated using Equation 1. Accordingly, the mismatch of a cluster c (containing N agents) at time t is calculated using Equation 2. In this paper, a positive mismatch denotes overproduction (surplus), while a negative mismatch represents underproduction (shortage of supply). Zero mismatch means that the cluster is in perfect balance. Surplus of electricity in a cluster is fed into the backbone grid, while lack of supply is covered by drawing the electricity from the main grid. Clusters can reconfigure based on changes in supply and demand, e.g. cluster composition can change every hour or every day, depending on the determined time period for which it is performed. Thus, the generated clusters are virtual groups of consumers, prosumers and producers, which are able to dynamically change their group composition according to changes in the (external) environment or their (internal) preferences.

$$agent\ mismatch = Supply_{(t)} - Demand_{(t)} \tag{1}$$

$$cluster\ mismatch(t) = \sum_{n=1}^{N} Supply_{(n,t)} - Demand_{(n,t)} \tag{2}$$

To join another cluster, the absolute mismatch between an agent and members of a cluster is calculated using Equation 3. For every sample at time t, supply and demand mismatch of all N agents is calculated. Then, the absolute values of all the mismatches are summed to obtain the total absolute mismatch between N agents. Absolute values are used so that the amount of overproduction or underproduction per hour is preserved. The agents join clusters that are closest to their profiles, i.e., with the minimum *absolute* and *cluster mismatch*. This approach ensures that agents join the cluster that most closely matches their profiles.

$$absolute\ mismatch = \sum_{t=0}^{T} \left| \sum_{n=1}^{N} (Supply_{(n,t)} - Demand_{(n,t)}) \right| \tag{3}$$

This mechanism can be used to encourage demand to follow supply, since consumers can shift their load to join a cluster which meets their objective at a given time period. This is more realistic in a more dynamic scenario, where clustering is performed every 8 hours or on hourly basis.

Clustering in this way gives local empowerment to every agent, and allows flexibility in adapting to changes in supply and demand, without rerunning the process for the entire system. Thus, nodes entering or leaving the system can use the local view of the neighborhood to decide which cluster to join.

Currently, the same simple, local objective functions (per agent type) are used to form initial clusters. However, due to its configurability, different (individual) objective functions can be used per agent, allowing the objectives to include preferred type of electricity supply, cost functions, duration of service provisioning, or priority level as clustering criteria.

4 Experiments

This section studies the outputs of the proposed clustering mechanism by assessing supply and demand mismatches of generated clusters, as well as the number of clusters obtained. To demonstrate the ability of generated clusters to reconfigure based on changes in the environment (changes in supply and demand), time periods for which clustering is performed are varied, and static and dynamic clusters are compared.

4.1 Experiments assumptions

The daily load profile data used for the experiments is obtained from NEDU [2], the Dutch energy data exchange, and represents an average load profile of a Dutch household consumer. To diversify household profiles, the load profile data is varied for a sampling period applying a normal distribution, generating variations of maximum $\pm 20\%$. Prosumers with solar production are modeled. Solar power production of prosumers is calculated as in [25], using the Dutch solar irradiance data [1]. The data from July 1, 2015 is used in the experiments. To ensure that there is enough supply to meet the demand for a period of a day, diesel generators with capacities of 10 kW which run constantly for the period of a day, are modeled as production units. Clustering is performed for a maximum period of a day (24 hours). This work assumes that every agent has perfect information of their own demand and/or supply for the clustering period. Future work will explore how forecasting mechanisms can be used to deal with partial information about both energy demand and supply.

4.2 Key performance indicators (KPIs)

As the main objective of power systems is to match supply and demand of electricity [3], supply and demand mismatch is taken as the main clustering criteria, with the main objective being to minimize the mismatch within clusters.

The key performance indicators (KPIs) used for evaluation of obtained clusters are the following:

1. **Supply and demand mismatch of a cluster**: Total supply and demand mismatch of cluster members is calculated by summing up all the members' mismatches.

2. **Average supply and demand mismatch of all the clusters for a given period**: Supply and demand mismatches of all the clusters are summed at every hour, and an average is taken.

3. **Average negative supply and demand mismatch of all the clusters for a given period**: Supply and demand mismatches of all the clusters with negative mismatches are summed at every hour, and an average is taken.

4.3 Experimental setup

The experiments are run with 500 agents, each with full knowledge of its own production, consumption, and geographic location.

To ensure that there is enough total supply to meet the demand for a period of a day, experiments varying the percentage of consumer, prosumer, and producer agents are conducted. The system configuration which gives the average mismatch closest to zero is chosen.

The experiments use three case studies to assess the outcomes of the proposed clustering mechanism, namely: (i) daily clustering (static), (ii) clustering every 8 hours (dynamic), and (iii) hourly clustering (dynamic). In this work, dynamism refers to how frequently clusters reconfigure within the longest time period for which clustering is performed.

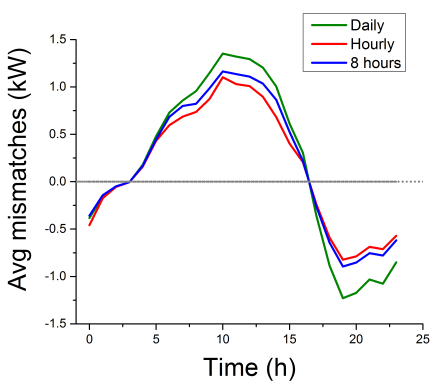
The first set of experiments observes the behavior of static clusters with the chosen system configuration in terms of mismatches and number of clusters obtained. Clustering is performed for a full-day period, where supply and demand of each agent for a period of 24 hours is aggregated. The percentage of prosumers is varied from 10% to 90%, while the percentage of producers (diesel generators) is varied from 0% to 4%.

The next set of experiments aims at observing the reconfiguration of clusters when adapting to changes in supply and demand. For this purpose, the original clustering timespan (full day) is divided into two sets of experiments, namely (i) 8 hours, where clusters are reconfigured every third of the day (8 hour period is chosen to reflect a typical household load profile), and (ii) 24 hours, where clusters are reconfigured every hour.

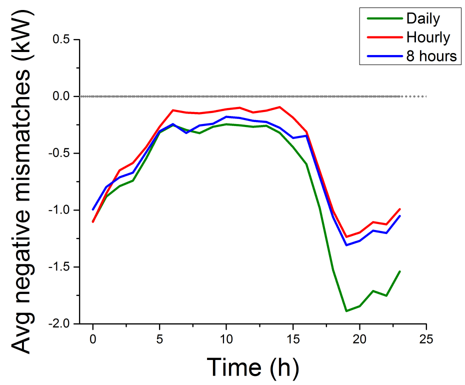
The comparison in outcomes of static (daily) and two types of dynamic clustering (8 hours and hourly) is made in terms of average mismatches, average negative mismatches, and number of clusters. Average negative mismatches served as the main means of comparison, as these indicate in which cases there is underproduction of electricity.

5 Results and discussion

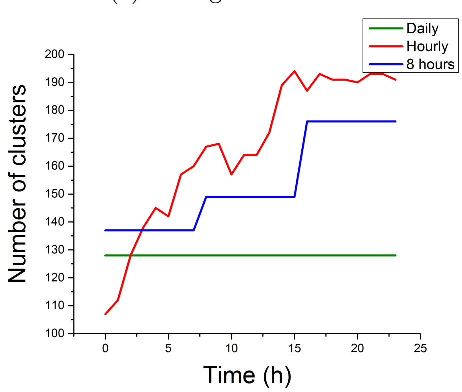
The obtained results indicate that self-organization based only on local information is feasible, and that using the proposed mechanisms, supply and demand can be to an extent locally satisfied. In terms of dynamism, static and dynamic clustering follow similar trends in terms of average mismatches (Fig. 2a), but differ significantly in terms of number of clusters generated (Fig. 2c). As seen in Fig. 2b, hourly clustering generates the overall lowest underproduction compared to both daily and clustering every 8 hours. This is due to the ability of clusters to rapidly adapt to sudden changes. Consequently, hourly clustering results in the highest level of fluctuations in terms of number and sizes of clusters. Thus, more dynamic clustering results in overall lower mismatches, but requires more frequent changes in number and sizes of clusters. The results in Tables 1 and 2, as well as the figures Fig. 2a–d, are based on 100 algorithm runs. Tables 1 and 2 show the obtained clusters' parameters for static (daily) and dynamic (8 hours) clustering. As shown, static clusters generate an overall low average mismatch. Clustering every 8 hours shows



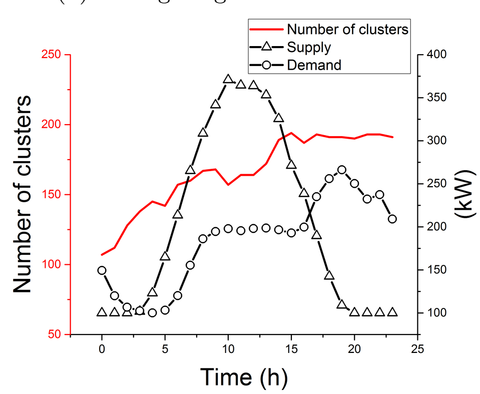
(a) Average mismatches



(b) Average negative mismatches



(c) Number of clusters



(d) Hourly clustering

Figure 2: A comparison of static (daily) and dynamic (every 8 hours and hourly) clustering (based on 100 algorithm runs)

average mismatches that follow the standard load and (solar) production profiles. In the first part of the day, there is enough supply to meet the low demand, while in the second part there is a high level of overproduction due to relatively low demand compared to high solar irradiation. However, in the last part of the day, when the demand increases, there is not enough supply to meet the demand, indicated by the negative average mismatch.

Time period	Average mismatch (kW)	Number of clusters	Average cluster size	Smallest cluster size	Largest cluster size
0-24	4.25	128	3	2	56

Table 1: Static daily clustering (based on 100 algorithm runs)

Time period	Average mismatch (kW)	Number of clusters	Average cluster size	Smallest cluster size	Largest cluster size
0-8	1.54	137	3	2	35
8-16	7.64	149	3	2	33
16-24	-4.58	176	2	2	34

Table 2: Dynamic clustering every 8 hours (based on 100 algorithm runs)

Fig. 2a compares average mismatches for three types of clustering, namely (i) daily, (ii) hourly, and (iii) every 8 hours, while Fig. 2b compares average underproduction at every hour. Both figures indicate that static clustering generates clusters with overall highest mismatches and most underproduction at every hour of the day, compared to those in dynamic clustering. This is due to more flexibility to adapt to sudden changes in supply and demand. Even though both types of dynamic follow similar trends, hourly clustering generates overall less underproduction. Fig. 2c shows how the number of clusters changes rapidly when the granularity of the period for which the clustering is performed is increased. As indicated by the graphs, the more dynamic clustering mechanism, the higher the number of clusters and its variation.

Fig. 2d shows the relation between total supply, total demand, and generated number of clusters for hourly clustering. When both supply and demand are low, the number of clusters is relatively low. As the demand increases, the number of clusters increases. This is the most evident when the supply starts decreasing in the last part of the day, indicating that the agents organize in smaller groups to try to compensate for the lack of supply. Since the prosumers do not generate enough electricity in this period, there are fewer rounds of cluster merging.

6 Conclusions

This paper proposes mechanisms for decentralization of supply and demand matching by letting consumers, prosumers and producers organize themselves into clusters that locally match electricity. The main motivation is twofold, namely (i) to demonstrate that supply and demand matching can be decentralized when only local information is available, and (ii) to assess the outcomes of static and dynamic clustering. The results show that the techniques developed can provide mechanisms for enabling self-organization based on local information. In terms of dynamism, the results show that the more dynamic clustering methods produce overall better clusters with lower negative mismatches. However, more dynamism means more communication, frequent reconfiguration and changes in cluster sizes and numbers. Thus, there is a tradeoff between overall reduction of mismatches and the burden on the infrastructure itself. The developed mechanisms can be used to decide where to place alternative sources of power generation, storage units, or to decide when to turn the generators on.

Besides the aforementioned extension of the model with supply and demand forecasting techniques, other extensions left for future work are to explore the effect of storage on the formation of clusters and to explore the potential of the proposed mechanisms as a means of achieving a more reliable power supply and a more resilient power system. The main idea here is to let consumers, prosumers and producers in an area affected by a power outage, temporarily organize themselves in (dynamic) clusters that distribute available supply to preferred consumers.

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References

[1] Koninklijk Nederlands Meteorologisch Institut.

[2] NEDU - Verbruiksprofielen.

[3] G. B. S. Allen J. Wood, Bruce F. Wollenberg. *Power Generation, Operation and Control.* Wiley-Interscience, 3 edition, 2013.

[4] M. Amin. Toward self-healing energy infrastructure systems. *Computer Applications in Power, IEEE*, 14(1):20–28, 2001.

[5] M. Amin and J. Stringer. The Electric Power Grid: Today and Tomorrow. *MRS Bulletin*, 33(04):399–407, 2008.

[6] A. Andrieux, K. Czajkowski, A. Dan, K. Keahey, H. Ludwig, T. Nakata, J. Pruyne, J. Rofrano, S. Tuecke, and M. Xu. Web Services Agreement Specification (WS-Agreement) Version 2005/09. Technical report, Grid Resource Allocation Agreement Protocol (GRAAP) WG, 2005.

[7] P. Asmus. Microgrids, Virtual Power Plants and Our Distributed Energy Future. *The Electricity Journal*, 23(10):72–82, 2010.

[8] F. M. Brazier, E. F. Y. Ogston, and M. Warnier. The Future of Energy Markets and the Challenge of Decentralized Self-management. In *Proceedings of the Eighth International Workshop on Agents and Peer-to-Peer Computing (AP2PC09)*, pages 95–103. 2009.

[9] F. M. T. Brazier, H. La Poutré, a. R. Abhynakar, K. Saxena, S. N. Singh, and K. K. Tomar. A Review of Multi Agent Based Decentralised Energy Management Issues. *International Conference on Energy Economics and Environment (ICEEE)*, pages 1–5, 2015.

[10] G. Chalkiadakis, V. Robu, R. Kota, A. Rogers, and N. R. Jennings. Cooperatives of distributed energy resources for efficient virtual power plants. *The 10th International Conference on Autonomous Agents and Multiagent Systems - Volume 2*, (Aamas):787–794, 2011.

[11] K. P. Clark. *Negotiation and Monitoring in Open Environments.* PhD thesis, Delft University of Technology, 2014.

[12] S. Das, A. Abraham, and A. Konar. *Metaheuristic pattern clustering - An overview*, volume 178. Springer-Verlag Berlin Heidelberg, 2009.

[13] M. Duckham. *Decentralized Spatial Computing.* Springer-Verlag Berlin Heidelberg, 1 edition, 2013.

[14] B. S. Everitt, S. Landau, M. Leese, and D. Stahl. Cluster Analysis. In *Cluster Analysis.* Wiley, 5 edition, 2011.

[15] H. Farhangi. The path of the smart grid. *IEEE Power and Energy Magazine*, 8(1):18–28, 2010.

[16] N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay. Microgrids. *IEEE Power and Energy Magazine*, 5(4):78–94, 2007.

[17] A. K. Jain and R. C. Dubes. Algorithms for Clustering Data.

[18] M. Jelasity, A. Montresor, and O. Babaoglu. Gossip-based aggregation in large dynamic networks. *ACM Transactions on Computer Systems*, 23(3):219–252, 2005.

[19] K. Kok. Multi-Agent Coordination in the Electricity Grid , from Concept towards Market Introduction. *9th Int. Conf. on Autonomous Agents and Multiagent Systems*, (Aamas):10–14, 2010.

[20] K. Kok, Z. Derzsi, J. Gordijn, M. Hommelberg, C. Warmer, R. Kamphuis, and H. Akkermans. Agent-based electricity balancing with distributed energy resources, a multiperspective case study. *Proceedings of the Annual Hawaii International Conference on System Sciences*, pages 1–10, 2008.

[21] D. G. A. Mobach. *Agent-Based Mediated Service Negotiation*. PhD thesis, Vrije Universiteit Amsterdam, 2007.

[22] E. Ogston, B. Overeinder, M. van Steen, and F. Brazier. A method for decentralized clustering in large multi-agent systems. *Proceedings of the second Int. Joint Conf. on Autonomous Agents and Multiagent Systems - AAMAS '03*, page 789, 2003.

[23] E. Ogston, A. Zeman, M. Prokopenko, and G. James. Clustering distributed energy resources for large-scale demand management. *First International Conference on Self-Adaptive and Self-Organizing Systems, SASO 2007*, (Saso):97–106, 2007.

[24] M. Panteli and P. Mancarella. The Grid: Stronger, Bigger, Smarter? *IEEE Power and Energy Magazine*, (April), 2015.

[25] M. R. Patel. *Wind and Solar Power Systems*. CRC Press, 1999.

[26] N. Shigei, H. Miyajima, H. Morishita, and M. Maeda. Centralized and Distributed Clustering Methods for Energy Efficient Wireless Sensor Networks. In *Proceedings of the International MultiConference of Engineers and Computer Scientists*, volume I, pages 0–4, 2009.

[27] G. Strbac, N. Hatziargyriou, J. P. Lopes, C. Moreira, A. Dimeas, and D. Papadaskalopoulos. Microgrids: Enhancing the Resilience of the European Megagrid. *IEEE Power and Energy Magazine*, 13(3):35–43, 2015.

[28] K. H. van Dam, M. Houwing, Z. Lukszo, and I. Bouwmans. Agent-based control of distributed electricity generation with micro combined heat and power-Cross-sectoral learning for process and infrastructure engineers. *Computers and Chemical Engineering*, 32:205–217, 2008.