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Fast Electrical Demand Optimization Under Real-Time Pricing

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1 Introduction

The introduction of smart meters for measuring and controlling electrical demand at home has motivated the electricity industry to seek scalable mechanisms for matching electrical demand to supply. Electrical demand can be managed if households allow some flexibility in the scheduling of certain tasks such as washing clothes. If smart meters in an area connected to a given power transformer are all coordinated, this flexibility allows peak demand to be flattened, thus obviating the need to upgrade transformer capacity or deploy costly electricity generation capacity when the peak demand grows. Real-time pricing (RTP) is an effective scheme to reduce peak demand (Albadi and El-Saadany 2007). Under RTP, the electricity price varies at different times of the day, reflecting the real-time supply and demand conditions in the market. Consumers can reduce their costs by shifting the demand outside the peak times, therefore reduce the peak demand. The overall aim of demand management is to minimize electricity generation and distribution costs while meeting the demands and preferences of consumers. This research aims at investigating a new approach that elicits globally optimal demand schedule to achieve this overall aim under RTP, and easily scales to large groups of households.

An autonomous system that rapidly schedules demand for a large number of households is a challenge. This has given rise to research on electrical demand management under RTP (Samadi et al. 2010; Van Den Briel, Scott, and Thiébaux 2013; He et al. 2014). One approach described in (Barbato et al. 2011) is to gather data on planned tasks for a single day from all households within an area, in an electrical demand coordination centre (EDCC). All tasks are then scheduled centrally, and the schedules are communicated to smart meters in all households. It is not possible to optimally schedule tasks for thousands of households in realistic timescale. A second approach delegates the task scheduling in each household to its smart meter. In (Samadi et al. 2010; Li, Chen, and Low 2011), smart meters schedule tasks against an initial set of prices across the day, and communicate only their resulting demands to the EDCC, from which new prices are computed. The smart meters iteratively compute new schedules from which the EDCC computes new prices until a stopping condition is met. We call it *central pricing*. However, naturally if the price is lowest at time T, then all households will tend to run tasks at time T which causes a spike in the demand at that time, resulting in a high cost. This paper proposes an innovative scalable approach which delegates task scheduling to household smart meters, but avoids the limitations of central pricing. We term it *mixed initiative*. This approach, like (Li, Chen, and Low 2011) uses an iterative process, but the end result is not a set of prices. Instead it is a globally optimal consumption level (maximum demand for all households) for each period of the day.

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2 Demand Optimization Problem

We investigate a non-linear multi-objective optimization problem that minimizes the total electricity cost and inconvenience cost of households. An electricity cost is specified at each period of the day that increases non-linearly with the total demand. An inconvenience cost is incurred for starting a task at its non-preferred start time. The inconvenience cost is designed to balance inconvenience against the cost of electricity provision. The optimal solution to this problem is a set of consumption levels that minimizes the total costs. We find this solution by computing a probability for each task to start at each feasible time, such that the expected total demand per period of all tasks incurs the lowest total costs, and the optimal expected total demands are the optimal consumption levels we seek for this problem. These probabilities of start times for tasks are then used by smart meters to schedule tasks in practice. As in (Van Den Briel, Scott, and Thiébaux 2013), we assume that the number of tasks is large enough that the total demands are highly likely to be close to the optimal consumption levels.

3 The mixed initiative approach

We propose a mixed initiative approach to find the optimal consumption levels in an iterative manner, illustrated in the complementary material. At each iteration, each household optimally schedules its own tasks, given a set of prices. Then a demand coordinator computes a probability for these new start times and a new price per period, with a convex optimization method, also known as Frank-Wolfe (FW) algorithm. In our implementation of FW, firstly, the coordinator computes the total demand per period $\mathbf{D}_k$. Secondly, it takes the optimal consumption level per period found at the previous iteration $\tilde{\mathbf{D}}_{k-1}$, and finds a point $\tilde{\mathbf{D}}_k = \tilde{\mathbf{D}}_{k-1} + \alpha \times (\mathbf{D}_k - \tilde{\mathbf{D}}_{k-1})$ between $\mathbf{D}_k$ and $\tilde{\mathbf{D}}_{k-1}$ that minimizes the total electricity cost and inconvenience cost, given the current set of prices. $\tilde{\mathbf{D}}_k$ is the optimal consumption levels found at iteration k, and the associated α is the probability we seek for this iteration. Finally, the coordinator computes the new prices for the next iteration based on $\tilde{\mathbf{D}}_k$. The mixed initiative approach iterates until a stopping condition where no household can reschedule any task to reduce its electricity cost and inconvenience cost, thus every household is, in a sense, satisfied. After that, smart meters uses the probability produced at each iteration to compute the probability distribution of start times for tasks in each households. The complexity of this approach is independent of the number of households. At each iteration, the coordinator does not need to know the details of individual tasks of households, but the aggregate demands. This property allows this approach to be applied to problems with tens of thousands of households.

4 Experimental Results

We generated 200 artificial problem instances based on real data, ranging in size from 1000 to 21000 households (each household has ten tasks). We recorded the convergence rate, run time, and peak and cost reductions in each problem instance. Figure 1 shows that the average convergence rate first increases slightly with the number of households, then remains similar. The convergence rate for 21000 households (210000 appliances) is less than 50 iterations. Figure 2 shows the run-time of the task scheduling algorithm per household and our version of Frank-Wolfe for the coordinator, at each iteration. When 21000 households schedule tasks independently in parallel, the average run time of one iteration is less than 0.012 second. Figure 3 shows that on average, the proposed approach reduces the peak demand by 18%, and the electricity cost by 12%.

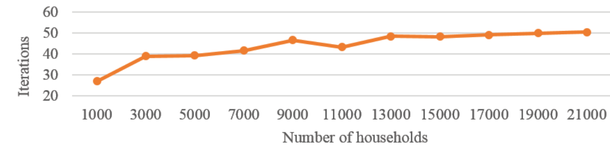

Figure 1: Average convergence rate

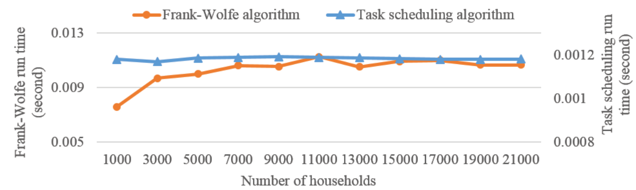

Figure 2: Average run time

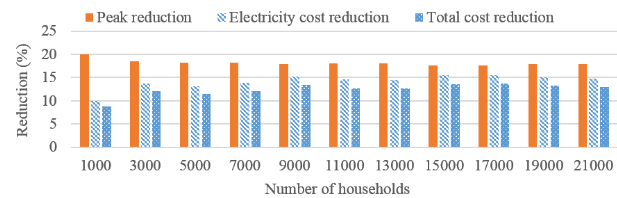

Figure 3: Average peak and cost reductions

5 Conclusions

The mixed initiative approach presented in this paper finds the optimal consumption levels for households in an iterative manner. The intermediate results of this approach can be used by smart meters to compute probabilities of start times for tasks in each household. With these distributions, smart meters can schedule tasks with a simple randomized method, and the resulting total demands will be highly likely close to the optimal consumption levels that are computed before. The complexity of this approach is independent of the number of households, which allows it to be applied to problems with tens of thousands of households. Our results show that the proposed approach has fast convergence, high scalability and effective peak demand and cost reduction. More details are available at http://tinyurl.com/jc9apq6.

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