

A Load Scheduling Algorithm for the Smart Home Using Customer Preferences and Real Time Residential Prices

Siddharth Suryanarayanan,^{*} Marvin Antony Devadass,^{*}
 Timothy M. Hansen^{**}

^{*} *Department of Electrical & Computer Engineering,
 Colorado State University, Fort Collins, CO 80523-1373, USA
 (e-mails: sid@colostate.edu; marvin.devadass@colostate.edu).*

^{**} *Electrical Engineering and Computer Science Department,
 South Dakota State University, Brookings, SD 57007, USA
 (e-mail: timothy.hansen@sdstate.edu)*

Abstract: A load scheduling method in the Smart Home using a combination of customer preferences and the price of electricity is presented. To translate the customer preference of loads into a time-varying priority curve, the Analytical Hierarchy Process (AHP) and Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) methods are used. The resulting curves of customer priority are combined with the available time-varying pricing information for determining the schedule for each load. An example with four loads is presented to demonstrate the effectiveness of the algorithm.

© 2015, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.

Keywords: Analytical Hierarchy Process (AHP), load scheduling, Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), residential real time pricing (RRTP), Smart Home.

1. INTRODUCTION

The Energy and Independence Security Act of 2007 of the 110th Congress of United States (2007), mandated the Smart Grid Initiative to modernize the national electricity grid in the U.S. One of the features of the Smart Grid is its attempt to increase customer participation in the grid. This paper focuses on achieving this feature by determining a load scheduling algorithm which shifts some loads away from peak hours based on customer preferences and real time prices of residential electricity service. This effort will eventually lead to reduction of electricity generated from expensive conventional peaking generators if this technique is applied widely. The objective of this paper is to create a mathematical framework for making automated decisions on load scheduling in the Smart Home via a ranking of loads. This ranking is obtained by the application of a shape-preserving interpolation technique—Piecewise Cubic Hermite Interpolating Polynomial (PCHIP), Moler (2013)—to a decision-making algorithm—Analytical Hierarchy Process (AHP), Saaty (2006).

AHP has a wide range of applications in a variety of fields; an example of the the application of this technique to power engineering is in the design of a load shedding algorithm for shipboard power systems, Ding et al. (2009). Dynamic prioritization is achievable in changing scenarios with the algorithm's ability to differentiate between critical and non-critical loads, so that load curtailment does not affect critical systems when yielding improved benefits. In our paper, we use AHP for load scheduling rather than for load shedding. An algorithm for scheduling thermostatically controlled loads in households is presented in Du and

Lu (2011), where price and consumption forecasts are considered for scheduling loads to achieve minimum payment or maximum comfort using optimization techniques.

A load scheduling methodology using AHP and PCHIP is applied empirically for a specific case in Armas (2010). Our approach differs from Armas (2010) in developing a *generic* structure for the algorithm presented in Armas (2010) that can be applied for scheduling loads such as a dishwasher, a washing machine, a clothes dryer, and an electric vehicle (EV) in the Smart Home while taking residential real time pricing (RRTP) of electricity, such as ComEd (2015), into consideration. Load priorities, weights for customer preferences of loads, and day-ahead dynamic market pricing of electricity are used to calculate load rankings by combining the load priority curve and price curve and maximizing the resultant curve. Each load can then be scheduled at the time corresponding to the maximum in the respective load ranking curve.

2. PROBLEM STATEMENT

The Smart Home is expected to possess increased penetrations of loads that can be scheduled, sensors and actuators enabled by the Internet of Things (IoT), and an active end-user with access to information, Zipperer et al. (2013). One of the challenges in the Smart Home is the ability to engage the end-user in demand response (DR) programs such as peak reduction, without increasing the burden of participation on the end-user. Indirect methods of engaging the end-user by introducing a dynamic (time-varying) rate of electricity is the state-of-the-art, ComEd

(2015). However, there exists a need for developing intelligent and adaptive algorithms that can enable the end-user to make the most of the enablers such as dynamic pricing. For instance, an end-user may be amenable to rescheduling some loads in the Smart Home by utilizing the information on times when electricity pricing may be competitive or less expensive than peak times. However, it is not practical to expect the end-user to be constantly engaged in providing inputs to the energy management system (EMS) for scheduling loads based on changing electricity rates; neither is it practical to assume that end-users will relinquish comfort and convenience in favor of reducing their electricity bill. We develop an algorithm in which the end users may only provide preferences for some times during the day that may not be as frequent as the resolution of the forecast dynamic electricity pricing data. By using PCHIP to interpolate between the user inputted preferences (end points or knots) we minimize the end user effort and still capture the full range of electricity pricing dynamics. It is in this regard that we present the following problem statement: *How to determine the daily schedule of select loads in a Smart Home, enabled by dynamic pricing of electricity, by soliciting a reasonably small set of subjective information from the end-user on their comfort and priority of loads?* We will use the following techniques to address a solution to the above problem statement: a) AHP; b) PCHIP; and c) a linear combination of priorities and RRTP. Descriptions of the above-mentioned methods—albeit brief—and the algorithm follow immediately in Section 3.

3. TECHNIQUES AND ALGORITHMS

3.1 Analytic hierarchy process

AHP is a decision-making methodology that includes subjective input in determining priorities of options. Here, we provide a concise description of the procedure using the definitive resource on this subject, Saaty (2006). Subjective information from the end-user is obtained in the form of pairwise comparisons between choices. This is based on a fundamental numeric scale where 1 indicates an equal importance between two choices (or the self-importance of a choice), and 9 indicates the maximum preference of the first choice over the second. Non-zero numbers lying between 1 and 9 are used to indicate increasing levels of the dominance of one choice over the other in this pairwise comparison. It is reasonable to assume that the reciprocals of these value indicates the importance of the second choice over the first one. Decimal values between 1.1 and 1.9, and their respective reciprocals, are also used to indicate relatively close importance between two choices. The pairwise comparison of N choices are arranged in a $N \times N$ matrix A , with the $\frac{N^2-N}{2}$ upper triangular elements reflecting the reciprocal of the corresponding lower triangular elements, and ones on the diagonal indicating the self-importance of a choice. However, prior to manipulations, the matrix is checked for consistency of inputs by computing the *consistency index*, $CI = \frac{\lambda_{max} - N}{N - 1}$, where λ_{max} is the largest eigenvalue of A . CI is normalized over a random consistency index (RI), obtained from Saaty (2006) and presented in Table 1, to yield a *consistency ratio* $CR = \frac{CI}{RI}$. Typically, we limit the number of choices in pairwise com-

parisons to 7 for maintaining consistency and cognizance. Conventionally acceptable levels of consistency are given in Table 1.

Inconsistent inputs are routinely encountered due to the subjective nature of populating the pairwise comparison matrix (PCM). In such cases, they are suitably modified by the eigenvector $\tau_{1 \times N}$ corresponding to λ_{max} . The procedure is: i) $A_{i,k}^{new} = a_{i,k} \times \frac{\tau_k}{\tau_i}$; ii) Replace largest element (most inconsistent) in $A_{i,k}^{new}$ with $\frac{\tau_k}{\tau_i}$ such that the new PCM moves closer to consistency; and, iii) Repeat above steps until desired CR is attained.

After correcting for consistencies, AHP is executed to establish a prioritized list of the options. Due to the popularity of AHP and the availability of numerous references on the procedure for executing the AHP, we point the interested reader to Saaty (2006) for the details.

Table 1. Some RI values and acceptable CR from Saaty (2006)

N	3	4	5	6	7
RI	0.58	0.9	1.12	1.24	1.32
Acceptable CR (%)	5	8	≤ 10	≤ 10	≤ 10

3.2 Piecewise cubic hermite interpolating polynomial

PCHIP is a shape-preserving cubic interpolation polynomial that prevents overshoots at or about the data points. The description of this popular method of interpolation is given in Moler (2013) and presented briefly here for the sake of completeness. PCHIP is determined by four functions: the two data points (also known as *knots*) at the boundary, $A(x_k) = y_k$ and $A(x_{k+1}) = y_{k+1}$; and the slopes at these two knots, $A'(x_k) = d_k$ and $A'(x_{k+1}) = d_{k+1}$, respectively. $A(x)$ is the cubic Hermite interpolant in each subinterval $x_k \leq x \leq x_{k+1}$. Let $h_k = (x_{k+1} - x_k)$ be the interval length and $\delta_k = \frac{y_{k+1} - y_k}{x_{k+1} - x_k}$ be the first divided difference or the discrete slope. The condition $\delta_k = d_k$ is not always true for cubic interpolants. In order to fit the curve between the given knots using the PCHIP, we must determine the value of d_k at every knot x_k without introducing an overshoot. For this, let us consider three scenarios:

- (1) If δ_k and δ_{k-1} are of opposite signs or if either is zero, it indicates that x_k is a discrete local extremum. This implies that $d_k = 0$.
- (2) If δ_k and δ_{k-1} are of same sign and equal interval length then the slope is harmonic mean of the individual discrete slopes, i.e., $\frac{1}{d_k} = 0.5 \times \left(\frac{1}{\delta_{k-1}} + \frac{1}{\delta_k} \right)$
- (3) If δ_k and δ_{k-1} are of same sign and unequal interval lengths, h_{k-1} and h_k , then the slope is a weighted harmonic mean of the individual discrete slopes, i.e., $\frac{3 \times (h_{k-1} + h_k)}{d_k} = \left(\frac{2h_k + h_{k-1}}{\delta_{k-1}} + \frac{h_k + 2h_{k-1}}{\delta_k} \right)$

The coefficients of the cubic function are chosen such that the first derivative (slope) of the cubic hermite interpolant is equal on both sides of the knots; while the second derivative may be non-continuous. For every interval, with

Download English Version:

<https://daneshyari.com/en/article/711060>

Download Persian Version:

<https://daneshyari.com/article/711060>

[Daneshyari.com](https://daneshyari.com)