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Published in:
European Journal of Control

DOI:
[10.1016/j.ejcon.2015.04.005](https://doi.org/10.1016/j.ejcon.2015.04.005)

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Document Version
Publisher's PDF, also known as Version of record

Publication date:
2015

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Scherpen, J. M. A. (2015). Distributed supply-demand balancing and the physics of smart energy systems. *European Journal of Control*, 24(7), 63-71. <https://doi.org/10.1016/j.ejcon.2015.04.005>

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Distributed supply–demand balancing and the physics of smart energy systems

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ARTICLE INFO

Article history:

Received 27 January 2015

Received in revised form

20 April 2015

Accepted 20 April 2015

Recommended by A. Astolfi

Available online 7 May 2015

Keywords:

Smart energy

Distributed control

Dual decomposition

Market structure

Energy based modeling

ABSTRACT

This paper presents an overview of two different perspectives that we take to smart energy systems, both in the power and the gas grid. The first is taking a distributed optimal control point of view, applicable to a network of households with production devices, but also with demand side control, and with power-to-gas facilities. The expected future market structure is also considered. The second perspective considers the physics of the power grid, and the full order models that we can build. A port-Hamiltonian perspective is briefly considered, and some questions about the coupling of the two perspectives are raised.

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1. Introduction

The current centralized energy systems are facing major challenges as we move towards systems that increasingly rely on renewable and sustainable energy sources, such as solar, wind, biofuels and geothermal energy [46]. Many of these are to be produced and distributed in a more decentralized manner than current fossil energy sources, and their availability will fluctuate because the production of renewable energy is often tied to weather and environmental factors, while storage is still inefficient. Hence, the integration of variable modes of renewable and distributed energy production has major implications for the design and management of energy systems.

In this paper, we present an overview of our work in the area of smart energy systems, in particular focussing on the power and gas grids, two types of grids that are on the move to develop into smart grids. Smart grid represents a vision on future grids, where individual users can contribute to optimize the system by means of demand response [26]. This means that the demand energy of the individual users in the network will be balanced dynamically and continuously to match the supply of energy. This principle is the same for the power and gas grid.

The end-users of energy systems are currently mainly passive actors, i.e. their energy production and consumption are not influenced by for example real-time prices. Thus, to achieve an energy balance a few central plants are controlled to meet the demand from a large number of end-users. In fact, the control loops to ensure the balance are implemented in a hierarchical fashion. The control layers include day ahead planning as well as real-time balancing, because electricity cannot be stored efficiently in large quantities. At the same time, all business components in the energy system should be allowed to compete fairly and freely, see e.g. Amin [4].

However, as many households, industry, and office buildings, now next to being consumers also become producers (they become so-called prosumers), because they have photovoltaic cells or produce electricity from Combined Heat Power systems, the energy flow becomes a bi-directional flow with many actors. To deal with such complexity, distributed control is necessary, e.g., [24]. For both the power and the gas grid, balancing supply and demand are important. This is generally formulated as an optimal control problem with a central goal, but in order to make it feasible, a distributed formulation is necessary. Optimal control via dual decomposition, and shadow prices are then a natural way to formulate a centralized problem in a distributed manner [42,9]. Here we provide an overview of the application of this method to supply demand balancing for embedding of so-called micro Combined Heat Power (μ -CHP) systems in the power grid. Furthermore, we use distributed optimal control for optimizing the local costs for power-to-gas facilities embedded in the power

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¹ This work is an overview of joint work with a.o. Gunn K.H. Larsen, Nicky D. van Foreest, Desti Alkano, Marcel Volkerts, D. Bao Nguyen, Jarno Pons, Wouter Neffkens, Shaik Fiaz, Daniele Zonetti, Romeo Ortega, and Arjan van der Schaft. The work is partially supported by the Flexines project and the EdGaR project.

and gas grid and we review the application of these methods for the use of bio-gas in the gas grid.

The physics of the above smart energy systems are in general embedded in the constraints of the optimal control problem, making it possible to interpret the above as economic optimization, via shadow prices. Nevertheless both for the gas and power grid, there exist models for their dynamical behavior, capturing the physics. A relation with the above-mentioned optimal control point of view is not so clear yet, even though recent work aims at making a step towards such coupling through the analysis and control of power systems with generators described by 2nd order equations, e.g. [48,13]. However, these 2nd order models for generators are approximations of the original 8 order models that capture the full transient behavior of the system [28]. Here we review the application of the port-Hamiltonian modeling framework [16,51], to power networks with full order models for the generators in order to gain insight in the overall physics, and to set a first step towards using this structure for the stability analysis and for control. We provide some hints on how to proceed in coupling the two seemingly different perspectives, i.e., the economic optimization and the study of the dynamics of the physics of the grid, in future research.

This paper aims to provide an overview of the distributed optimal control methods we developed, presented in Section 2 for the power and in Section 3 for the gas grid. Furthermore, in Section 4 the physics of the grid in a port-Hamiltonian setting is briefly treated, seemingly disconnected from Section 2, but necessary to fully understand and couple the two perspectives in the future.

2. Distributed optimal control for the power grid

As argued above, embedding new energy systems and moving towards prosumers as agents in the network results in such complexity of the grids that distributed control is the most feasible approach to deal with new energy systems [24,30]. There are a number of approaches on handling the complexity of the power grid in a distributed manner, not always taking the future predictions into account. An example where prices, auction and bidding are done to embed devices in the smart grid via a combined hierarchical and distributed structure, but without taking predictions into account is the much cited and used Power Matcher concept developed in [27]. Forecasting is done in a method relying on neural network based optimization in [5]. However, application to the real-time control in the operation phase is more problematic because of the computational complexity. Therefore, distributed optimal control is of interest for the application of real-time control in the operation phase of the power grid, though it can also be applied to the one-day-ahead forecasting phase, e.g. [25]. A common approach to make it possible for an optimal

control problem to be solved in a distributed fashion is via dual decomposition, e.g., [10], which is studied in a Model Predictive Control (MPC) setting in [18,19].

In this section we review our application of distributed control methods to a network of households with controllable production and demand. However, the current market structure, as well as perspectives on the future market structure cannot be ignored, and we provide some first steps about how to embed distributed control methods into such structure.

2.1. Dual decomposition MPC for micro-CHP's in a network of households

We briefly summarize the results and approach of [32–34,30]. We consider heat and power production from micro-Combined Heat Power systems (μ -CHP's) and heat storage in a network of households. The goal is to balance the local heat demand in combination with balancing the power supply and demand in the network.

2.1.1. The system model

The setup of an agent is shown in Fig. 1. The agent has a μ -CHP fueled on natural gas, where the power output is connected to the power network while the heat output is stored in a hot water storage present in the house. The μ -CHP consists of a prime mover whose power and heat output is coupled, and an auxiliary burner which only has a heat output. For the characteristics of the μ -CHP, see [34]. The auxiliary burner produces heat like a conventional boiler, and also stores the heat in the hot water storage. The auxiliary burner is part of the control problem because if the power demand is low and the heat demand is high, we prefer that the heat demand is covered by the auxiliary burner. In other words, we aim to avoid a net power production in the network due to high heat demand. Further, the heat storage has to meet the households demand for hot water and central heating.

The μ -CHP can be modeled with different degrees of technical detail. For a detailed model, see e.g., [17]. Here we are interested in a model capturing the main features of the μ -CHP suitable for control of the electric power and heat output. Such a model of a prime mover was presented in [22] for demand response in one household. We assume that each household has a μ -CHP with the same characteristics.

We assume that there are no thermal losses in the conversion and storage system, therefore, the dynamics of the heat storage level $h_{s,i}(k) \in \mathbb{R}_+$ is given by

$$h_{s,i}(k+1) = h_{s,i}(k) + h_{p,i}(k) + h_{a,i}(k) - h_{d,i}(k), \quad (1)$$

as in [22] and we have the following constraints:

$$h_{c,i}(k) = -\eta_i p_i(k), \quad (2)$$

$$p_i(k) \in \{0\} \cup [-p_{\max,i}, -p_{\min,i}], \quad (3)$$

$$h_{a,i}(k) \in \{0\} \cup [h_{a,\min,i}, h_{a,\max,i}]. \quad (4)$$

$$h_{\min(\max),i} = m_i c_p \Delta T_{\min(\max),i}, \quad (5)$$

$$h_{\min,i} \leq h_{s,i}(k) \leq h_{\max,i}, \quad (6)$$

where agent i has an electric power demand $d_i(k) \in \mathbb{R}_+$, and a heat demand $h_{d,i}(k) \in \mathbb{R}_+$. The prime mover produces electric power $p_i(k) \in \mathbb{R}_-$ and heat $h_{p,i}(k) \in \mathbb{R}_+$, the power and heat output of the prime mover $h_{c,i}$ are related to the power output via efficiency η_i when it is on. Note that the power production $p_i(k)$ is opposite in sign to the power demand $d_i(k)$. There is a minimum and maximum power output the μ -CHP can deliver when it is on, $p_{\min,i}, p_{\max,i} \in \mathbb{R}_+$. The auxiliary burner can produce additional heat

Fig. 1. This setup is taken from [23], and shows the energy flow in one household.

$h_{a,i}(k) \in \mathbb{R}_+$ at times of high heat demand. The minimum and the maximum heat production of the auxiliary burner when it is on are given by $h_{a,\min,i}, h_{a,\max,i} \in \mathbb{R}_+$. The maximum and minimum heat storage levels of the hot water tank are $h_{\min,i}, h_{\max,i} \in \mathbb{R}_+$. They depend on the mass m_i of the water, the heat constant $c_p = 4.18 \text{ kJ}/(\text{kg} \cdot \text{K})$ and the difference in minimum (maximum) temperature of the water and the room-temperature $\Delta T_{\min(\max),i}$.

The prime mover has a slow response after having been turned off. Therefore, it can stay in an idle on-state, and consumes the minimum gas $g_{r,i}$ required to keep the reforming unit at the operating temperature, even if no power and heat are produced.

2.1.2. The information network

The agent's operation of the μ -CHP will influence the power balance in the power network. We propose an information sharing model in a network of n agents connected through an information network, which does not need to have the same structure as the corresponding power network. This will help us to implement a completely distributed control strategy in the network. Here we repeat the network modeling considerations presented in [32,33], in order to be as self-contained as possible.

We call the difference between power production $p_i(k) \in \mathbb{R}_-$ and demand $d_i(k) \in \mathbb{R}_+$ at an agent i , the real imbalance $\tilde{x}_i(k)$ at agent i . We introduce the state $x_i(k)$ representing information about the imbalance of agent i , depending also on information about imbalance of neighboring agents. Agent i 's set of information neighbors N_i is given by $N_i \subseteq \{1, \dots, n\} \setminus \{i\}$, where the agent itself is excluded.

The information topology is represented by a weighting A_{ij} for the coupling between the agents' information about the imbalance. The change in production is given by $u_i(k) = p_i(k+1) - p_i(k)$, and the model for the imbalance information $x_i(k)$ at agent i is given by

$$x_i(k+1) = A_{ii}x_i(k) + \sum_{j \in N_i} A_{ij}x_j(k) + u_i(k) + w_i(k), \quad (7)$$

for all $i = 1, \dots, n$, where $w_i(k) = d_i(k) - d_i(k-1)$ represents the change in power demand at agent i , A_{ii} weighs the power imbalance information of agent i itself, and A_{ij} weighs the information received from neighbors $j \in N_i$. We take $x_i(0) = d_i(0) + p_i(0)$ and $w_i(0) = 0$. As time evolves, demand changes are spread through the network through the neighboring agents N_i . In Fig. 2, the solid lines represent one possible information network.

In addition to the information network, all agents $i = 1, \dots, n$ are physically connected to the power grid, as illustrated by the dashed lines in Fig. 2. In the same time, the overall power imbalance of the system is given by $\sum_{i=1}^n \tilde{x}_i(k)$, which we require to be equal to the information imbalance, i.e., we require

$$\sum_{i=1}^n \tilde{x}_i(k) = \sum_{i=1}^n x_i(k).$$

This is achieved by relating the imbalance information to the physical power imbalance with the choice of the information matrix $A \in \mathbb{R}^{n \times n}$ satisfying

- $A_{ij} \neq 0$ if and only if information is exchanged from agent j to agent i .
- All weights are non-negative: $A_{ij} \geq 0$, $i, j = 1, \dots, n$.

Fig. 2. Three agents which are connected to the power grid (dashed lines), and connected to an information network (solid lines).

- All columns sum up equal to one:

$$\sum_{i=1}^n A_{ij} = 1, \quad j = 1, \dots, n.$$

- The graph corresponding to information matrix A is strongly connected [49]. Loosely said: there is a path in the communication graph from any agent to any agent.

See [32] for details. We assume that the overall power shortage (excess) in the information network is imported from (exported to) an external network, and we will formulate our objective with the aim to minimize this exchange.

2.1.3. Distributed model predictive control for a network of households

We now formulate a constrained optimal control problem, which can be solved by MPC, see e.g. [12]. The network goal will be expressed by means of an objective function, and local forecast about future energy demand can be taken into account when the control actions are determined. We include prediction models based on the agents' and network dynamics and constraints presented above. New measurements of power demand, heat demand and heat storage levels are included as initial conditions at each MPC cycle.

The non-convex constraints ((Eqs. (3) and 4)) are included in our MPC problem by introducing binary decision variables, as was done for a single household in [37]. We also have introduced two new binary variables to indicate whether the primary mover is still in the start-up phase, or is shut down. See [34] for the details.

The agent has different choices for how to cover its energy need. It can get power from the network, or from its μ -CHP, and it can get heat from the primary mover or the auxiliary burner. We formulate the global control goal to minimize the overall power imbalance in the network, while keeping the appropriate temperature in the local heat storage, and while also trying to minimize the heat output of the auxiliary burner. For this purpose we define the local objective function

$$V_i(x_i(k), x_i(k), h_{a,i}(k)) = Q_{ii}x_i^2(k) + R_{ii}u_i^2(k) + H_{ii}\Delta h_{a,i}^2(k), \quad (8)$$

where Q_{ii}, R_{ii}, H_{ii} weigh the relative importance of the imbalance information, change in power production and change in auxiliary heat output respectively. We use hat-notation to indicate predictions, and minimize the following global objective:

$$\sum_{\tau=k}^{k+T_{\text{pred}}} \sum_{i=1}^n V_i(\hat{x}_i(\tau), \hat{x}_i(\tau), \hat{h}_{a,i}(\tau)), \quad (9)$$

subject to the prediction models of (Eqs. (1), (2), (6), (7), and the binary constraints mentioned above for all $i = 1, \dots, n$, and $\tau = k, \dots, k+T_{\text{pred}}$.

Solving (9) requires a central controller that has full information about states, measurements and forecasts of all agents in the network. However, the decision to turn on or off the primary and auxiliary burner in such a centralized way does not scale well [32]. The decisions will instead be taken completely distributed only based on local information, as presented next.

The minimization (9) can be approximated by dual decomposition and sub-gradient iterations, as explained in [18,19,32]. The main idea is that the neighbor influence in (7) is replaced by a local guess $v_i(k)$ constrained by

$$v_i(k) = \sum_{j \in N_i} A_{ij}x_j(k), \quad (10)$$

which decomposes the state equation (7)

$$x_i(k+1) = A_{ii}x_i(k) + v_i(k) + u_i(k) + w_i(k). \quad (11)$$

Then the constraints (10) are moved to the objective function by standard Lagrangian relaxation, which introduces the Lagrangian multipliers $\lambda_i(k)$ related to the constraints (10). The complete decomposition is achieved by including sub-gradient iterations.

For convex problems the solution of the distributed problem converges to the solution of the centralized problem (9). However, due to the non-convex constraints (3) and (4) such a convergence cannot be guaranteed. We may encounter that in the gradient iteration switching between binary values at each time step will occur. We approach this problem by fixing the binary value once a non-converging sequence is detected, see [34].

For simulation results, we refer to [34], where a number of cases of 10 and 25 households in a network are compared. The distributed method can be implemented in a large network, since the number of optimization variables per node is constant. Increasing the network, however, slowly increases the number of sub-gradient iterations needed to match the stopping criterion. The centralized problem cannot be solved for large problems, in particular due to the large number of binary variables. Already with 25 households we were unable to solve the centralized problem for a case study with μ -CHP's in all households, and with only connections with two neighbors, i.e., a circular topology. The distributed problem is solvable though, even though the non-convexity results in a dual gap, i.e., the distributed optimization formulation is not providing the same solution as the centralized optimization formulation.

Based on the simulation results, we conclude that when embedding the μ -CHPs and heat storage in the network, the network as a total uses less resources than when no μ -CHPs are present, and the auxiliary burner is needed to stay within the heat limits. Furthermore, the distributed control approach is feasible, as it scales well and helps balance the network.

2.2. Demand side control

The above optimization problem is completely focussing on controlling the production side of prosumers in the power grid. However, the approach can be used for demand side control as well.

Domestic devices with flexibility to participate in demand response are typically devices such as refrigerators and washing machines, since the temperature can be controlled to stay within a certain temperature range, and the washing machine program can be shifted in time, respectively. When the number of households gets large, this flexibility can help to drive the power demand in the grid towards a target value when the decisions for when to turn on are coordinated. In the literature, in order to make the problem scalable, the problem is often solved in an hierarchical fashion where one decision making element is present [35]. However, in case of a network of households, a distributed approach similar to the production side control as described above can be used.

In [31] we model a network with washing machines whose switching time can be coordinated with the overall power demand in the system. We use a similar information structure as above, and the constraints from the washing machines have a binary nature. We use the distributed MPC method explained above to coordinate washing machines in a local power network. Due to the binary nature of the constraints a Mixed Integer Quadratic Program is used to find the solution of the local problem, given shadow price signals from information neighbors.

The state $x_i(k)$ of household i is this households information about demand which will be shared with the neighbors. It is a

combination of the households own and its information neighbors demand, where the weights are specified by the information matrix A , similar to the model for the production side described above. Further, $u_i(k) = f_i(k+1) - f_i(k)$ is the change in electric power demand from the washing machine at household i , and $w_i(k) = g_i(k+1) - g_i(k)$ is the change in the rest of electric power demand at household i .

The goal is to make the power demand of the network more flat. This means that we aim to move shiftable demand away from peaks in the demand pattern. The cost is given by

$$\sum_{\tau=k}^{k+N} \sum_{i=1}^n [\hat{x}_i(\tau) - a]^2, \quad (12)$$

which will be minimized when the individual demand information $\hat{x}_i(\tau)$ is close to a target value a .

Clearly, a washing machine, or any other device has constraints. The machine is not always filled. However, when it is filled, and once it is turned on, it should complete its program. Furthermore, the wash should be finished before a certain end time set by the user. The task is to choose when to turn on the washing machine, while minimizing (12), and given all the constraints. With the binary on-off decisions, the problem is no longer convex, see [31]. Furthermore, the IF and AND operators that occur in some of the constraint equations are included by rewriting the equations in terms of several inequality constraints. See [41,7] for details. In addition, a typical power consumption behavior of a washing machine has to be taken into account. An example of such behavior is given in Fig. 3. It can be seen that there are three major power peaks, where the first one is taking the longest time. The behavior is described by a combination of step functions. As before, we can expect a situation to occur when the binary decision variable oscillates between on and off. When such a situation occurs, we will fix the binary variable so that the sub-gradient iterations can converge to the optimal solution given the fixed binary variable.

2.2.1. Simulation

For the non-shiftable demand we use realistic power demand patterns [40] provided by the Energy research Centre of The Netherlands (ECN). The simulations use demand patterns from one evening in a November month, with a resolution of seven

Fig. 3. Demand pattern of a 40 °C cotton program of the Whirlpool Texas 1400 washing machine. The power demand patterns of the washing machine is obtained from consumption patterns provided by the Flexines project [52].

Fig. 4. The benchmark case; an uncontrolled network.

Fig. 5. With communication and d-MPC algorithm.

Table 1
Scalability of the d-MPC problem.

n	8	16	32
Average time per k (s)	5.7	5.9	6.4
Average # of iter	32.7	33.5	37.1

minutes. Each of the 20 households has a unique demand pattern, based on five typical household profiles.

The information network consists of $n=20$ household exchanging information according to

$$A = \begin{bmatrix} 0.6 & 0.2 & 0 & 0 & \dots & 0.2 \\ 0.2 & 0.6 & 0.2 & 0 & \dots & 0 \\ 0 & 0.2 & 0.6 & 0.2 & \dots & 0 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & 0.2 & 0.6 & 0.2 \\ 0.2 & \dots & 0 & 0 & 0.2 & 0.6 \end{bmatrix}, \quad (13)$$

which means that each households has two information neighbors. They weigh themselves with a weight 0.6 and two neighbors with a weight 0.2.

The power demand patterns of the washing machine is obtained from consumption patterns in Fig. 3.

We perform the simulations, see [31], for one evening in a November month, and assume that 10 of the 20 households have one wash to be done this evening, and we randomly load the washing machines during the first 2 h and 20 min of the evening. As above, in the uncontrolled case the households immediately turn on the machine, see Fig. 4. The green solid line is the total demand in the network, the blue stippled line is the unshiftable demand and the red dotted line is the shiftable demand from the washing machines. This is the case where no controller is added. The resolution of the simulation Δk is 7 min, the simulation time T_{end} is 7 h, the prediction horizon N is 4 h and 40 min, and after the machine is loaded it must finish before $T_{\text{if}}=4$ h and 40 min. The target value for each household is chosen to be approximately the average load per household over the simulation, i.e. $a=500$ W. See the blue stippled line in Fig. 4.

Fig. 5 shows the situation with the d-MPC scheme presented above. Compared to Fig. 4 where all washing machines turn on during the first 2 h and 20 min, the load from the washing machines is now spread out over the two periods where the overall demand in the network is lowest, i.e. $k=0-120$ min and $k=220-320$ min. In fact, when the unshiftable demand is high, then the demand from the washing machines is low, and thus the washing machines are shifted to the moment that the unshiftable demand is somewhat lower. If we compare the cost

$$\sum_{k=0}^{T_{\text{end}}} \sum_{i=1}^n [x_i(k) - a]^2, \quad (14)$$

of the uncontrolled case of Fig. 4, with the controlled case of Fig. 5, we see that the first one has a cost of 248.56 kW², while in the d-MPC case in Fig. 5 has a cost of 231.61 kW². All programs are finished before the specified finish-time.

In the simulation presented above, the average computation-time for one time-step k was 6 s and the maximum computation-time for one time-step k was 15 s. This is well within the simulation time resolution Δk of 7 min. Using the centralized setup of the problem, it was not possible to solve the problem with our software.

For scalability it is important to know that the computation time is not exploding. To check the scalability of the d-MPC optimization, the average computation-time per time-step k , and the average number of sub-gradient iterations per optimization per time-step k are given in Table 1. All n households are loaded with one wash.

2.2.2. Scalability of the algorithms

So far, we assume that the household network and the computational network are the same. Because each household has a similar computational requirement, this solution scales quite well. However, the situation can be more flexible, with for example geographically scattered small computation centers across the network or only some households also being one computational node, whereas some others are clustered on a node. The only requirement is that the number of computational cores in total is high enough in order for a time step k in the d-MPC scheme to finish within the time resolution of the system Δk .

The computational load of each household varies a lot, i.e. it is high when the washing machine is loaded and low when there is no shiftable demand. In our simulation the computation-time for a household with a loaded washing machine was approximately

Fig. 6. The planning, validation and operation phase in USEF.

Fig. 7. The optimal control structure in the operation phase.

50 times longer than a household without shiftable demand. Hence, if the number of available processors in the network is limited, it is important to make optimal use of the available processors. We therefore need to make the mapping of households to cores dynamic. Concretely the mapping can change each cycle in the computation. This means that the computation for a household sometimes has to migrate from one core to the next. In this migration we only have to migrate the execution segment [47] of the program, because the code segment is the same everywhere. See [31] for more details.

2.3. Embedding in the market structure

The above implementations and developments have been done for a network of households. The distributed setting is a promising setting to work out further. However, the market structure is important and to be taken into account. The Smart Energy Collective (SEC) [53] has developed the so-called Universal Smart Energy Framework (USEF). The framework provides a set of specifications, designs and implementation guidelines for establishing a fully functional smart energy system [53,39], see Fig. 6 for the overall structure. USEF consists of a planning, validation and the operation phase. In both the planning and operation phase optimizations take place. The planning phase corresponds to the one-day-ahead market, where we refer to [1] for an optimal control approach on the wholesale market. In [25] MPC is considered for both the planning and operation phase. Our focus is on the operation phase as presented in Fig. 7. The structure fits well with the current ideas about how the market structure is set up for smart energy systems, see [53,39]. In [38] a first step has been set to embed the distributed algorithms presented above into this mixed hierarchical/distributed setting, which is naturally in the operation phase, at the prosumer level. The connection of a set of prosumers with another set of prosumers under a different aggregator is going through the aggregators. The aggregators form a new network themselves, and each cluster of aggregators belongs

Fig. 8. Physical system illustration of a micro gas grid consisting of N prosumers and connected to the low pressure gas grid.

Fig. 9. An overview of Power-to-Gas concept, adapted from [21]. Hydrogen produced from excess power generation can be injected to a gas grid, utilized by a chemical industry/mobility sector, or stored in a storage device and reconverted back to electrical energy using a fuel cell. Some amount of hydrogen needs to be flared in case that surplus hydrogen exceeds the remaining space in the storage device.

to a Balanced Responsible Party (BRP). For the role of aggregators, see [20]. The current market legislation does allow consumers/prosumers to be free in their choice of BRP, resulting in clusters of prosumers that are not necessarily physically nearby. Therefore, a Distribution Systems Operator (DSO) takes care of congestion detection, and is allowed to take actions if congestion in a certain region is detected, complicating the embedding of the distributed optimal control mechanisms at the level of prosumers. This is a topic of ongoing research.

In addition to the difficulty of different BRP's and the role of a DSO, USEF is also foreseeing a goal function to be communicated by the aggregators and BRP's to the nodes below them, related to the available flexibility. How to set these goal functions, and how to embed them in the framework is still a topic of ongoing research.

3. Distributed control in the gas and the coupled grid

3.1. Control of the gas grid

Similar methods as above could be of potential interest for other grids than the power grid as well. We have studied the gas grid and the embedding of bio-gasses from farmers in the grid. In The Netherlands, the gas grid is well developed, most of the households and industry are connected. The Dutch government has an ambition to meet 20% of the gas consumption with sustainable biomass supply in 2030, see [43]. As in the power grid, there is a high, medium and low pressure grid. We have studied the embedding of biogas producing farmers in the gas grid in [3], maximizing the profit for the farmers.

A main difference of the gas grid with the power grid is that the storage possibilities are better for the gas grid, even though for the power grid, the optimal size for certain configurations is studied in e.g., [44]. The produced biogas can be used in different ways. Prosumers can use special household appliances that can reliably and safely consume biogas. Alternatively, prosumers can convert the raw biogas into green gas before injecting it into the low pressure domestic grid in order to deliver it to consumers. The conversion is done to meet the gas quality requirements for the low pressure gas grid. The third scenario is that prosumers convert biogas to green gas, compress, and transport it per lorry for injection in e.g. medium or high pressure gas grids. The combination of these three scenarios is shown in Fig. 8 [3]. Here p_i is the biogas production of prosumer i , d_i is the biogas that is used by prosumer i , f_i is the biogas offered by prosumer i to meet the demand on the low pressure gas grid, g_i the biogas excess generation of prosumer i shipped per lorry, and u_i is the biogas prosumer i takes from the storage device. In [3] we set up and solve a constrained optimization problem for the setting of Fig. 8. The gas grid has a broader tolerance for fluctuations in the grid than the power grid, and thus it is not directly useful to minimize the imbalance. The bounds on these fluctuations are implemented as part of the constraints. Hence, we do not aim at minimizing the imbalance, but at optimizing the revenue for the local farmers. For scalability purposes distributed optimal control is implemented via coupling of the prosumers and as for the power grid, applying dual decomposition.

3.2. Power to gas facilities

New technology in the form of power to gas facilities are increasingly of interest as storage possibility for a surplus of power produced by e.g., photovoltaic cells. Furthermore power to gas facilities offer the possibility to couple the gas and power grid in a natural manner. In this section we report about new results from [2]. As a power grid with high penetration of renewables is likely to increase in the near future, the need for avoiding an overloading of the grid will increase. Batteries are being widely regarded as one of the potential solutions. However, storing large amounts of electricity in batteries has not been put to general use and requires high maintenance efforts [6]. The existing most cost effective energy storage options for large-scale power are compressed air energy storage (CAES) and pumped hydro storage (PHS) [14]. CAES relies on a specific geological structure, requiring an underground cavern that is difficult to find around renewable generators. The main drawbacks of PHS are its high capital cost, long project lead time (10 years), and its consequence on environmental damages by flooding 10–20 km² of land to create reservoirs [6,14]. An alternative energy storage namely the newly developed Power-to-Gas (PtG) facilities have gained popularity. It is a technological concept to convert excess electrical energy into a gaseous energy carrier, i.e. hydrogen. See [21] for more information. The schematic description of PtG embedded in the different grids is shown in Fig. 9. The produced hydrogen can be (1) directly injected in the gas grid, (2) sold to the chemical industry/mobility sector, (3) stored in the hydrogen buffer and later on reconverted into electrical energy using a fuel cell. It should be noted that the amount of hydrogen that is allowed in the gas grid differs per country. In The Netherlands, the percentage is rather low ($< 0.1\%$), whereas it is much higher in some other countries with a different infrastructure. In [2] we present a framework for PtG facilities which prevents overloading in the gas grid, the industry sector, and the power grid in a distributed fashion and in which each PtG facility can locally make its decisions, yet still coordinate them with the DSOs of the energy grids. We build further on the methods developed in [9]. This allows centralized entities, i.e.

Fig. 10. An example network (left) and its graph (right) [15].

DSOs, to manage PtG facilities via prices associated with the distribution grid constraints in an effort to avoid overloading.

4. The physics of the power grid

The above methods rely on a optimal control procedure in discrete time, having the physics of the grid captured in the constraints. This means that the dynamics of the grid are captured in one way or another in the constraints. However, the dynamics of power systems are separately studied as well, resulting often in a so-called two-layered approach, i.e., an approach that on one hand controls the physics and the power quality in a lower layer, and next the available flexibility of the different prosumers from discrete devices is controlled in an optimal way as described in the previous sections. See [29] for such approach, where droop control is done in one layer, and optimal control of the flexibility in the other layer. In addition, much of the power grid research is considering frequency deviation as a measure of imbalance, which can then be translated into dynamic price signals. Current research focusses on the frequency regulation of micro-grids, see e.g., [48], relying on the swing equation models for synchronous generators interconnected in the grid. Recently, this is also coupled to an optimal steady state distribution of the power [36], which can be interpreted as a way to balance the network and optimize the local imbalance at the prosumers. In addition, studying voltage control via droop control is increasingly popular, e.g. [45], and coupled to the economic dispatch problem [13], though not so explicit as in the two-layered approach from [29]. These methods in general rely on 2nd order swing equation models or on the structure preserving network models introduced by [8], often called the Bergen–Hill models.

The use of the swing equations or the Bergen–Hill models that neglect some of the fast transients and losses sometimes may result in an unpredicted behavior of the system, and loss of physical structure that can be useful for control purposes. In our paper [15] we deal with energy based modeling and control techniques in order to capture the full order dynamics, and to use the rich structure of such models for stability analysis and for control purposes. In particular, we use the port-Hamiltonian (pH) system framework to model a power network with generators. The use of port-Hamiltonian (pH) systems has proven highly successful in many applications, see [16,51] and references therein. A pH system in input-state-output form is given by

$$\dot{x} = (J(x) - R(x)) \frac{\partial H}{\partial x}(x) + g(x)u \quad (15)$$

$$y = g(x)^T \frac{\partial H}{\partial x}(x) \quad (16)$$

where $J(x) = -J(x)^T$, $R(x) = R(x)^T \geq 0$, and $H(x)$ is the Hamiltonian. $x \in \mathbb{R}^n$ is the state, and $u, y \in \mathbb{R}^m$ are the port input and output.

A main advantage of using pH models is that in general the Hamiltonian H serves as a storage function for passivity, i.e., $\dot{H}(x) \leq u^T y$, and thus as a Lyapunov function.

A power network can be viewed as a graph where generators, transmission line elements and loads correspond to elements in a graph. Buses are an integral part of such network, but it is common practice to eliminate interior buses by applying Kron reduction [50] resulting in a network with only boundary buses. See Fig. 10 for an example network and its corresponding graph. It is common practice to estimate the dynamics of a transmission line by a so-called Π model, e.g. [28]. We have used these assumptions in order to build our pH model of a power network with the above elements. We use as the states of the synchronous generator the 3 phase rotor and stator flux linkages $\psi_r \in \mathbb{R}^3$ and $\psi_s \in \mathbb{R}^3$, the momentum $p \in \mathbb{R}$ and the angle $\theta \in \mathbb{R}$. The inputs are given by the applied electrical field E_f and the mechanical torque T_m . The states of a transmission line are given by the flux of the inductor $\psi_L \in \mathbb{R}$ and the charge on the capacitor $q_C \in \mathbb{R}$. Together with the incidence matrix provided by the graph structure, a pH model is obtained for the full network dynamics. In [11] a similar model is obtained, but with a few less states, i.e., not all fluxes of the generator are included.

A few issues now arise why it is not straightforward to analyze the system stability with the Hamiltonian as Lyapunov function. Namely, the Hamiltonian is degenerate in the sense that there is no energy term directly related to the angle, though the angle does show up in the parameters of the other energy elements. In addition, clearly the generator does not converge to a constant angle, but is regulated via the torque and the electrical field to yield a constant frequency, i.e., we deal with a steady state solution. The $dq0$ transformation may resolve the latter problem, i.e., for single machine, these coordinates allow to consider it a stabilization problem, in stead of tracking a desired steady state solution. However, such transformation is possible for one single machine, but difficult to apply in the multi-machine case (see also [11] for the rather restrictive assumptions that have to be made in order to deal with the multi-machine case), as each machine has their own angle. In [15] we therefore only handle the case of a single synchronous generator connected to an infinite bus. Further research is necessary to determine the full potential of the use of the Hamiltonian for the stability analysis of a multi-machine power network.

The framework nevertheless offers a clear picture on the physics in the system, and the coupling between frequency and voltage stability may in principle be studied by considering the full order models of the generators in the network. In reality these problems are not fully decoupled, and thus can be studied using our model. Still, then the embedding of renewables and other devices, and the coupling to supply-demand balancing of the previous sections and the embedding of such model in a market

structure is a largely open question, where the approaches of [29,36] provide openings to be explored further.

5. Concluding remarks

This paper presents an overview of two different perspectives that we take into smart energy systems. The first is taking a distributed optimal control point of view, applicable to several settings, and very suitable for future implementation in field labs for smart energy systems. Current work considers how to embed this in the market structure that we have, and on integration of the different methods to consider the full complexity of the network. The second perspective, which was explained here in a very brief manner, considers the dynamics of the grid as leading. We propose for future research to further explore the link with the economic dispatch problem as proposed in [13], the coupling to distributed optimization as in [36], and the two-layered approach of [29] to provide means for integrating both perspectives as they are necessary to get a full grasp on the complexity of smart energy systems.

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