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

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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.

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

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(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 comparisons 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*) $A^{new}_{i,k} = a_{i,k} \times \frac{\tau_k}{\tau_i}$; *ii*) Replace largest element (most inconsistent) in $A^{new}_{i,k}$ 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, $A\prime(x_k) = d_k$ and $A\prime(x_{k+1}) = d_{k+1}$, 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 the slopes at the knots available, the piecewise cubic function is given by

$$A(x) = u_k t^3 + v_k t^2 + d_k t + y_k \tag{1}$$

where $u_k = \frac{d_k - 2\delta_k + d_{k+1}}{h^2}$ and $v_k = \frac{3\delta_k - 2d_k - d_{k+1}}{h}$.

The interested reader is directed to Moler (2013) for a detailed presentation of the PCHIP method. PCHIP prevents overshoots at the knots and gives a cubic function between two knots. Therefore, the relative priorities stay within the desired range of the user.

3.3 The algorithm

Below are the steps associated with our algorithm for load scheduling using the above-mentioned techniques. [1]

Step 1 Users input preferences of relative load priorities at a few different times in a day based on the fundamental scale mentioned in Subsection 3.1. This forms the pairwise comparison matrices at the end points (or knots). The user interface connected to the EMS should be designed in such a way that the inputs must be given for a particular load for all the times before moving on to the next load. It is essential to have all the customer inputs without which the algorithm would not work in line with the user's preferences.

Step 2 Using PCHIP, the preferences are interpolated for every desired time step, t, throughout the time period of interest (i.e., 24 hours). This is done because end users may only provide preferences (which form the knots) 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 end points (knots) we minimize the end user effort while capturing the full range of electricity pricing dynamics.

Step 3 Using AHP, individual load priorities, P_i, are found at every time step.

Step 4 A moving average window of length l_i corresponding to the respective load run time is used to compute the final load priorities vector, $P(t)$.

Step 5 Dynamic electricity prices vector, $C(t)$, such as the residential real time pricing data from ComEd (2015), is interpolated for the same time step, t, throughout the day.

Step 6 The interpolated load priorities, $P(t)$ are normalized on a range of $[0, 1]$ by $P(t)^n = \frac{P(t) - min(P(t))}{max(P(t)) - min(P(t))}$

Step 7 The electricity prices are normalized on a range of $[1, 0]$ by $C(t)^n = \frac{max(C(t)) - C(t)}{max(C(t)) - min(C(t))}$

Step 8 The newly found prices are added with the load priorities to get the resultant load rankings, $R_t = P(t)^n + C(t)^n$.

Step 9 For a particular load, the scheduled start time is obtained t at which the R_t is at its maximum value.

Step 10 Schedules of all the other loads are obtained in a similar way.

Note that the user does not have to follow a standardized pattern everyday. Instead, changes to the relative load priorities can be made any time and the algorithm will be executed again to give the new load schedules. If a load has already run for the day, the command for the new schedule will not be sent to the load. B increasing the frequency of input from the user in a day, the resolution of the proposed algorithm can yield a load schedule of finer resolution.

3.4 An example

In this example, we will present the scheduling of four loads in a Smart Home. These loads are typically considered to be 'smart', i.e., with the ability to communicate with an EMS and receive input from the EMS for automatically being turned on or delayed until a desired time. Table 2 shows the type, ratings, and run time duration of the loads considered in this example.

Table 2. Smart loads rating and run time duration from Roche (2012) and Morrow et al. (2008)

Load		Rating (kW)	Duration (minutes)
Dishwasher	Load1	1.6	60
Washing machine	Load2	1.6	60
Clothes dryer	Load3	2.5	75
EV battery charger (type 2)	Load4	3.3	60

Table 3 represents the synthetic input generated by a typical end-user for the relative priorities of the four loads at different times during the day; in this case, the choices of times for which user input on the relative priority of loads are solicited are: midnight; 6 AM; noon; 6 PM; and midnight. The EV battery charger (Load4), which typically takes about 60 minutes to charge, is inputted to have the highest priority at 6 AM (see row 4 of the PCM corresponding to 6 AM in Table 3), so that the end user may have a desirable state of charge in the EV at a time conducive for a morning commute. Similar subjectivity in the input from the end user is observed in the relative priorities of other loads at various times. Note that the PCMs at the end points of the 24-hour period are the same. The consistency ratio of the user-generated input is also given in the same table and it is observed that this value is less than the desired 8% for problems with four input choices (see Table 1). The improved PCMs, after correcting for consistency as indicated in Subsection 3.1, are also given in Table 4.

However, these values of the relative load priorities are for the specified times only; in order to determine the suitable start time for scheduling the load according to the use preference (from AHP) and from the forecast of the day-ahead dynamic electricity pricing, we desire

[1] MatLab® codes for this algorithm are available at: `http://projects-web.engr.colostate.edu/sgra/`

Table 3. User inputted PCMs

at 00:00	at 6:00	at 12:00	at 18:00	at 11:59
$\begin{bmatrix} 1 & 2 & 8 & \frac{1}{7} \\ \frac{1}{2} & 1 & 5 & \frac{1}{6} \\ \frac{1}{8} & \frac{1}{5} & 1 & \frac{1}{7} \\ 7 & 6 & 7 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & \frac{1}{8} & 4 & \frac{1}{9} \\ 8 & 1 & 7 & \frac{1}{7} \\ \frac{1}{4} & \frac{1}{7} & 1 & \frac{1}{9} \\ 9 & 7 & 9 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{9} & 5 \\ 2 & 1 & \frac{1}{8} & 2 \\ 9 & 8 & 1 & 9 \\ \frac{1}{5} & \frac{1}{2} & \frac{1}{9} & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & \frac{1}{5} & \frac{1}{2} & 7 \\ 5 & 1 & \frac{1}{3} & 4 \\ 2 & 3 & 1 & \frac{1}{5} \\ \frac{1}{7} & \frac{1}{4} & 5 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 2 & 8 & \frac{1}{7} \\ \frac{1}{2} & 1 & 5 & \frac{1}{6} \\ \frac{1}{8} & \frac{1}{5} & 1 & \frac{1}{7} \\ 7 & 6 & 7 & 1 \end{bmatrix}$
CR = 17.97%	CR = 25.85%	CR = 14.3%	CR = 129.04%	CR = 17.97%

Table 4. PCMs improved for consistency

at 00:00	at 6:00	at 12:00	at 18:00	at 11:59
$\begin{bmatrix} 1 & 2 & 8 & \frac{1}{7} \\ \frac{1}{2} & 1 & 5 & \frac{1}{6} \\ \frac{1}{8} & \frac{1}{5} & 1 & \mathbf{.061} \\ 7 & 6 & 7 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & \frac{1}{8} & 4 & \frac{1}{9} \\ \mathbf{3.811} & 1 & 7 & \frac{1}{7} \\ \frac{1}{4} & \frac{1}{7} & 1 & \frac{1}{9} \\ 9 & \mathbf{2.938} & 9 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{9} & \mathbf{2.341} \\ 2 & 1 & \frac{1}{8} & 2 \\ 9 & 8 & 1 & 9 \\ \frac{1}{5} & \frac{1}{2} & \frac{1}{9} & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & \frac{1}{5} & \frac{1}{2} & \mathbf{2.2} \\ 5 & 1 & \frac{1}{3} & 4 \\ 2 & 3 & 1 & \frac{1}{5} \\ \frac{1}{7} & \frac{1}{4} & \mathbf{0.853} & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 2 & 8 & \frac{1}{7} \\ \frac{1}{2} & 1 & 5 & \frac{1}{6} \\ \frac{1}{8} & \frac{1}{5} & 1 & \mathbf{.061} \\ 7 & 6 & 7 & 1 \end{bmatrix}$
CR = 2.92%	CR = 0.26%	CR = 1.65%	CR = 1.7%	CR = 2.92%

the PCM at every time instant corresponding to that of the resolution of the forecast. This is where we employ the PCHIP. Noting that the day-ahead forecast in the RRTP in ComEd (2015) is hourly and the duration of loads are in blocks of 15-minute intervals (see Table 2), we will divide the 24-hour period into 96 blocks of 15-minute intervals for application in PCHIP. This implies that PCHIP will be used to obtain the elements of the PCMs between each end point (i.e., midnight, 6 AM, noon, 6 PM, and midnight) by splitting the interpolation range between the following 15-minute intervals corresponding to the respective periods between the end points (or knots): $(1, 24), (24, 48), (48, 72), (72, 96)$. The coefficients of $A(x)$ are given in Table 5. Remember that the PCM is symmetric and the diagonal elements are 1, hence only the values of the non-diagonal upper triangular elements as a function of time, t, are given in Table 5.

Data corresponding to the day-ahead forecast and actual real-time pricing for a sample day (July 9, 2011) in the ComEd system are used in this example and shown in Fig. 1. Interpolating the day ahead price over 96 15-minute intervals yields the blue line in Fig. 2 and normalizing it over a range of $[1, 0]$ is shown as the bold-green line in Fig. 2.

Figs. 3 and 4 show the results of steps 2 and 3, respectively, and Fig. 5 shows the results of steps 4 and 6, from the algorithm given in Subsection 3.3. Fig. 6 shows the load priorities as a result of step 8. Table 6 depicts the following:

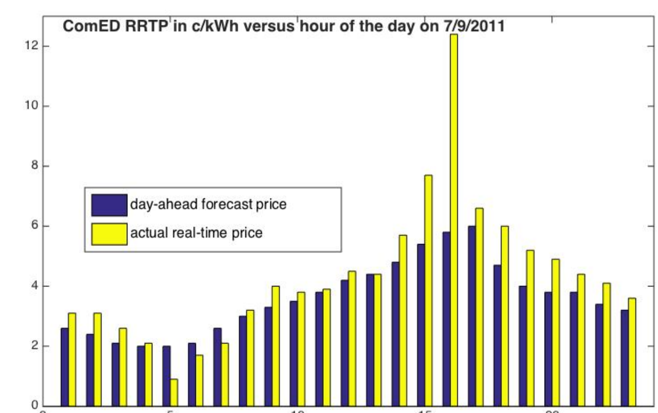

Fig. 1. Forecast and actual real-time price of electricity from ComED on 7/9/2011.

the desired schedule start time of the load and the actual cost of running this load as a function of the actual RRTP on the day. Note that this value is different from the expected cost of running the load, which is a function of the forecast price on the day.

Although user preferences and RRTP are taken into consideration for determining the load schedule, very high values of user-inputted priorities (such as 8 or 9) in a specific time window (say 12AM to 6AM for a battery charger) may schedule the load at a time when the electricity price is relatively high. Thus, this algorithm is practical in

Table 5. PCHIP coefficients of off-diagonal upper diagonal elements of PCMs

a_{12}

	u_k	v_k	d_k	y_k
$(1, 24)$	0	0	-0.13	2
$(24, 48)$	0	$2e-3$	0	0.125
$(48, 72)$	0	-0.002	0	0.5
$(72, 96)$	0	0.044	0	0.2

a_{13}

	u_k	v_k	d_k	y_k
$(1, 24)$	0	0	-0.18	8
$(24, 48)$	0	-0.006	-0.17	4
$(48, 72)$	0	0	0	0.111
$(72, 96)$	0	0.017	0.031	0.5

a_{14}

	u_k	v_k	d_k	y_k
$(1, 24)$	0	0	-0.004	0.143
$(24, 48)$	0	0.0112	0	0.111
$(48, 72)$	0	0	0	2.34
$(72, 96)$	0	-0.004	-0.011	2.2

a_{23}

	u_k	v_k	d_k	y_k
$(1, 24)$	0	-0.011	0.261	5
$(24, 48)$	$1e-3$	-0.036	0	7
$(48, 72)$	0	0	0	0.125
$(72, 96)$	0	0.011	0.017	0.333

a_{24}

	u_k	v_k	d_k	y_k
$(1, 24)$	0	0	-0.003	0.167
$(24, 48)$	0	0.006	0	0.143
$(48, 72)$	0	0.004	0.08	2
$(72, 96)$	0	-0.007	0	4

a_{34}

	u_k	v_k	d_k	y_k
$(1, 24)$	0	0	0	0.061
$(24, 48)$	-0.001	0.046	0.004	0.111
$(48, 72)$	0.001	-0.046	0	9
$(72, 96)$	0	0	-0.006	0.2

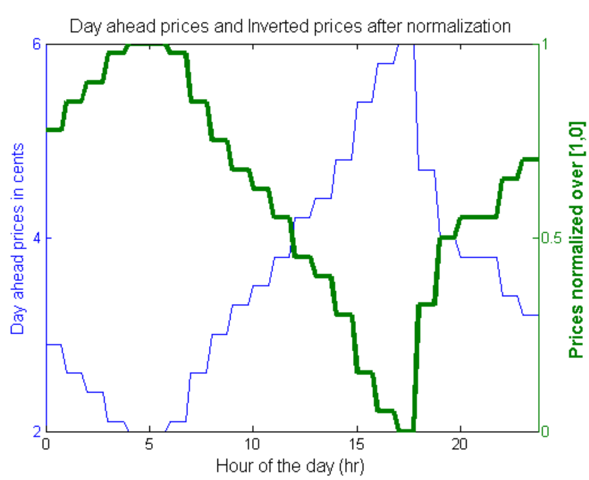

Fig. 2. The interpolated 96 15-minute intervals of the forecast price of electricity from ComED on 7/9/2011 (blue line, on the left y-axis) and the normalized value over [1,0] (bold-green line, on the right y-axis).

prioritizing the user comfort/preference over the influence of price, if required. In other cases where the load priorities are lower, the algorithm shifts the load schedule away from peak pricing hours to times when the electricity price is relatively low.

4. CONCLUSION

The framework and example of an algorithm for managing schedulable loads in a Smart Home is presented in this paper with the objective of increasing the end user participation in the Smart Grid. This algorithm may further be enhanced by employing user-generated inputs for a weighted optimization approach in lieu of steps 8 and 9 in Subsection 3.3. Furthermore, we envision enhancements and quantification of performance of the algorithm based on large data sets conducive for high performance computing environments.

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Table 6. Results of load scheduling and the actual and expected costs

Load	start time (hour)	actual cost (¢)	expected cost (¢)
Dishwasher	2200	7.04	6.08
Washing machine	0845	5.12	4.80
Clothes dryer	1045	11.88	10.94
EV battery charger	0400	8.58	6.93

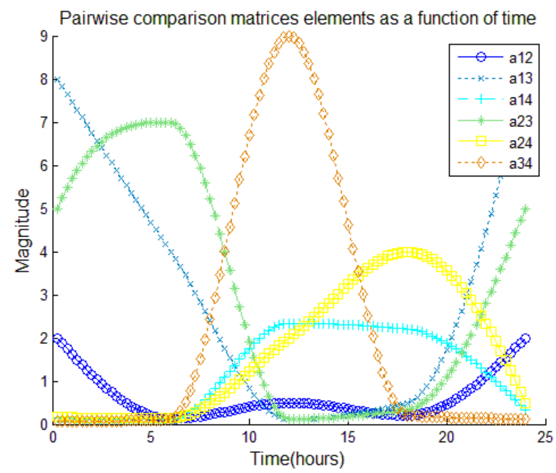

Fig. 3. The off-diagonal upper triangular elements of the PCMs as a function of time obtained by interpolation using PCHIP and (improved) user generated input over 96 15-minute interval blocks.

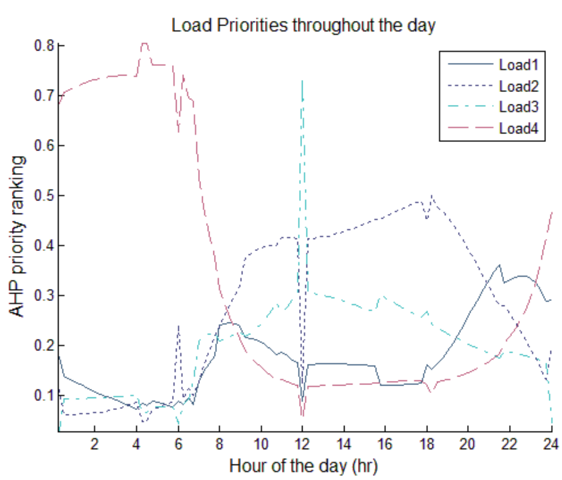

Fig. 4. The un-normalized priority of loads from running AHP using all the over 96 15-minute interval blocks prior to the moving average window.

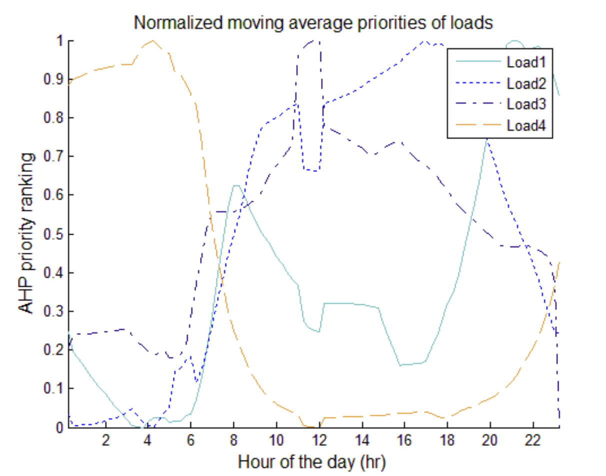

Fig. 5. Priority of loads from running AHP using all the over 96 15-minute interval blocks prior and normalized over a range of $[0, 1]$ and the respective load's run time as the length of the moving average window.

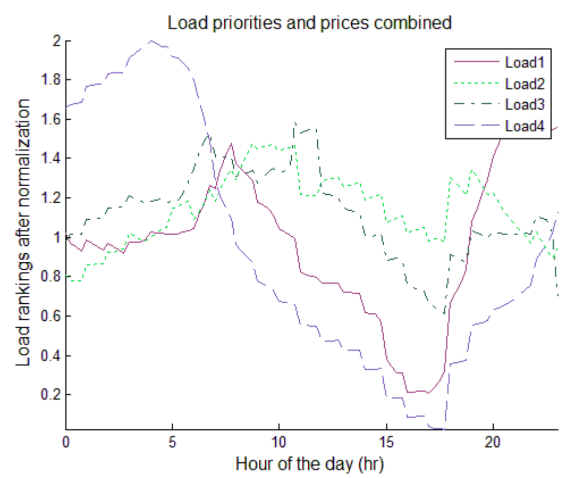

Fig. 6. Resultant load priorities over 96 15-minute interval blocks.

REFERENCES

110th Congress of United States (2007). Energy independence and security act of 2007.

Armas, J.M. (2010). *A customer driven energy management system for a distributed energy resource installation incorporating local energy storage and a photovoltaic source.* M.S. thesis, Division of Engineering, Colorado School of Mines.

ComEd (2015). Comed residential real time pricing program. URL `https://rrtp.comed.com/`.

Ding, Z., Srivastava, S., Cartes, D., and Suryanarayanan, S. (2009). Dynamic simulation-based analysis of a new load shedding scheme for a notional destroyer-class shipboard power system. *Industry Applications, IEEE Transactions on*, 45(3), 1166–1174. doi:10.1109/TIA.2009.2018965.

Du, P. and Lu, N. (2011). Appliance commitment for household load scheduling. *Smart Grid, IEEE Transactions on*, 2(2), 411–419. doi:10.1109/TSG.2011.2140344.

Moler, C.B. (2013). *Numerical Computing with MATLAB.* The MathWorks, Natick, MA,. URL `http://www.mathworks.com/moler/interp.pdf`.

Morrow, K., Karner, D., and Francfort, J. (2008). Plug-in hybrid electric vehicle charging infrastructure review. URL `http://goo.gl/ClzNfE`.

Roche, R. (2012). *Agent-Based architectures and algorithms for energy management in smart grids : Application to smart power generation and residential demand response.* Ph.D. thesis, Université de Technologie de Belfort-Montbeliard.

Saaty, T.L. (2006). *Fundamentals of Decision Making and Priority Theory with the Analytic Hierarchy Process*, volume VI. RWS Publications, Pittsburgh, PA.

Zipperer, A., Aloise-Young, P., Suryanarayanan, S., Roche, R., Earle, L., Christensen, D., Bauleo, P., and Zimmerle, D. (2013). Electric energy management in the smart home: Perspectives on enabling technologies and consumer behavior. *Proceedings of the IEEE*, 101(11), 2397–2408. doi:10.1109/JPROC.2013.2270172.