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Distributed economic dispatch of embedded generation in smart grids

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ABSTRACT

In a smart grid context, the increasing penetration of embedded generation units leads to a greater complexity in the management of production units. In this paper, we focus on the impact of the introduction of decentralized generation for the unit commitment (UC) problem. Unit commitment problems consist in finding the optimal schedules and amounts of power to be generated by a set of generating units in response to an electricity demand forecast. While this problem has received a significant amount of attention, classical approaches assume that these problems are centralized and deterministic. However, these two assumptions are not realistic in a smart grid context. Indeed, finding the optimal schedules and amounts of power to be generated by multiple distributed generator units is not trivial since it requires to deal with distributed computation, privacy, stochastic planning, etc. In this paper, we focus on smart grid scenarios where the main source of complexity comes from the proliferation of distributed generating units. In solving this issue, we consider distributed stochastic unit commitment problems. We introduce a novel distributed gradient descent algorithm which allows us to circumvent classical assumptions. This algorithm is evaluated through a set of experiments on real-time power grid simulator.

1. Introduction

The economic dispatch and unit commitment (UC) problem consists in finding the optimal schedules and amounts of power to be generated by a set of power generators (units) in response to an electricity demand over a planning horizon (Aoki et al., 1989; Borghetti et al., 2001; Guan et al., 2003). Earlier approaches for solving UCs including branch-and-bound methods, dynamic programming and Lagrangian relaxation techniques assume that units are fully reliable and share all together their states, technical specifications and schedules (Cohen and Yoshimura, 1983; Snyder et al., 1987; Fisher, 2004). However, the increasing penetration of embedded units in distributed networks together with the liberalization of electricity markets make these assumptions less and less realistic on both demand and supply sides (Kok et al., 2010; Nikovski and Zhang, 2010; Ramchurn et al., 2012).

On the demand side, more and more customers supplement the amount of power their own units generate by that of the electrical utilities, which makes demand forecast inaccurate. On the supply side, the amount of power generated by an electrical utility influences the amount of power other electrical utilities need to generate in order to meet the demand. Furthermore, the liberalization of the electricity markets precludes electrical utilities to share their private information with one another including: schedules, generation capabilities, technical specifications, generator failure histories, blackouts, etc. As a consequence, centralized and deterministic models are no more relevant to unit commitment problems. Even more importantly, these limitations highlight the impetus for models that can produce operational schedules that are robust in face of both: supply and demand uncertainties and privacy-preserving constraints.

Traditional responses to supply and demand uncertainties have been to schedule enough reserve so as to face forecast inaccuracies or generator failures. Typically, a safety margin of 3% in the production is commonly used in power generation as a *reliability rule-of-thumb* (Sheble and Fahd, 1994). This heuristic strategy often results in the generation of amounts of power that significantly exceed the expected demand, and thus the operational costs of electrical utilities are overestimated. Clearly, as the penetration of embedded units increases, such heuristics are likely to overestimate the operational costs and amounts of power units generated.

A more promising approach assumes that the uncertainty constraints are parts of unit commitment problems, which makes

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the latter stochastic. The goal, then, consists in finding schedule strategies that minimize the expected operational costs while preserving the ability to meet the expected demand, and ensuring the robustness in face of supply and demand variability. Schedule strategies implicitly provide safety margins by taking into account all possible contingencies. Notice that the idea of using stochastic unit commitment (SUC) problems in order to deal with supply and demand uncertainties is not new. It can be traced back to Takriti et al. (1996), who developed a stochastic programming model and solution method based on Lagrangian relaxation techniques.

Since then, numerous authors have refined both the model and the solution, exploiting Lagrangian heuristics (Nowak and Rmisch, 2000), security-based probabilistic models (Bouffard et al., 2005), market-based mechanisms (Vytelingum et al., 2010) and Markov decision processes (Nikovski and Zhang, 2010) to cite a few. Unfortunately, the number of all possible contingencies in SUCs may grow exponentially with the planning horizon, making exact approaches intractable (Nikovski and Zhang, 2010). Instead of considering the entire contingencies, Takriti et al. (1996) suggest to plan only over a few scenarios, which significantly improves the scalability of the solution method. But there is no free lunch, such an approach often fails to address all future possible realizations that are not part of the selected scenarios.

Though approaches to solving SUCs can handle uncertainty, they all assume electrical utilities share with one another all their private information. That is, there exists a centralized coordinator agent that computes a centralized schedule strategy on behalf of the entire set of electrical utilities. However, the liberalization of electricity markets tends to enforce a system of competition where electrical utilities compete to offer their electricity output to retailers, making centralized approaches no longer reliable. In such a setting, schedule strategies, the centralized coordinator agent computes, are obsolete as they centralize private information of all electrical utilities.

To tackle the privacy-preserving bottleneck, the past few years have seen many distributed approaches to preserve private information of electrical utilities involved in a distributed system. In distributed approaches, each electrical utility is an autonomous processing node, we will call an *agent*, which works together with the other nodes in order to solve a unit commitment problem. The agents collaborate to coordinate their resources and activities while preserving their private information. Notable examples include the work by Kim and Baldick (1997), who developed a distributed algorithm that extends deterministic and centralized Lagrangian relaxation methods; or that of Miller et al. (2012), who introduced a message passing algorithm to UCs in the form of distributed constraint optimization problems (Kumar et al., 2009; Modi et al., 2005). Unfortunately, none of these distributed approaches can handle the uncertainty in supply and demand. So, it would seem like we are constrained to either face the variability of supply and demand, or preserve private information of electrical utilities. To the best of our knowledge, none of the existing approaches can overcome both: supply and demand uncertainties; and privacy-preserving constraints.

In this paper, we introduce an algorithmic framework that extends both stochastic and distributed approaches to UCs in order to ensure that electrical utilities do not explicitly communicate their private information to their competitors during the planning phase. In particular, we recast distributed stochastic unit commitment (DSUC) problems into linearly constrained quadratic programs (LCQP). In this form, the primary contribution of this work is to extend existing distributed algorithms for solving unconstrained quadratic programs to LCQP and thus DSUC. This is achieved by means of communication protocols that allow electrical utilities to choose which part of their private information to share with one another in order to collectively find an optimal or near-optimal schedule strategy. The resulting algorithm, namely *protocol based distributed projected gradient-descent optimization* (P-DPGO), is guaranteed to terminate after a finite number of iterations with a near-optimal solution.

We demonstrate the performance of the P-DPGO algorithm on an IEEE 14 nodes network, which consists of several virtual power plants with controllable generator units. The principal source of uncertainty in such a setting is the unpredictable break-downs generator units can experience, which make the supply uncertain. Experiments over different stochastic scenarios show that P-DPGO produces efficient schedule strategies in term of costs. This is expected given that our approach exploits three advantages: first, it preserves private information of electrical utilities; next, it takes into account long term decision effects; and finally, it can handle uncertainty in supply and demand.

The remainder of this paper is organized as follows. First, we provide some motivating scenarios that illustrate the key features in DSUCs (Section 2). Next, Section 3 describes different models of UCs, and Section 4 discusses distributed algorithms for solving unconstrained quadratic programs we build upon. Then, in Section 5, we describe P-DPGO, which combines existing distributed algorithms to communication protocols in order to ensure that local information electrical utilities do not want to share remain private. Finally, we present an empirical evaluation of this algorithm on a real experimental platform.

2. Motivating scenarios

In the following, we distinguish between three scenarios that illustrate the characteristics of unit commitment problems we target. The primary scenario involves no competition at all and no uncertainty, the second augments the former by taking into account uncertainty and the last scenario complements the second one assuming a competitive setting.

Scenario 1. In this first scenario, we consider a smart grid that consists of two controllable units, e.g., diesel power generators, each of which is owned by a single electrical utility. This electrical utility needs to find the least-cost dispatch of available generation resources to meet the electrical load over 24 h. In this world, each unit can generate power profiles that range from 10% to 95% of its nominal generation capacity. In addition, each unit incurs operations and maintenance costs that increase quadratically with the amount of power it generates. Furthermore, each unit is subject to a number of complex and private technical constraints, e.g., the maximum rate of ramping up or down and the minimum period the unit is up and or down.

Such a non-competitive and deterministic scenario is amenable to centralized branch-and-bound methods, dynamic programming and Lagrangian relaxation techniques (Cohen and Yoshimura, 1983; Snyder et al., 1987; Fisher, 2004). However, there are various sources of uncertainty in real-world unit commitment problems. Examples, such as unpredictable failures in the transmission network or the introduction of uncontrollable units, make consumers at different nodes in the distribution network to experience cuts in the power supplied. As a consequence, the other distribution networks compete to offer their electricity output in order to meet the demand of these consumers. A stochastic scenario, which complements that in Scenario 1, follows.

Scenario 2. In this second scenario, each unit can experience unpredictable breakdowns, which result in cuts in the power supplied. More precisely, at the end of each time step, each unit can sense some information, which in this case corresponds to whether or not a breakdown occurs.