Computational Challenges in Smart Grid

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Abstract

Designed largely from an energy generation and power distribution perspective, todays electrical power grid is faced with significant challenges in meeting growing demand in the face of an expanding variety and distribution of energy sources and increased requirements for local control, robustness, resilience and efficiency. Unlike many traditional distributed systems and control problems, the driving forces underlying energy demand include economics and human behavior. The electric power grid is poised to undergo a revolution from a largely centralized system built for long-haul distribution to a more decentralized system with more emphasis on local production and intelligent distribution to reduce system complexity; improve power management, system resiliency and security; and minimize cost and power loss. Enabling this revolution necessitates the combined expertise and synergy of several disciplines including power systems, computer science, telecommunications, and economics. In particular, problems such as optimal scheduling of demands and determining how to best meet those demands given a variety of potentially energy generation and distribution choices pose novel computational challenges and present exciting new interdisciplinary research opportunities.

I. Smart Grids

It is expected that demand for electricity in the U.S. alone will increase 25%-50% by 2040 from the 2011 demand [1]. This dictates the need for an increase in generation capacity, much of which is expected to be in the form of distributed generation (DG), mainly at the distribution level (voltage) [achieved mostly via alternative energy DG (AEDG) including some highly heterogeneous sources e.g., wind, solar photovoltaic (PV)]. In addition, there are tremendous efforts and planning underway to modernize the electrical grid; defining how to achieve “smart grid” solutions [2], [3]. Key attributes of future smart grids include higher reliability, improved power quality, stronger energy security, and improved system efficiency. In this regard, two enabling technologies stand out towards the achievement of these smart grid objectives: microgrids and hybrid renewable generation systems. Microgrids, defined as a collection of localized generation, load, and storage assets that are integrated and controlled independently, offer a distributed means of autonomously controllable power system entities, which can operate in islanded or grid-connected modes. The proposed smart grid system includes local control and data acquisition and will require extensive communications capabilities. The local power generation, consumption, and storage units are intelligent with information-processing capability to respond to power supply and demand within the local microgrid. We envision that local units will operate in a distributed manner. The optimization and control problems will be solved locally but computationally hard problems with real-time requirements might be most cost-effectively solved using cloud-computing resources.

II. Example One: Efficient Power Distribution and Control in Smart Grids

As power generation becomes more decentralized, determining how best to distribute power in grids and microgrids becomes a key component in increasing efficiency, reducing costs and limiting losses. For example, if there is excess generation capacity at one production facility it maybe more cost effective to increase its production rather than bring another resource online. Likewise, if several paths of distribution can be used to reach consumers, the paths may have different marginal costs. This bears some resemblance to “green networking” problems where networking resources can be turned on at some energy-use cost and the problem is to meet traffic demand adequately, while minimizing energy-use [4], [5]. It has been argued [6] that the grid system shares a number of similarities with the Internet and that the similarities will increase as the grid evolves into a smarter and more distributed system.

There are potentially multiple objectives (e.g. generation cost, distribution cost and loss, CO2 emissions, etc.) to consider in determining the optimal levels of production and each generation source and how best to distribute this generated power to the intended users. For example, suppose we seek to determine the production levels, say g_i, of the i-th generation source, given the demand d_j of the j-th load. If we consider electrical power as a “single-commodity flow”, then the problem becomes that of minimizing the above mentioned linear cost objective function subject to conservation of power flow, generation and demand constraints being met. The problem is further complicated as there is some loss along the distribution links; this loss must be taken into account. In addition to losses, there can also be operational costs in the distribution system; such costs may contain a fixed component (a start-up or initialization cost) and potentially a cost that scales proportionally with the flow/load associated with the component. As an example, Hedman *et al.* [7], considers switches in the transmission system and finds the optimal power flow over the system considering that you can open and close the switches. The switches change the topology of the network and thus affect power flow over the network according to Kirchhoff’s laws.

III. Example Two: Power Scheduling

Smart grid technology has the opportunity to revolutionize our visibility and control over power consumption at both the consumer and utility provider levels. Smart appliances and appliance specific energy traces will provide the ability to track and control power draw for individual appliances. This capability will enable consumers and utility providers to control costs by shifting demand based on current load, projected load, and flexibility of appliance specific job parameters. Currently power-requesting jobs are scheduled in an on-demand fashion; power draw begins when the consumer requests power (turns on an appliance) and ends when the job is complete (appliance is tuned off). Often such jobs may have some flexibility in their starting times (e.g. a dishwasher or electric vehicle charger). Recently, we looked at the problem of scheduling power jobs so as to minimize peak demand (see Figure 1) [8].

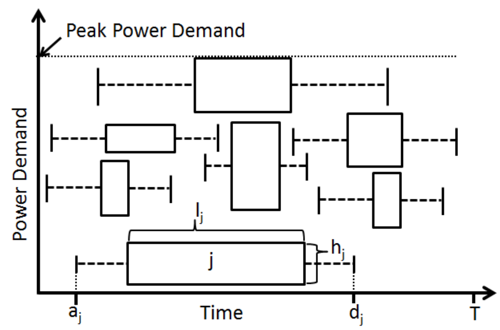
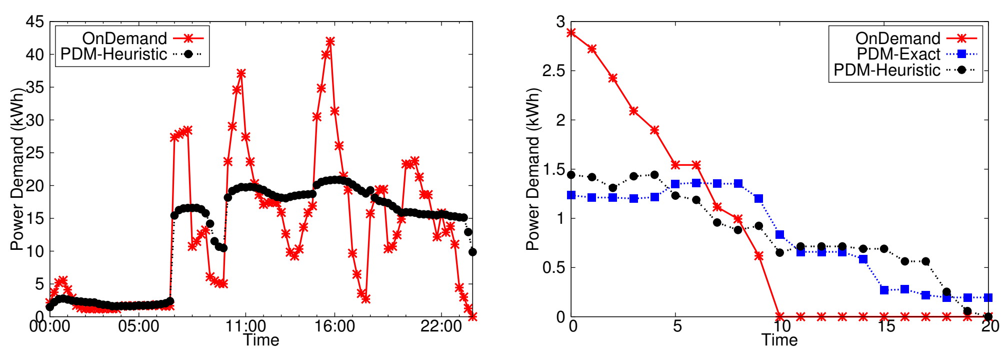


Fig. 1. Non-preemptive power jobs to be scheduled. Jobs, j, are defined as 4-tuples: (a_j, d_j, l_j, h_j), where a_j is the arrival time and d_j is the deadline within the time interval $[0, T]$, l_j is the job length (duration), and h_j is the job height (instantaneous power requirement). The goal is to schedule jobs in such a way as to minimize the peak power demand within the schedule.

While the problem turns out to be computationally challenging, we were able to advance the state-of-the-art as follows:

1) First we considered a general version of the problem in which the job intervals can be staggered. While the problem is known to be NP-hard (we show it is even NP-hard to approximate), we presented an optimal algorithm (PDM-Exact) based on dynamic programming that is *fixed-parameter tractable* (FPT), as well as an effective heuristic algorithm (PDM-Heuristic).
2) We developed approximation algorithms for some special cases: When jobs have the same arrival times and deadlines, we presented a 4-approximation algorithm (PDM-CW). Prior to our results, a 7.82-approximation algorithm was the best existing algorithm [9]. For a special case of the peak demand minimization problem where jobs cannot be nested within each other, we presented a $O(\log \Delta)$-approximation algorithm, where Δ is the ratio of the widest job to the narrowest.
3) Based on recent energy disaggregation results [10], we modeled power demands for appliances (e.g. dishwasher, washing machine, dryer) and compared our algorithms against simple on-demand scheduling and some other recent approaches [9]. Figure 2 shows some of our results.



(a) Domestic Power Scheduling (24 hour scenario) (b) Comparison with Optimal

Fig. 2. Some recent results on peak demand minimization from [8]; peak power demand can be lowered considerably using intelligent job scheduling.

Peak demand minimization is by no means solved; the case where the input contains preemptive jobs should be considered as well as online and distributed versions of problem.

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