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

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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.

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 geothermic 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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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].

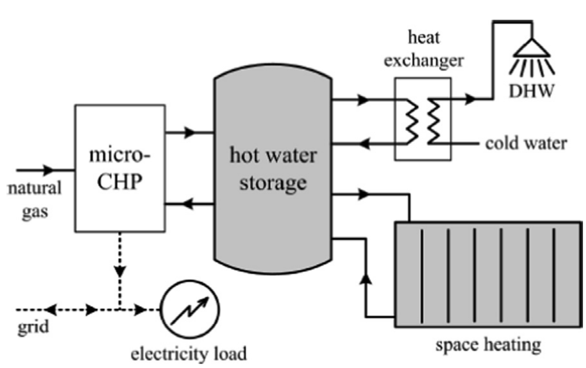

Fig. 1. This setup is taken from [23], and shows the energy flow in one household.

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

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

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

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

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

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

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

$$h_{\min,i} \le h_{s,i}(k) \le h_{\max,i}, \tag{6}$$

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