Scheduling in smart grids

Arun Srikanth[a], Divya Pathak [b], Harsha Panjwani [c], Varun Pillai [c]

[a] Department of Chemical and Biological Engineering, Drexel University

[a] Department of Electrical and Computer Engineering, Drexel University

[c] Lebow Business school, Drexel University

Abstract

Recent increase in demand of domestic elctric power consumption has triggered an interest to develop efficient strategies that minimizes the cost of electric power consumption by appropriately scheduling the run time of home appliances. In this technical report, an NLIP (Non-linear Integer Programming) problem is proposed that minimizes the total expected electric cost by taking into account the cost of delay when an appliance is scheduled at a later time, the randomness involved in both the request time and the duration for which the appliance is to be used. An average shceduling policy is obtained by solving the NILP model. The formulation is first motivated by considering the power consumption of a single household with three appliances. This formulation is then extended to a neighbourhood which is limited by power availability. The mathematical formulation, the solution methodolgy and the results are discussed in detail. The results obtained can be used as an estimate for designing efficient grids for distributing electric power in a neighbourhood.

Keywords: Smartgrids, NLIP, optimization, power consumption, appliances

1 Introduction

Electricity consumption in the Unites states is projected to increase by 29% from 2012 to 2040 [EIA, 2015a]. The average US residential electricity prices increased at the highest rate of 3.1% since 2008 and is projected to increase by 1.0% in 2015 and by 1.8% in 2016 [EIA, 2015b]. In order to meet the residential demands of a neighbourhood as well as minimize the cost of electric power consumption, a grid should uitlize an efficient strategy for distributing power to a neighbourhood which is carried out by appropriately scheduling the run time of appliances.

Mathematical models and research works related to energy efficient strategies for an electric grid, distributing power to a neighbourhood or a household have been done in the past. For eg., [Bu et al., 2011] proposed a stochastic sheduling model which takes into account the dynamic power demand loads and intermittent avrenewable energy resources. They obtained a reduction in cost thus leading to a lower green house gas emissions. The difficulty involved in demand response models when the information is shared in a smart grid was hadled by [Caron and Kesidis, 2010]. They proposed a dynamic pricing scheme which is advantageous to the consumers and obtianed a reduction in cost when the information is shared within an electric grid. An optimization model that minimizes the total electricity cost by scheduling appliances upon receiving request from the customer has been studied by [Burcea et al., 2013]. They provide an optimal offline algorithm which runs in polynomial time. A feedbabck control approach to minimize the cost by allowing interactions between individual users and supplier was asolved by [Joe-Wong et al., 2012] and a game theoritic approach to reduce the peak load and minimize the total cost has been proposed by Chen et al. [2011].

An MILP (Mixed Integer Linerar Programming) model was formulated and solved to minimize the energy consumption of homes [Zhang et al., 2013]. Specifically they minimize the one day ahead (forecasted) energy consumption cost. The expected value (long term average) of a power grid operational cost was minimized by [Koutsopoulos and Tassiulas, 2012]. They solve the optimization problem by developing a stochastic model and by introducing two scheduling policies TP (Threshold Postponement) and CR (Controlled Release). In the present work a very simplified version of the optimization model proposed by [Koutsopoulos and Tassiulas, 2012] is solved. The rest of the document is organized as follows.

Firstly, the motivation to solve an optimization model is explained followed by preliminary analysis of the data. The optimization model and the mathematical formulation is explained in detail. The solutions of the optimization model are discussed and conclusions are drawn.

2 Motivation

The time at which an appliance is used and the time duration for which it is used in a day is often flexible. This is advantageous for an EMC (Electrical Maintanence Company), since an appliance if requested during a time slot when the cost of electric consumption is high, can be rescheduled to a later time to reduce the cost, since the cost of electric power may be low at a later time. However, such resheduling may result in an additional delay cost associated with an appliance which EMC has to entail. Hence a tradeoff exists between delaying the run time of an appliance and the cost associated with delaying that appliance. This tradeoff can then be utilized to reduce the overall cost of electric power by appropriately scheduling the appliances. In this work, the problem of scheduling appliances is considered for three scenarios and an optimization model is developed. The three scenarios are,

- Base case (Fig. 1): Scenario consisting of a single household with three appliances.
- Basecase with capacity constraints: Single household restricted by power usage per time period.
- Scheduling appliances for neighbourhood consisting of individual homes.

For the analysis, the data provided in 4th AIMMS-MOPTA optimization modelling competition is considered. Specifically the data provided in "smalldata.xls" is considered in this work. The description of the data and a preliminary analysis of the data is explained in the next section.

Figure 1: A schematic representation of base case scenario

3 Data generation and analysis

The "smalldata.xls" contains the data obtained for single household with N_a appliances where $N_a = 3$, representing a dish washer, clothes dryer and a water heater. Further the data collected is such that, a day is split into n equal time where each time slot is denoted by t. If an appliance is off in period t, then the probability that it is requested in period $t+1$ is a_{nt} . Similarly, if an appliance is on in period t, then the probability that it is off in period $t+1$ is b_{nt}. Based on this probability data for each appliance and by using random number generator from a uniform distribution, the request time slots and the duration time slots (the time slots upto which an appliance is in use) for the appliances used in a day are generated. This procedure is schematically represented in Fig.2 for an appliance. A Frequency distribution of the timeslots and duration slots for the three appliances are generated by considering 10000 samples i.e., appliance usage per day over a period of 10000 days. Further the sampling is restricted to appliance usage that is not beyond 23 hours (samples for which the duration slots exceeding 23 are not allowed). A request slot of zero implies that the appliance is not used in that day. The frequency distribution provides useful insights about an appliance usage which are helpful in two aspects.

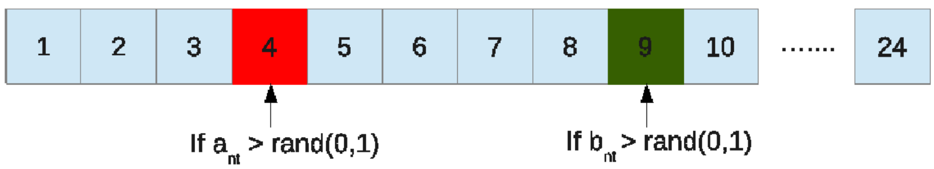

Figure 2: Generation of request time slot and duration slots for an appliance

First, the distribution assists in performing importance sampling. For eg., when no equipment is in use in a particular day, then the there is no electric power consumption. From Fig.2, it can be observed that out of 10000 days, the dish washer has been used only for about 5000 days and like wise for the clothes dryer and the water heater. Hence, these scenarios can be removed to reduce the computational burden of cost function evaluations in computing or minimizing the expected cost.

The second is for developing heuristic approaches or greedy alogorithms for scheduling. For eg., the probability that the dish washer is requested to be used is high during the 17^th time slot which is a period where the cost of electric power is high (Fig. 3). Hence one can schedule the dish washer to a later time if one receives a request for the dishwaher between 17^th and 22^{nd} time slots. However, such greedy alogorithms do not yield long term profit and a formal optimization model needs to be formulated and solved. The optimization is explained in the next section.

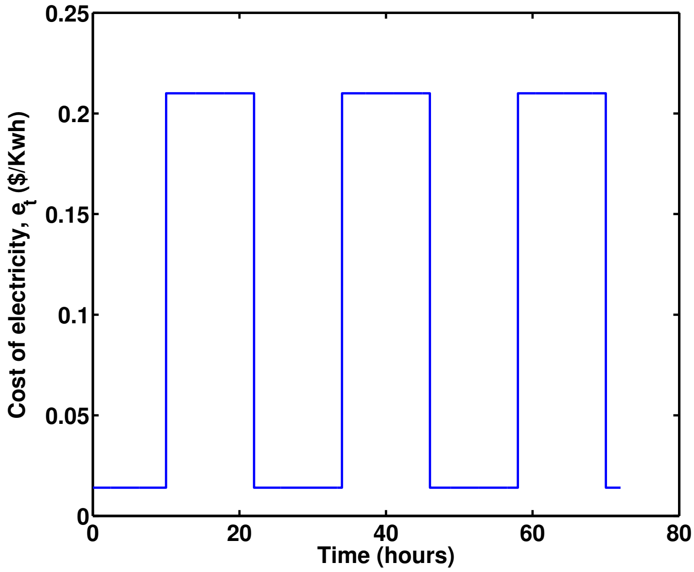

Figure 3: Costfunction

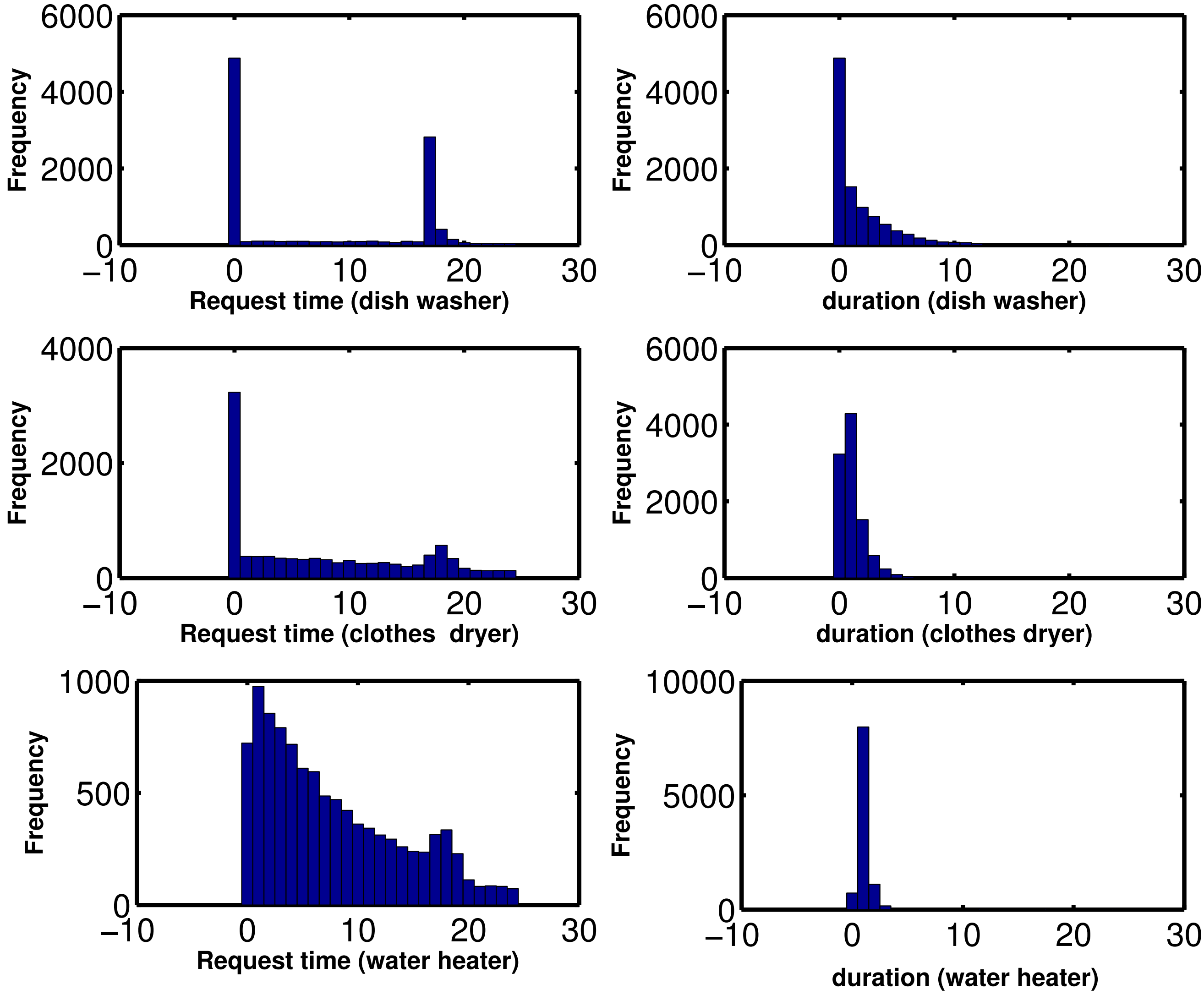

Figure 4: Frequency distribution of request time slots and the corresponding duration time slots of appliances

4 Optimization

As explained in section 2, a trade off exists between between delaying the run time of an appliance and the cost associated with delaying that appliance. In this section, a formal optimization model is then proposed to explore this trade-off. The optimization model for each of the scenarios mentioned in section 2 is then solved and the results are discussed below. The decision variables in the optimization model are the delay time periods, $\tau_j, j = 1...N_a$ associated with each appliance and are used integer variables. The various costs associated with scheduling an appliance is given below.

The cost of electric power consumption by an appliance given by,

$$c_{e,j}(\tau_j, R_{k,j} = r_{k,j}) = \sum_{i=1}^{r_k+d} e_t(\tau_j, R_{k,j} = r_{k,j})P_j \quad , j = 1, 2....N_a, \;\; k = 1, 2....N \tag{1}$$

where P_j, r are the power (\$/KWh) consumed by an appliance and the request time slot respectively. The request time slot is a stochastic variable and is obtained as mentioned in section 3

The cost of delay associated with an appliance when it is delayed by τ_i time slots is then,

$$c_{d,j}(\tau_j) = c_{nj}\tau_j \;\; \tau_j \leq m_n, \;\; , j = 1...N_a \tag{2}$$

if τ_i exceeds m_n time periods, an additional cost is involved in scheduling that appliance which is given by,

$$c_{ad,j} = c_{nj}, \;\; \tau_j > m_n \;\; j = 1...N_a \tag{3}$$

The total cost of running an appliance is,

$$C_{T,j}(\tau_j, R_{k,j} = r_{k,j}) = c_{e,j} + c_{d,j} + c_{ad,j} \quad , j = 1.....N_a \tag{4}$$

The cost associated with a household is then given by,

$$C_H(\tau_{j=1..N_a}, R_{k,j=1..Na}) = \sum_{j=1}^{j=N_a} C_{T,j} \tag{5}$$

The expected cost per day is then calculated using the following approximation,

$$E(C_H) \sim \frac{C_H}{N} \tag{6}$$

The optimization model to be solved is then given by,

$$\underset{\tau_{i=1...N_a}}{min} \;\; E\left[C_H(\tau_{j=1..N_a}, R_{k,j=1..Na} = r_{k,j=1....N_a})\right] \;\; , .., , , , \tau_i \epsilon \mathbb{Z} \tag{7}$$

4.1 Solution methodology

The optimization problem is an NILP (Nonlinear Linear Integer Programming) problem. This is then solved using MIDACO-SOLVER [$MIDACO$, 2015], a global optimization software for MINLP (Mixed Integer Nonlinear Programming) problem. This solver utilizes ant colony optimization technique to obtain the optimal solution. The solution obtained may not be a global solution and different initial guesses are used

The optimization model is solved on a

5 Basecase scenario

The optimization model described in section 4 is solved for the base case scenario with the parameters $m_n = 6$, $N_a = 3$ and for $N = 100, 1000, 10000$ to obtain the optiaml scheduling policy. The results of the optimal solution is summarized in Table. 1.

Table 1: Optimal solutions

$E^*(C_H)$/day (\$)	N (days)	$(\tau_1^*, \tau_2^*, \tau_3^*)$
0.27354000	100	(6,3,8)
0.31673280	1000	(6,3,8)
0.30562032	10000	(6,3,8)

Since the solution obtained may not be global a consistency check was performed with different initial guesses. The optimal solutions indicates the mean scheduling policy i.e., the average of the daily scheduling should flutuate around the mean values of $\tau_1^*, \tau_2^*, \tau_3^*$ and the expected cost represents a long term average of the cost of electric power incurred every day.

6 Base case scenario with capacity constraints

In the basecase scenario it was assumed that the household has no restrictions on the power consumption. However a household is usually restricted by power consumption. Typically a house hold is restricted by the power consumption per time slot. Hence the optimization model that needs to be solved is,

$$\min_{\tau_{i=1...N_a}} \; E\left[C_H(\tau_{j=1..N_a}, R_{k,j=1..Na} = r_{k,j=1....N_a})\right] \quad \tau_i \epsilon \mathbb{Z} \tag{8}$$

s.to

$$\sum_{l=1} P_{jl} = P_{max} \quad l = 1........ \tag{9}$$

where l represents the number of time slots in a period of N days. The P_{max} was chosen to be 3.6 which is the power required to run utmost two apliances in the time slot. To reduce the computational burden and for illustration a small sample size of 100 (100 days) is chosen.

The optimization model is then solved. For the 100 scenarios that are generated it can observed from Fig. 5 that on certain time slots the home exceeds P_{max}. From Fig. 6 it can be observed that after optimally rescheduling, the load constraints per time slot are satisfied and the optimal solution is again (6,3,8) for $(\tau_1^*, \tau_2^*, \tau_3^*)$

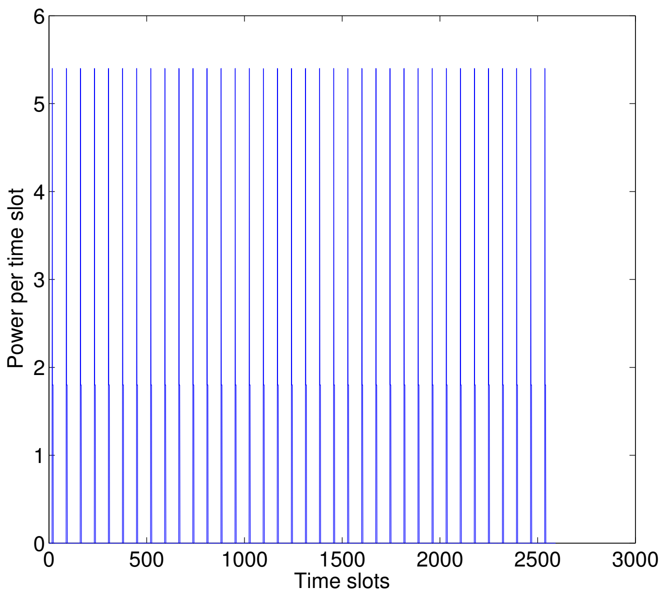

Figure 5: Load distribution in a time slot before scheduling

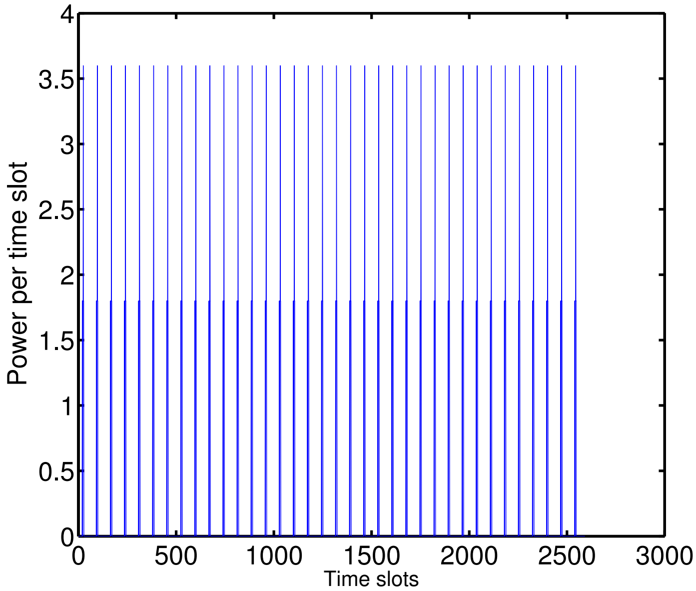

Figure 6: Load distribution in a time slot after scheduling

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