Smart home appliances scheduling considering user comfort level

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ABSTRACT

Smart home appliances scheduling, employing optimization optimization algorithms to reduce utility costs, is gaining traction under the introduction of time-of-use tariffs and the development of Internet of Things (IoT). The prior electricity cost reduction scheduling algorithms, however, causes substantial discomfort to users for restricting users from using the appliances at their desired times. To address the problem, a novel versatile systematic method is proposed by pricing the mismatch of proposed schedule with users' usage preference pattern to quantify discomfort, coupled with comfort-cost weight factor. The method employing customizable user preference patterns, user-perceived pricing of mismatch and user-specified comfort-savings weightage, not only captures the complex dependence of comfort to individual preference, but the evolution with time by continuous user survey. The proposed method, formulated to be simple enough to be applied on an Excel spreadsheet, demonstrates substantial reduction of electricity cost and users' discomfort simultaneously. Studies on the algorithm found it to be robust against of fluctuations of parameters, with optimization performance comparable to prior work. The work demonstrates that despite the complex nature of comfort to users' behaviors and perception, simple pricing surveys can be used to accurately quantify, compare and optimize users' comfort together with economic savings.

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1. INTRODUCTION

Smart home energy management system for monitoring and scheduling is gaining popularity around the world as the technology improves and as small-scale power with storage become viable. It becomes more important as stricter standards are imposed [1], especially with respect to appliance design [2], but energy conservation is still mainly depend on users' behaviours [2]. Smart meters [3] play key roles as them are being installed in most U.S., Canadian and European houses for logging and trending electricity consumption [4].

The SHEMS prototype with scheduling algorithm and hardware system was demonstrated in [5-8], with the use of IoT to monitor appliance consumption [7-9]. In some work, the concept is refined, using binary/Boolean variable to describe appliance operating status [5], shifting loads off peak-hours to reduce tariffs [10], and mixed linear programming to demonstrate cost savings algorithm [11].

However, many proposed algorithms [12-18] were focusing on maximum bill savings but disregarding users' scheduling preferences. To most users, they are willing to accept lesser savings in exchange for a non-disrupted life style and comfort, adjustable according to users' preference. Nevertheless, some work attempted to approach the comfort issue using grouping of appliances into different categories of priority, either in primitive rating [6] or sophisticated priority matrix [19]. In some work, comfort/discomfort indices, proportional to number of satisfied user preference has been attempted [20-22], while user survey is used to profile user priority preference of appliances [23, 24].

However, the exploration of quantifying comfort and profiling user preference, while being insightful, faces challenges of interchangeability. This is due to the subjective nature of the comfort perceived by user and the fact that user preference may change over time. For instance, adjusting priority ranking perceived by user requires the user to re-evaluate every combinatorial possibility of the relative priority among appliances, while such tedious adjustment is needed whenever the user habit shifts, or when an appliance is added or removed.

Furthermore, the conventional home scheduling algorithm is pre-set to behaves like a black box, difficult to be comprehended by users for troubleshooting. For instance, the labyrinth of priority rating matrix does not allow a lay user to visualize the effect of their preference with respect to utility prices for them to make informed decision. Specifically, a lay user would not reasonably understand the economic value of shifting priority ranking up or down by one unit compared to energy prices.

This paper proposed smart home appliance scheduling that considers both users' comfort level and preferred bill savings, including a slidescale continuum to customize their usage preference between Maximum Comfort and Maximum Savings, as illustrated in Figure 1. The algorithm relates, by means of user survey, the user preference to direct economic values that is not only simple to understand for user and universally transferrable among the user population, but also simpler and robust to compute.

Figure 1. Concept of customizable preference between maximum comfort and maximum savings

2. PROPOSED ALGORITHM

Mixed integer programming is used because the load scheduling problem involves integer variables such as number of units and appliances, as well as continuous variables such as power and utility cost.

2.1. Optimization formulation

For demonstration, the time is organized in unit of 1 hour. For instance, it assumes the idealized scenario where the washer operates from 10:00 instead of 10:05. Let the index of the hours of a day be:

$$i \epsilon (1,2,3,\dots,23,24) \tag{1}$$

While the index of the equipment be:

$$j \epsilon (1,2,3,\dots,n) \tag{2}$$

Where n is the total number of equipment.

Defining the Boolean Algebra U_{ij}, $U_{ij} = \begin{cases} 0, & At\ Time\ i,\ Equipment\ j\ is\ off \\ 1, & At\ Time\ i,\ Equipment\ j\ is\ on \end{cases}$

So, the Power Cost P, can be calculated from utility rates p_i and power rating q_j:

$$P = \sum_j \sum_i p_i q_j U_{ij} \tag{3}$$

The Comfort Value C is a subjective valuation by user, on the discomfort of deviation from user behaviour C_M, and disruption of session C_D:

$$C = C_M + C_D \tag{4}$$

The discomfort of deviation from user behaviour C_M can be quantified by evaluating mismatches between present usage U_{ij} and user history B_{ij}. Finally, the parameter to be optimized is a weighted average based on the disturbance factor D, as compromise between power cost P and comfort cost C:

$$W = DP + (1 - \mathrm{D})C \tag{5}$$

The disturbance factor is a user preferred weightage that increases with the desire of power cost savings, at the expense of desire of comfort. For instance, at $D = 1$, it means a zero weight of comfort that the user does not compromise on existing user specification, so the optimization considers only power cost savings, and vice versa at $\mathrm{D} = 0$. This allows user to adjust the comfort level preference to own satisfaction.

2.2. Fundamental constraints

For simplicity, it is assumed that the energy price is independent of appliance, Energy price/policy function $p_i\{t\}$. This means the energy meter cannot differentiate whether the power is being drawn from a washer or an air conditioner. As ideal case assumption, the machines/equipment are assumed to be independent of each other, in terms of specification and operation constraints, allowing the optimization algorithm to be split into optimizing each equipment usage separately, and run faster.

2.3. Equipment specifications

Equipment specifications manifest itself as the power rating: q_j which can be obtained from manufacturer/supplier data. For future work, it may be refined to include operating current and voltage.

2.4. Utility price

While time-of-use pricing for residential customers has not been in effect in Malaysia yet, in this paper the bench-mark chosen is the time-of-use utility cost in Ontario, Canada [25]. Due to Malaysia is a tropical country, the demonstrative utility price data is chosen to be the summer rates (May to October) all year round. The time of use electricity tariff used in this paper is 6.5 Cents/kWh from 7pm to 7am, 9.4 Cents/kWh from 7am to 11am, 13.2 Cents/kWh from 11am to 5pm, and 9.4 Cents/kWh from 5pm to 7pm.

2.5. User behaviour

2.5.1. Behavior mismatch quantification:

User preference is related to measure of comfort because it involves a clash of what time do the users prefer using the electrical equipment, against what time is the present usage. Figure 2 demonstrates the comfort cost based on behaviour mismatch quantification. To gauge the comfort level, a set of user preference matrix is first obtained, by logging user data on their use of the appliances:

$$B_{ij} = \begin{cases} 0, If\ user\ is\ not\ comfortable\ using\ Equipment\ j\ at\ Time\ i \\ 1, If\ user\ is\ comfortable\ using\ Equipment\ j\ at\ Time\ i \end{cases} \tag{6}$$

The mismatch matrix M_{ij} is defined as the conflict between present usage U_{ij} and user behavior B_{ij}:

$$M_{ij} = \begin{cases} 0, & B_{ij} = 1\ and\ U_{ij} = 0 \\ 0, & B_{ij} = 1\ and\ U_{ij} = 1 \\ 0, & B_{ij} = 0\ and\ U_{ij} = 0 \\ 1, & B_{ij} = 0\ and\ U_{ij} = 1 \end{cases} \tag{7}$$

Because user behavior may span a larger hour range (such as comfort for 16 hours of choices of a day to sleep, while only 8 sleep is needed) than actual usage, the mismatch is only counted if a present usage steps onto the discomfort hours. The user comfort cost from mismatch of behavior C_M can then be evaluated from the user-perceived valuation/price of mismatch m_j customizable by the user:

$$C_M = \sum_j \left(m_j \sum_i M_{ij}\right) \tag{8}$$

This also allows user to selectively relax certain constraints based on preference. For instance, being not able to sleep at night usually carries a higher (hence different) weightage/price as not being able to wash clothes after work. The matching relation also allows user to customize and enforce certain hard constraints, such as enforcing alarm to wake up user at 8am for work, or in some cases to meet certain external deadlines:

$$M_{ij(alarm\ at\ 8\ am)} = 0 \tag{9}$$

This approach is simpler than similarity coefficients, especially the famously-known by Rand [26] or Jaccard [27] indices, providing straightforward way for users to understand and tweak their own habits.

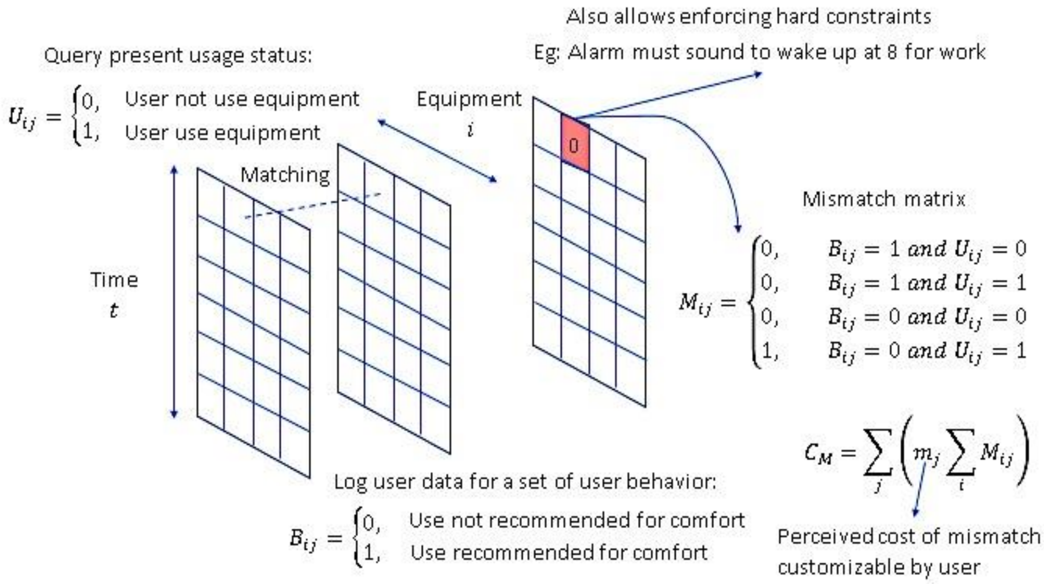

Figure 2. Detailed quantification of comfort cost resulted from deviations of user behavior

2.5.2. Usage disruption quantification

There is user behavior of how many hours the equipment j must be used, H_j. For instance, if the user likes to turn on air con throughout an 8-hour sleep:

$$H_j = \sum_i S_{ij} = 8 \tag{10}$$

Another constraint from user behavior applies including for instance the hours of sleep should be consecutive. Figure 3 illustrates comfort cost based on usage disruption quantification. An elegant way to gauge such consecutive property is to define a “switching” parameter s_{ij}, a magnitude of change in status from previous use, as a measure of dispersion to describe the user behaviour:

$$s_{ij} = \begin{cases} \left|U_{ij} - U_{24,j}\right|, & i = 1 \\ \left|U_{ij} - U_{i-1,j}\right|, & i \epsilon [2,24] \end{cases} \tag{11}$$

For $i = 1$, U_{24} is used in place of U_0, under the assumption of the schedule of a day to be cyclic. This matrix describes the number of subunits the sessions can be split. The number of total uses is then half is the summation of s_{ij} because s_{ij} doubles counts for turning on and turning off. The basic number of uses is 1, because the equipment is used at least once, while further number of uses can cause nuisance. As such, the number of disruptions n_j is total number of uses minus one:

$$n_j = \left(\frac{1}{2}\sum_i s_{ij}\right) - 1 \tag{12}$$

To quantify the cost on the number of disruptions C_D, the cost of each disruption is defined by the user as d_j, so the total disruption cost can be calculated as the summation:

$$C_D = \sum_j n_j d_j \tag{13}$$

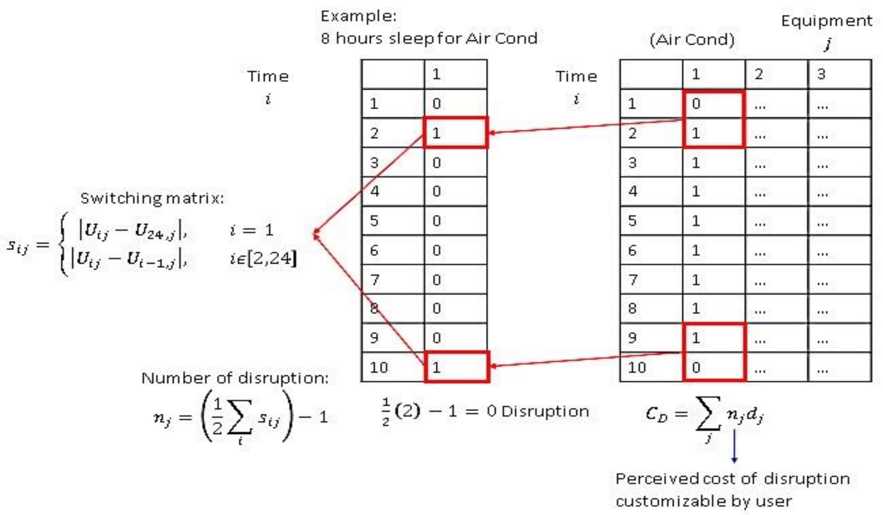

Figure 3. Detailed quantification of comfort cost resulted from disruption of equipment use

3. RESEARCH METHOD

The user behaviour is fundamentally subjective to the personality and habit of the specific user. The data involves mismatch cost, which is the user-perceived price on compromise from user habit per hour; and interruption cost, which the user-perceived price on interruption beyond the single use. Such costing depends on complex factors, such as the lost income/opportunity for missing important tasks on mismatch, the medical expense for interrupted sleep and the income reduction from reduced work performance. The user behaviour data with pricing allows a user survey to be logged over time and profile the user demographics, yet allowing each user to configure on individual preference, as demonstrated by the following sample data. Sample equipment and user behaviour data as shown in Table 1.

Table 1. Sample equipment (Power Rating) and user behaviour (Mismatch and Interruption costs) data

Equipment No.	1	2	3	4	5	6	7	8
Description	Washer	Air Cond	Televison	Light 1	Light 2	Computer	Water heater	Hot Plate
Power rating (kW)	0.8	3.8	0.2	0.1	0.05	0.2	18	1.2
Mismatch (Cents/hour)	1	20	8	3	5	10	6	7
Interruption (Cents/ Interruption)	2	30	10	5	10	20	15	10

The present usage can be arbitrary plan of the user that applies. To demonstrate the algorithm and its robustness, a poorly planned schedule assuming a reckless user is chosen as given in Figure 4 (left). As can be seen from the schedule, such reckless behaviour is obviously suboptimal because it splits usage into multiple sessions, such as for air-conditioner, television and Light 1. It also uses many pieces of equipment at hours where the tariffs are more expensive, such as the use of air-conditioner from 5pm-8pm. The algorithm performs optimization based on individual equipment, to achieve faster results. When the algorithm reaches a satisfactory result, the usage table is updated to the optimized schedule, as demonstrated in Figure 4(a).

Different simulations are also performed for different weightages savings versus comfort. While it is fundamentally difficult to compare researches due to different methodologies, a method of scaling has been proposed as statistical approach for meaningful comparison in relation to state-of-the-art. The performance is first compared by the percentage improvement of optimization $\hat{Z}$ parameters, with Z as either power cost or comfort. The stability of power cost and comfort against change in weightage of power-comfort compromise by proper scaling to $\overline{Z}$ parameters:

$$\hat{Z} = \frac{Z_{before} - Z}{Z_{before}} \times 100\% \tag{14}$$

$$\overline{Z} = \frac{Z}{Z_{max}} \tag{15}$$

Where Z_{before} and Z_{max} are respectively the value before optimization and the maximum value in the range of $D\epsilon[0,1]$. The literature values in [20] and [22] are selected for having complete set of comparable data.

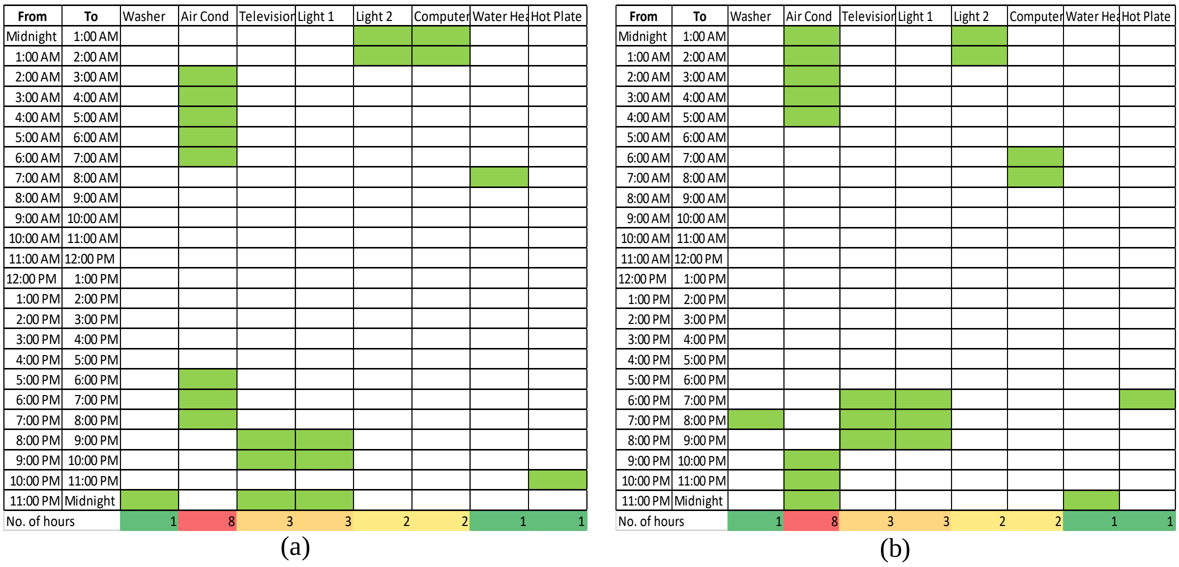

Figure 4. (a) Sample of suboptimal Present Usage to be optimized by the algorithm and (b) Sample of Present Usage after optimization by the algorithm smart home scheduling algorithm

4. RESULTS AND DISCUSSION

It can be seen from Figure 5(a) that the novel algorithm results in higher relative improvement compared to prior art [20]. When no comfort is considered in optimization, the proposed approach resulted in minimal comfort deterioration while the prior art [20] resulted in significant comfort deterioration up to 80%, yet with minimal energy savings. When comfort is combined into the optimization consideration, the present work resulted in significant comfort improvement only at minimal drop of energy savings, while the prior art [20] merely reduced comfort deterioration, at the expense of substantial drop in energy savings.

It can be seen from Figure 5(b) that the present work results in more stable performance from change in disturbance factor a weightage between energy cost and comfort, in contrast with previous work [22] that results in dramatical fluctuation. This means the proposed algorithm is more robust that prior art [22] for actual implementation, considering the complexity of actual home appliances usage and the ever-changing user preference. Nevertheless, both present work and prior art [22] demonstrate similar pattern that as the disturbance factor increases, the energy cost drops at the expense of comfort deterioration, and vice versa. The correlation in general agrees with the prediction that higher user comfort would lower the energy savings. However, the correlation is not linear but rather stepwise simply because often the changes would only result when the schedule has deviated big enough to overcome tolerance limits.

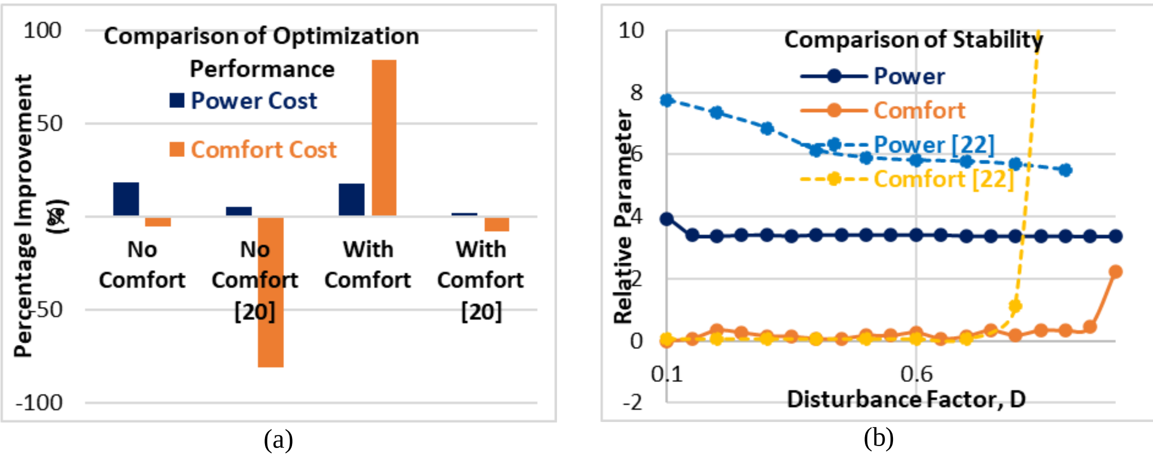

Figure 5. (a) Comparison of relative performance as percentage improvement with comparable research [20] and (b) stability against fluctuation with disturbance factor with comparable research [22]

The representative of resulting optimized pattern of usage is also compared in Figure 6. Different pattern of usages is recommended under the two extremes of maximum savings and maximum comfort, while the pattern is a hybrid of the two extremes if a weighted combination of savings and comfort is preferred.

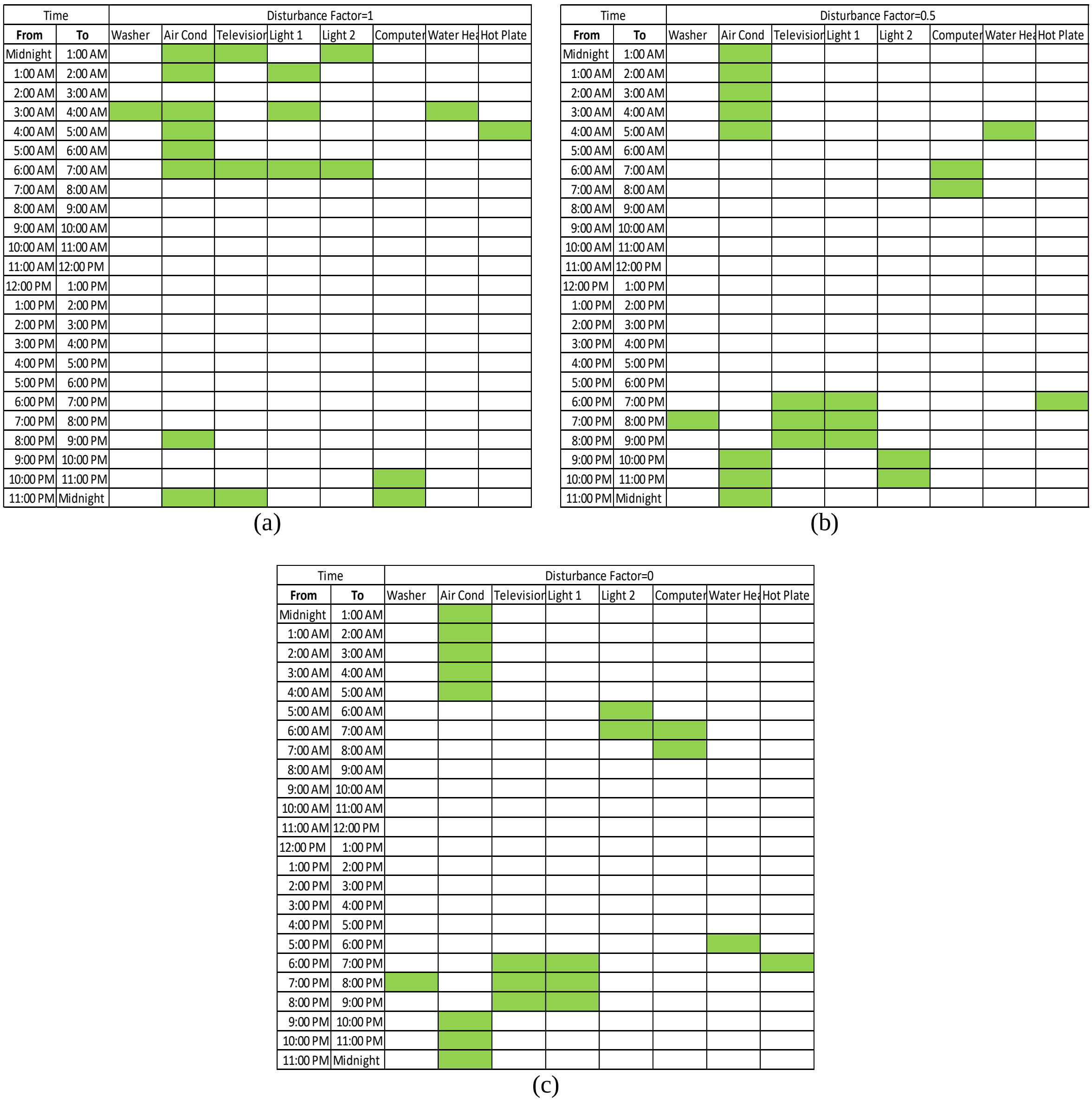

Figure 6. The optimized usage setting at Minimum Comfort, Disturbance Factor=1 (a), Intermediate Comfort, Disturbance Factor=0.5 (b) and Maximum Comfort, Disturbance Factor=0 (c)

It is notable from Figure 6 that the scheduling worked with mainly taking considerations of power cost only (TOU pricing). The consumptions are spread to the lowest cost period of the TOU pricing. Having said that, the user had least comfort experience at disturbance factor, D = 1. In such a way, the power cost, P is at lowest, where the objective function reduces the purely the utility cost, like other scheduling approach. At disturbance factor, D of 0.5, the comfortable of user had been considered by the scheduling. The scheduling not only considered lower power cost, but also scheduled the consumptions approaching user’s time preferences. In other words, the user experienced lesser disturbance and have a better comfort level at D = 0.5 compared to comfort level at D = 1, while achieving savings of power cost at moderate level. At disturbance factor, D of 0, the scheduling is further smoothed out with minimal odd hour power consumption. This is due to maximizing the consideration of comfortable of user in the scheduling, where savings of power cost is achieved but at a low level.

5. CONCLUSION

To address user discomfort in scheduling algorithm, a novel versatile system to quantify discomfort by pricing the mismatch to user preference, coupled with a comfort-savings weight factor, is formulated and tested. In contrast to hardline method of classifying load interruption, the algorithm introduces a novel way to treat load interruption as flexible economic pricing, to relax interruptibility upon user preference while simplifying the algorithm. The comfort-savings weight factor provides extra flexibility for user to switch seamlessly from maximum comfort to maximum savings, based on user preferred objective.

The algorithm system of quantifying comfort successfully demonstrates the optimization, with improved optimization performance in terms of relative savings improvement while preserving user comfort [20]. The optimization was found to be surprisingly robust, that the objectives converged to the optimized value rapidly even when only 15% of the each of the comfort or savings is considered. Intuitively, the optimized configuration considering comfort-savings compromise was found to be a hybrid configuration between maximum comfort and maximum savings.

In a nutshell, this paper presents a novel framework that allows comfort and savings to be compared on the same dimension, by creating a simple yet versatile comfort pricing structure that adapts to individual preferences and can be evolved over time from ongoing user feedback onto the user interface. The algorithm laid out the framework of which comfort can be quantified, where the comfort pricing and user dynamics affecting comfort can be further studied, by correlating to user demographics and individual preference evolution over time as the future work.

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Hui Ming Hoe graduated from Universiti Teknologi Malaysia (UTM)) in 2013 with B.Eng in Electrical Engineering. He joined power distribution industry and later return to the same university to pursue his Master degree in the same field. Currently, he is a researcher under the lead from Assoc. Prof. Ir. Dr. Md. Pauzi Abdullah at Universiti of Teknologi Malaysia Johor Bahru campus. His field of expertise is in the area of electrical storage and distribution, and wireless communication with automation settings. His research interests are on various scheduling algorithms especially in smart home appliances scheduling, energy storage and distribution, coomunication and automation, and IoT. His goal in research is to make use of his slight knowledge to improve and benefit the local society and community by technology means. His ambition is to bring ease of conversion towards smart homes from conventional homes in Malaysia as well as for other tropical countries.

Md Pauzi Abdullah is an Associate Professor at the School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia (UTM). He is currently the Director at the Centre of Electrical Energy Systems (CEES), Institute of Future Energy (IFE), UTM. He received the bachelors degree (B.Eng) in Electrical & Electronic Engineering from Universiti Tenaga Nasional (Uniten), Malaysia in 2002, masters degree (M.Sc) in Electrical Power Engineering and doctorate degree (Ph.D) from University of Strathclyde, Glasgow, United Kingdom in 2003 and 2008 respectively. His research interests include power systems analysis, systems security, deregulated electricity market and demand-side management.