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USING AGENT BASED SIMULATION AND MODEL PREDICTIVE CONTROL TO STUDY ENERGY CONSUMPTION BEHAVIOR UNDER DYNAMIC PRICING

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ABSTRACT

In the interest of increasing energy efficiency and avoiding higher generation costs during peak periods, utility companies adopt various demand response (DR) methods to achieve load leveling or peak reduction. DR techniques influence consumer behavior via incentives and cause them to shift peak loads to off-peak periods. In this paper we study the energy consumption behavior of residents in response to a variable real-time pricing function. We consider thermostatic loads, specifically air conditioning, as the primary load and apply the model predictive control (MPC) method to study the behavior of consumers who make consumption decisions based on a trade-off between energy cost and thermal comfort. An agent-based simulation is used to model a population where each household is an agent embedded with the MPC algorithm. Each household is associated with a multi-attribute utility function, and is uniquely defined via the use of stochastic parameters in the utility function.

1 INTRODUCTION

Residential electricity consumption behavior is by nature unpredictable and thus raises much interest in demand response (DR). In power economics literature, DR has long been proposed for incentivizing consumers to change their energy consumption behavior in achieving load leveling. Energy efficiency in a grid network can be achieved if the system load can be accurately predicted and balanced. DR tries to change the energy consumption behavior of consumers by providing them with financial incentives and education, encouraging them to use less energy during peak hours and more energy during off-peak hours in an attempt to level the system load. However, most DR programs provide financial incentives and assume that consumer behavior is driven primarily by cost. Fahrioglu and Alvarado (2000) applied game theoretical principles to study the interaction between the utility company and its customers. They obtained load relief during peak times by designing incentive compatible contracts that used nonlinear cost functions. Mohsenian-Rad et al. (2010) discussed the use of a distributed algorithm on smart meters to find optimal consumption schedules for subscribers. They achieved peak load reduction by using a pricing scheme based on non-linear cost functions and game theory analysis. Samadi et al. (2010) proposed a real-time pricing algorithm based on utility maximization. In our research, we study consumer behavior as a function of their comfort as well as cost incentives, because it is unrealistic to assume that all people value these incentives equally.

The Annual Energy Outlook 2012 report from the US Energy Information Administration (EIA 2012) indicated that residential customers contributed about 37% of the total energy used in 2011. Thermostatically controlled loads (TCL) make up about 45% of the total residential energy use; 23% is attributed to air conditioning alone. Therefore, in this paper we focus mainly on the consumer behavior of

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using AC, by applying model predictive control (MPC). MPC is a method of system control that is gaining much popularity in recent years for modeling thermostatic loads. MPC determines appropriate control actions, at every sampling step, by optimizing the control objective over a finite time horizon. The decision made by an MPC model is usually based on the evolving predictions of stochastic variables that affect the desired output. In the literature, Vasak, Starcic, and Martincevic (2011) used MPC to model the temperature control of a house by using the least possible energy. Avci et al. (2013) used MPC to control HVAC load under dynamic real-time pricing. Temperature set points were made variable and dependent on the day-ahead prices.

In this paper we propose methods of representing the trade-off between cost and convenience by consumers using multi-attribute utility functions. We study the change in energy consumption behavior in terms of thermostatic loads and use MPC to model consumers' periodic decisions on consuming TCLs. The finite time period optimization of the MPC is implemented through an agent-based simulation. Each household is an agent embedded with algorithms that facilitate the MPC model and thus independently react to the system. The simulation model, implemented in SIMIO (Kelton et al. 2010), allows us to study various scenarios with different pricing functions.

The remainder of the paper is organized as follows. In Section 2 we define a multi-attribute utility function representing the total expected utility of consumers. Then we discuss the method of using model predictive control to simulate consumers' behavior in maximizing total expected utility in Section 3. We then explain the simulation model in Section 4 and present some results in Section 5. We conclude with future research directions in Section 6.

2 MULTI ATTRIBUTE UTILITY FUNCTION

We propose that consumer behavior is not only affected by cost but also the convenience of energy usage or thermal comfort in the context of AC consumption. Although it remains a great challenge to quantify individuals' trade-offs between cost and convenience, an approximation of the distribution of cost-favoring and comfort-favoring consumers can be made in a large population if the latter is properly categorized. We use multi-attribute utility function to define the preference of different types of households. The two attributes considered herein are X_1 (cost of electricity per kWh) and X_2 (discomfort measured as the deviation from a preferred temperature).

In addition to varying trade-offs, consumers also vary in their risk nature. We also consider different utility functions based on whether a consumer is risk prone, risk neutral or risk averse. The term "risk" in this paper refers to the risk of incurring higher cost or experiencing higher discomfort. The classical method of representing economic utility with an exponential function, $U(x) = a + b\, e^{\alpha x}$, takes advantage of the constant absolute risk aversion for both convex and concave functions. The bounded form, equation (1), with upper and lower limits, x_u and x_l, of the attributes are used to represent the individual attribute utility function for each attribute.

$$U(x) = \frac{e^{\alpha x} - e^{\alpha x_l}}{e^{\alpha x_u} - e^{\alpha x_l}} \tag{1}$$

The parameter $\alpha \neq 0$ determines the convexity or concavity of the function, which defines the risk nature of the decision maker. The function becomes concave (corresponding to a risk-averse consumer) for $\alpha > 0$ and it becomes convex (corresponding to a risk-prone consumer) for $\alpha < 0$. In this paper we estimate α based on risk premium, which determines the amount of an attribute that a person requires or is willing to give up, such that he/she will be indifferent to a chance outcome. For $-9 \leq \alpha \leq 9$, the risk premium for X_1 is \$0.02, whereas for $-0.4 \leq \alpha \leq 0.4$, the risk premium for X_2 is 1°F. We then use a multi-attribute utility function, equation (2), to represent the combined utility of both attributes, where k_1 and k_2 are the scaling constants and k satisfies $1+k = (1+kk_1)(1+kk_2)$.

$$U(X_1, X_2) = k_1\, U_1(X_1) + k_2\, U_2(X_2) + kk_1k_2\, U_1(X_1)\, U_2(X_2) \tag{2}$$

A person that values cost benefits more than thermal comfort will have $k_1 > k_2$. Similarly, we will have $k_1 < k_2$ for someone who values his/her comfort more than cost savings and $k_1 = k_2$ for those who value both cost and comfort equally. One way to categorize a population would be according to economic status. We assume that high income households will have $k_1 < k_2$ and low income households will have $k_1 > k_2$. We analyze census data to determine the distribution of a population based on a rational criterion, e.g., annual household income, and generate appropriate coefficients from this distribution.

3 CONSUMER BEHAVIOR MODEL OF TCL

Thermostatically controlled loads (TCL) are ones that are dependent on ambient temperature, such as air-conditioner, space heater, water heater, etc. The Annual Energy Outlook 2012 report indicated that 23% of the residential energy usage was attributed to air-conditioning loads. We consider only AC loads in this paper. The amount of energy used by an AC unit to cool a room is dictated by the thermal dynamics of the house. The thermal dynamics of a house can be modeled in various ways (Balan 2009; Vasak 2011; Avci et al. 2013); we choose a simply linear model that is described in Section 3.2.

3.1 Thermal System Model

The pivotal part of MPC is the plant model that describes the model being studied. The optimization of AC input signals for the control process is based completely on the thermal dynamics of the house. There are various ways to model a thermal system such as a state space model with parameter identification, first order differential equations, thermal electric circuit representation, and a simplified linear model. The linear dynamic model given in equation (3) can be used to model the inside temperature of a room as a function of ambient temperature and energy consumed by the AC (Li, Chen, and Low 2011). Parameter identification and state space models will also be used in the future as it is an integral part of the MPC process. However, we simplify the system by using a linear form for now.

The inside temperature of a time period is dependent on the inside temperature of the previous time period, gradient with the outside temperature and amount of energy consumed.

$$T_t = T_{t-1} + \lambda\,(T^0_t - T_{t-1}) + \gamma\, w_t\, q \tag{3}$$

where, T_t and T^0_t are the inside and outside temperatures at time period t, w_t is the AC control signal during the interval right before time t, λ and γ are thermal parameters of the environment and q is the maximum power rating of the AC unit. We are considering only cooling loads and hence $\gamma < 0$.

3.2 Model Predictive Control in Behavior Modeling

The fundamentals of model predictive control (MPC) lie in obtaining appropriate control actions, at every sampling step, for a particular system by optimizing a finite time problem based on the predictions of stochastic variables that affect the desired output. Most of the literature in this field studies the control of energy consumption, by changing AC control signals or by controlling the thermostat set point, based on a system model that captures the thermal dynamics of the house. The use of MPC to control the thermostat settings of a house in exchange for cost benefits provides a valid method of load control. On the other hand, it also gives the authority of set point change to the service provider, neglecting consumers' desire to override. In this paper we are interested in the behavior of the consumer as a controller. The consumers will themselves control the AC according to changing electricity prices, ambient temperature and thermal comfort. We propose the use of MPC to model the consumer behavior, by maximizing an expected utility instead of minimizing total cost. Table 1 lists the notations used.

We divide the day into discrete intervals with length δ; a consumer makes a decision on choosing an appropriate set point at each interval. The MPC process optimizes the system for k intervals, thus the length of the prediction interval being $\Delta = k\delta$. The main parts of MPC are the objective function, system dynamic model, independent stochastic variables and control variables. The independent variables are ambient temperature and the price of electricity, the predictions of which are available to the consumer via smart meters. The control action or the dependent variable is the AC command signals. The objective is to maximize the total utility for the consumer during the prediction interval, as well as to minimize the fluctuation of set points between consecutive intervals, as formulated in equation (4).

Table 1: Table of notations.

δ	Length of time interval	X_1	$p_t. w_t$ = Cost of drawing w_t load
k	Number of intervals for optimization	X_2	$\|T_p\text{-}T_t\|$ = Deviation from preferred temp
Δ	$\delta.k$ = length of prediction interval	$U(x)$	Utility function of an attribute x
w_t	AC control signal at time t; $0 \leq w_t \leq 1$	k, k_1, k_2	Scaling constants for MAUF
T_t	Room temperature at time t	λ, γ	Thermal parameters of environment
T^0_t	Outside temperature at time t	q	Maximum power rating of AC unit
T^s_t	Thermostat set point at time t	p_t	Price of electricity at time t

3.3 Control Optimization Problem and Heuristics

Given a preferred temperature T^P, and the forecasted values of electricity prices p_t and ambient temperature T^0_t during the prediction interval Δ, we propose the control optimization problem (4)-(12) below to be solved by a consumer.

$$\max_w \; U = \sum_\Delta \left(k_1 U_1{}^t(X_1) + k_2 U_2{}^t(X_2) + k k_1 k_2 U_1{}^t(X_1) U_2{}^t(X_2)\right) - \sum_\Delta (T^s_t - T^s_{t-1})^2 \qquad (4)$$

Subject to:

$$U^t_1(X_1) = f(w_t\, p_t) \qquad t \in \Delta \qquad (5)$$
$$U^t_2(X_2) = f(|T^p - T_t|) \qquad t \in \Delta \qquad (6)$$

$$T_t = T_{t-1} + \lambda\,(T^0_t - T_{t-1}) + \gamma\, w_t\, q \qquad t \in \Delta \qquad (7)$$

$$(T_{t-1} - T^s_{t-1}) \leq M y_t \qquad t \in \Delta \qquad (8)$$
$$(T^s_{t-1} - T_{t-1}) \leq M(1 - y_t) \qquad t \in \Delta \qquad (9)$$
$$w_t \leq y_t \qquad t \in \Delta \qquad (10)$$

$$0 \leq w_t \leq 1 \qquad \forall t \qquad (11)$$
$$y_t \in \{0,1\} \qquad \forall t \qquad (12)$$

Constraints (5) and (6) define the individual attribute utility functions for X_1 and X_2. The thermal dynamics of the house is captured by constraint (7). Constraints (8) to (10) ensure that the AC signal will only appear ($w_t > 0$) when the thermostat set point T^S is less than the room temperature T. The AC command signal w_t denotes the percentage of time it is ON during an interval. Under the principal of MPC, the control optimization problem (4)-(12) will be solved for each prediction period [t,t+Δ], and the optimal control signal at time t, i.e., the first interval in the entire decision period, is implemented. This process is repeated again in the next decision interval [t+1, t+1+Δ]. Note that although the actual response of the system may differ slightly from the projected response, mainly due to inaccuracy in forecasting the independent variables, the continuous optimization of the MPC allows the system to converge to the reference output in a short period.

Because solving the above nonlinear optimization model at each iteration of the MPC process may require excessive computational time, and there usually are many iterations involved depending the length of unit time interval t, it is efficient to solve (4)-(12) repeatedly using a reasonable heuristic. Wilson and Dowlatabadi (2007) note that heuristics are adopted more often than exact methods by decision makers in practice due to reduced cognitive and computational requirements. In particular, they propose a recognition heuristic that favors familiar solutions, which matches with energy users behavior well. In this paper we will use a combination of recognition heuristic and bi-section search method to find an approximate solution to (4)-(12) at each iteration of the MPC process. The adoption of this recognition heuristic is to simulate the decision-making process for energy users who are more of satisfiers than optimizers in real life. Algorithm 1 first recognizes familiar set point values for particular times. Then, depending on whether the temperature is below or above this set point, the algorithm sets $w_1 = 0$ or 1 and solves the subsequent intervals based on the dynamics of the system. In the next step, the algorithm uses bi-section search technique to decide whether to increase or decrease w_1. The heuristic terminates if the improvement in the objective value is less than a predetermined threshold ε.

Algorithm 1: A Bi-section Search Heuristic for Optimal AC Control

Step 0 – Initialize forecast price and temperature data for all [t, t+Δ]
Step 1 – Find the familiar set point, T_t^s, for the current time on previous day
Step 2 – If $T_t^s < T_t$, then set $w_t = 1$; else $w_t = 0$
Step 3 – Calculate T_{t+1} using equation (3) and evaluate U from equation (2)
Step 4 – Estimate $U'(w)$ using finite difference method
Step 5 – Use bisection search method to find next candidate w_t, based on $U'(w)$ < or > 0
Step 6 – Calculate new T_{t+1} and U similar to Step 3
Step 7 – Stop if $U'(w) = 0$ or $|U_i - U_{i-1}| \leq \varepsilon$; Else Go to Step 4

4 AGENT BASED SIMULATION USING SIMIO

In this section we will describe the implementation of MPC using an object oriented simulation package, SIMIO. Object oriented simulation uses various objects that represent physical components of a system and the interactions between these objects to model the system. These objects can be of different classes with varying behavior definitions and characteristics. We can define the physical elements of a system as independent “objects” with different properties and construct the simulation model as a network of interactions between these objects.

The primary *entity* in our model is a consumer, representing an individual household or an agent. A fixed number of households are generated at the beginning of the simulation and this sample population is maintained throughout the run. Each household/agent is first assigned a set of characteristic parameters such as risk nature, utility functions, and preferred temperature for thermal comfort which help them to interact with the model by making distinct independent decisions. We consider a half hour time interval as a time window for evaluating utility functions. The households/agents make decisions of energy usage based on their utility function and the predicted electricity prices and weather data. The price of electricity is defined as a function of ambient temperature and total energy usage. Hence, the energy consumption decision of one agent will contribute to the total energy usage, thus affecting the price of electricity and subsequently the decision of other agents in the next period. This rather implicit interaction between agents also experiences adaptive learning from period to period. Particularly, the simulation model calculates/updates a probability distribution of the electricity rates using the successive average methods (discussed in Section 4.2.1) and historical rates that are recorded within the simulation model for each time period during the simulation length. Hence, the simulation model enables a learning based decision making of the agents. The simulation time is incremental and hence we use state variables *TimeOfDay* and *Day* to keep track of the respective model states.

4.1 Simulation of TCL Consumption

The decision regarding the use of AC is dependent on ambient temperature and the thermal dynamics of the house. Depending on the deviation of inside room temperature from the preferred temperature, consumers will feel certain discomfort, which they trade-off against electricity cost via utility maximization. The utility maximization is the central optimization problem for the MPC model used to generate appropriate AC signals, w_t, at every time interval. Figure 1 shows the logical steps of the MPC process. The forecast of ambient temperature is included as a *lookup-table* with uniformly varying temperatures, the average of which will be considered the actual temperature. *Lookup-tables*, which return certain values as a function of the time of day, are used to model the stochasticity of the input ambient temperature. The decision intervals for the households are set to be 30 minutes, and at every time step the household uses data from the forecast table to maximize the expected utility.

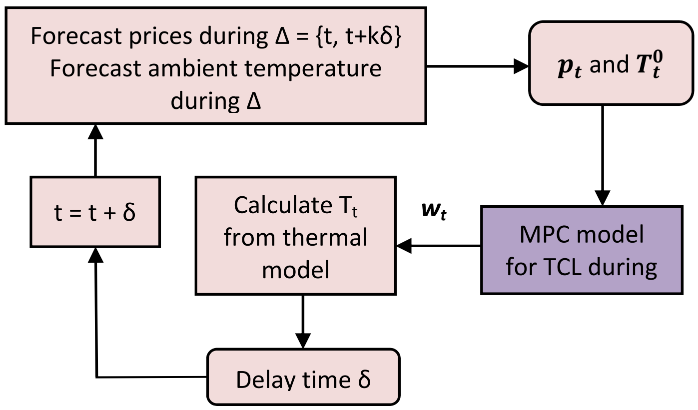

Figure 1: Flowchart of MPC applied to the control of thermostat with command signal w_t.

In order to reduce computational time, the household object is embedded with an optimizing algorithm that uses recognition heuristic and bi-section search as described in Algorithm 1 in Section 3.3. The algorithm optimizes the objective function of the MPC to a desired accuracy instead of solving the complex non-linear program (NLP). Recall that in the MPC model, the AC command signal ($\boldsymbol{w}$) is the controllable input variable that determines the dynamics of the AC unit. Particularly, when AC is turned off w=0, and when AC is turned on and consumes (100w)% of the full power rating during the duty cycle, w assumes a value between zero and one. The heuristic method optimizes the MPC by starting at a candidate input signal. The household starts with the current room temperature and checks whether it is less than the preferred temperature. If so, the AC signal is considered to be zero, else one.

Each consumer is assigned with a preferred temperature, uniformly distributed between 68˚F and 73˚F, at which they feel the most comfortable. The discomfort attribute is measured as the amount of deviation from the preferred temperature experienced by the consumer as result of the change in energy consumption behavior

4.2 Real Time Pricing Function

In a dynamic and real time rate structure, the cost of electricity is stochastic in nature and changes based on various parameters of the system, for example load on the system, duopoly market, bidding process, etc. This constantly changing rate is communicated to the consumer via display systems or smart meters on a smart grid network. A simple method of dynamic real time pricing (RTP) is studied in order to compare consumers' responses to flat rate pricing. The price of electricity is set as a function of energy usage as well as ambient temperature. Equation (13) is used in the model as the RTP rate, where p^f is the flat rate or base price and p^e and p^t are prices that are affected by energy usage and external temperature.

Δe and Δt are the proportional difference in energy drawn and external temperature from some pre-specified average values. We select p^f=\$0.1, p^e=p^t=\$0.05 and set the limits on the prices as p_{max}=\$0.25 and p_{min}=\$0.01. The possible rates are bound within these limits. We also conduct a sensitivity analysis by setting one of the coefficients to zero.

$$p = p^f + p^e \Delta e + p^t \Delta t \tag{13}$$

Since the cost of electricity affects the energy usage pattern by consumers and that in turn affects the cost of electricity, it is uncertain what the rate might be in the next time interval. However, there exists a probability distribution of the electricity rates at each time interval on a stable system. Household owners will predict future rate changes based on practical experience. The simulation model would accumulate a probability distribution table over time and use it as "experience" in mimicking consumers learning ability. As discussed previously, in the event of uncertainty, we evaluate the total expected utility of the household given by the multi attribute utility function (MAUF).

4.2.1 Modeling the Probability Distribution with Successive Average Method

Under the dynamic load based rate structure, the simulation model has to record past data regarding the rates in order for the *household* to predict the rates at different time windows. We will use only ten days of past data, successively averaged, in order to obtain a good probability estimate. By taking the successive average, we are giving high importance to recent data and low importance to older data. Let us consider a particular time interval, *t*, on day $d+1$, for which we want to know the probability distribution of electricity prices. Also for i = {1, 2, 3 … 25} and j = {d, d-1, d-2… d-9} let,

$$c_j^i = \begin{cases} 1 & if\ rate\ i\ had\ occured\ on\ day\ j \\ 0 & otherwise \end{cases}$$

The successive average of the occurrence (or frequency) of rate *i* can be expressed as,

$$SC^i = \frac{(10\, c_d^i + 9\, c_{d-1}^i + 8\, c_{d-2}^i + \cdots + c_{d-9}^i)}{(10 + 9 + 8 + \cdots + 1)} = \frac{C^i}{55} \tag{14}$$

where, $C^i = (10\, c_d^i + 9\, c_{d-1}^i + 8\, c_{d-2}^i + \cdots + c_{d-9}^i)$, is the successively weighted sum of the binary counts c_j^i.

When implementing this successive average in equation (14), instead of using the binary variable to count, we set the initial count at day *d* equal to 10 and reducing this value by 1 for every day that has passed until it is exhausted to 0. The probability of occurrence of rate *i* during the current time period *t* of day $d+1$ is thus calculated as $p_{d+1}^i = \frac{SC^i}{\sum_{i=1}^{25} SC^i} = \frac{C^i}{\sum_{i=1}^{25} C^i}$.

Two matrix arrays (see example in Figure 2) are defined with identical rows and columns, where each of the 48 rows corresponds to a time window and 25 columns record possible rates from \$0.01 to \$0.25 during the specific time window. One of the tables (see "CTable" in Figure 2) will be used to count the occurrence c_j^i, and the other table (see "PTable" in Figure 2) will be used to establish a probability distribution based on the first table. For instance, if the rate of electricity is \$0.07 at 8:00, the first table will increment the corresponding cell of the table by 10, each day reducing by one until it becomes zero. This way we can keep track of the rates at different time intervals and thus establish a probability distribution for these rates using successive average method. Since the probability of the rates is updated periodically and all the data of the rates is stored in *CTable* throughout the simulation run, we are able to model forecasting behavior of the consumers when evaluating their utility functions. We assume that in a stable system, the probability distribution of rates is exact and is provided by the energy provider via smart meters.

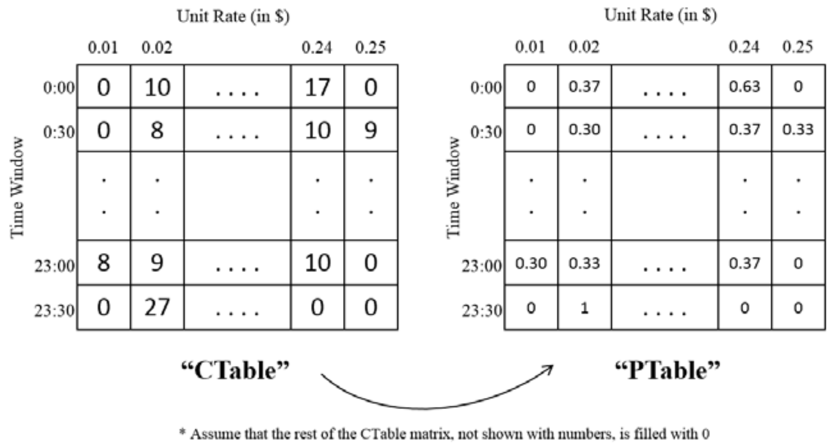

Figure 2: Example calculation of PTable from CTable.

5 RESULTS AND DISCUSSION

The total run time for the simulation model is set to be 30 days allowing for 5 days of warm-up period to initialize the probability of the rates (PTable). Figure 3 illustrates how the price is set over days. In order to estimate the number of replications required for a sensitivity analysis, we ran the model with an initial number of 25 replications. A 95% confidence interval on the average energy level at each time interval was studied and the half width, $\boldsymbol{h}$, and standard deviation, $\boldsymbol{s}$, at each interval were recorded. The correct number of replications required was then estimated using $h = t_{n-1}\frac{s}{\sqrt{n}}$. For any of the time intervals, the number of replications required did not exceed the initial value of 25.

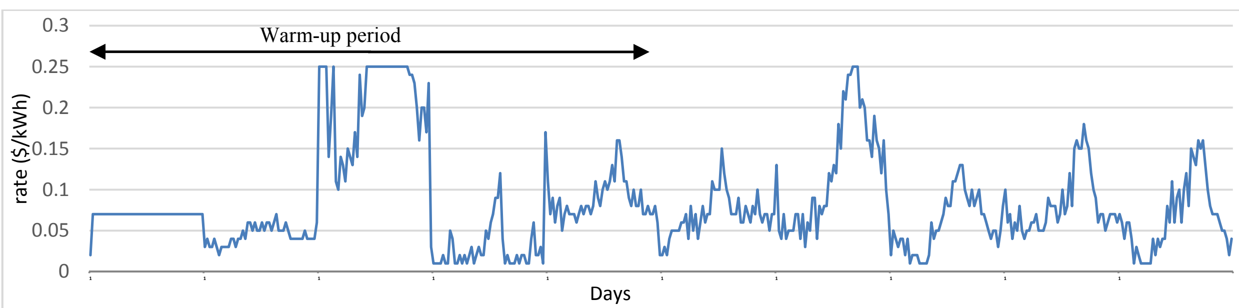

Figure 3: Simulation of electricity rates over time based on RTP, showing warm-up period.

We study three different variations of the RTP for all the households grouped individually as well as in the population mix. Firstly, we set the constant term $p^f = 0.1$ and $p^e = p^t = 0.05$, to capture the combined effect of both energy and temperature dependent coefficients (RTP). Then without changing p^f, we set $p^e = 0$ / $p^t = 0.1$, which means that the price is only temperature dependent (RTP1) and then we set $p^e = 0.1$ / $p^t = 0$, which means that the price is only energy dependent (RTP2). Figure 4 depicts the daily energy consumption for low- and high-income households, respectively. The characteristics of the households are evident from the different shifting behaviors in their TCL load. Group A exhibits the most load shifting behavior, mainly due to the fact that they are highly affected by change in electricity price. Group C, on the other hand, exhibits very little change in their behavior and signifies that they are not affected by cost as much as the others.

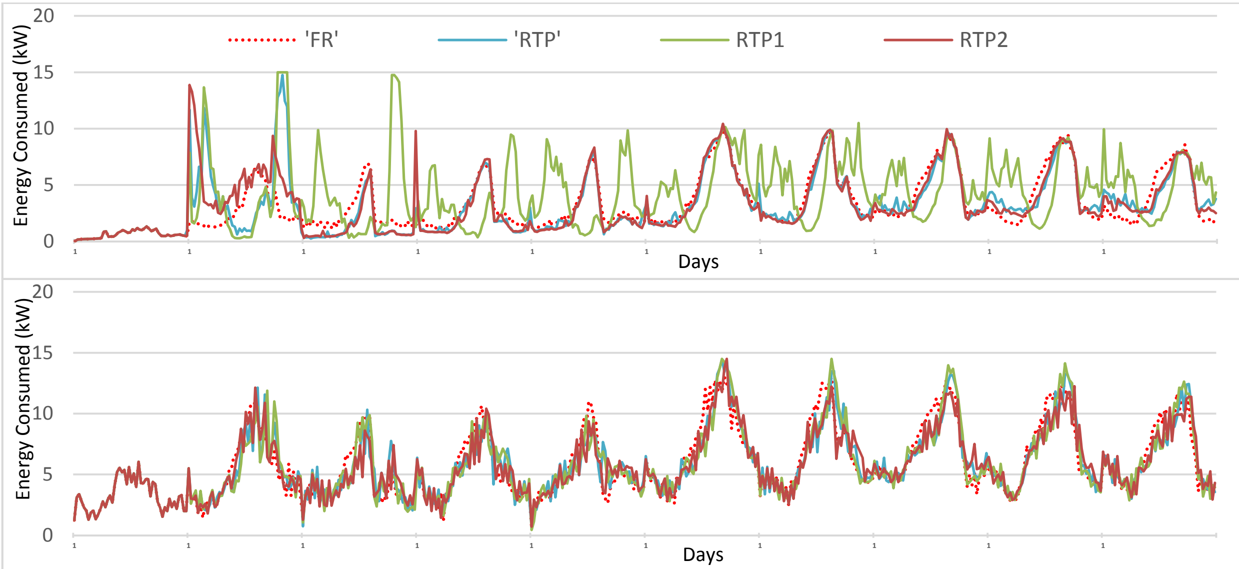

Figure 4: Energy consumption of TCL by Group A (top) and Group C (bottom).

Similar behavior can also be observed through their average room temperatures. Figure 5 shows the change in the households' room temperatures for different price structures. We can see that Group A maintains their average room temperature farthest from their preferred temperature in a trade-off between cost and comfort. They experience an average discomfort of approximately 4.5˚C, while Group C experiences only 0.6 ˚C of discomfort. As seen in Figure 5, Group C are the least likely to give up their average room temperature in return for cost benefits. In the case of RTP1 (temperature dependent price), we observe that specially Groups A and B use more energy during the off-peak price (when ambient temperature is lowest) in order to cool down the house nearer to their preferred temperature.

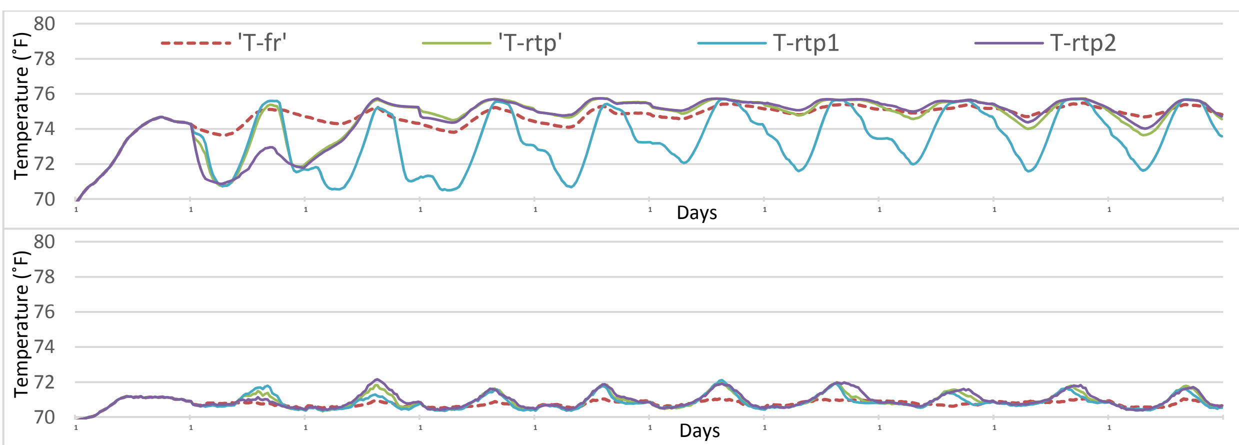

Figure 5: Average room temperatures for Group A (top) and Group C (bottom).

Finally, we compare the PAR and VAR values for the different price functions in Table 2. From the table, we see a strong evidence that RTP1, price dependent only on ambient temperature, does not improve these parameters but only makes it worse. Furthermore, for all household groups, RTP (p^e, p^t) and RTP2 (p^e) provide reduction on both PAR and VAR. The true effect of the values of these coefficients can be studied by conducting an experimental design with extensive sensitivity analysis on all the coefficients and combinations of these coefficients.

Table 2: PAR and VAR for TCL model under various RTP functions.

	PAR				**VAR**			
	Flat Rate	*RTP*	*RTP1*	*RTP2*	*Flat Rate*	*RTP*	*RTP1*	*RTP2*
Group A	2.086	1.853	2.424	1.856	13.084	6.719	14.561	7.498
Group B	1.867	1.953	2.459	1.912	8.208	6.522	16.346	6.614
Group C	1.753	1.807	1.874	1.734	6.980	6.115	6.735	5.887
Total Population	1.892	1.744	2.112	1.737	9.065	4.853	9.833	4.935

We then conducted a simple factorial analysis on the effects of varying p^e and p^t on the output of the system. By varying each of these coefficients from 0 to 0.1 at 0.02 increments, we set up an experiment in SIMIO to gather PAR and VAR from each of the scenario. From the output analysis using Minitab, we were able to conclude a high significance of both cost coefficients on PAR and VAR with R^2 value of 97.39% and 95.31%, respectively. We also analyzed a surface plot of the outputs against p^e and p^t, as shown in Figure 6. We see from this graph that a higher coefficient for p^e is desired in order to reduce PAR and VAR. In the direction of decreasing p^t, we also see reduction in PAR, but this is not as pronounced as the reduction in PAR due to p^e. This result gives us an idea about the effect of cost parameters on the response of the system. However, a higher number of replications is required in order to conclude these results with a high level of confidence, which will be done in the next phase of our research.

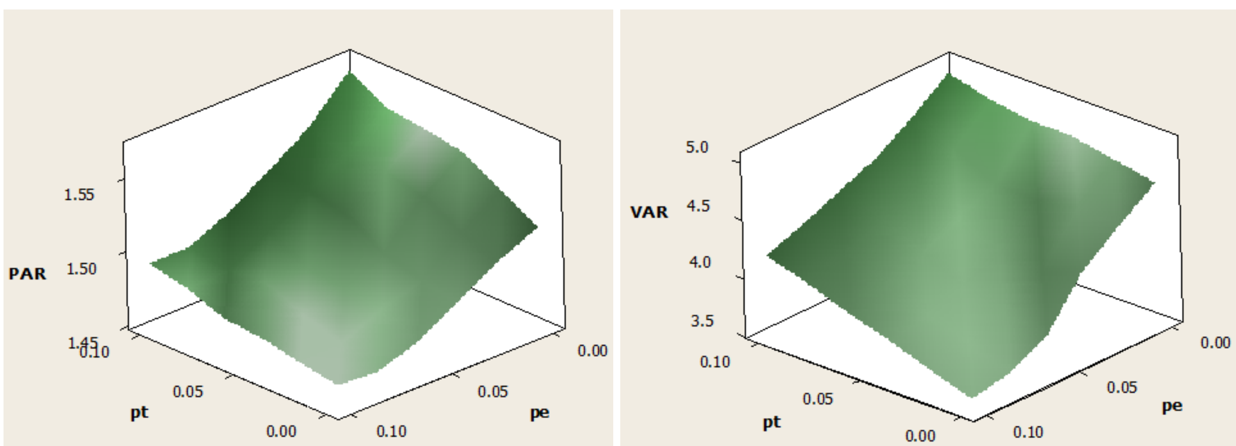

Figure 6: Surface plot of PAR and VAR against cost coefficients p^e and p^t .

6 CONCLUSION AND FUTURE WORK

The prevalent DR methods that attempt to reduce peak load on a power grid by providing various incentives to change consumers' energy consumption behavior, often assume cost is the only factor influencing users' behavior. We assume that achieving certain level of convenience and comfort plays an important role in consumer decision, and thus use multi-attribute utility theory and model predictive control (MPC) to model consumers' energy consumption decision in an agent-based simulation. In this paper we studied the effect of differential pricing on the usage of thermostatically controlled loads (TCL). A simple thermal model was used to define the dynamics of a house and a model predictive control (MPC) algorithm was implemented in the simulation model to study the behavior of consumers. We were able to simulate the behavior of different kinds of people by varying their respective utility functions. This behavioral analysis is very important in the context of DR as it helps us understand the consumer response and design pricing structures and other DR methods to facilitate better load control. As expected, the different pricing structures had a pronounced effect on households with equal importance for cost and convenience.

Our future research includes extensive experimentation and factorial design and analysis based on simulation results. In order for the utility company to optimize its pricing decision based on the predicted consumer behavior, a model of consumer behavior that can accurately represent the population dynamics will be essential. Further, we will incorporate both non-TCL and TCL in studying the effects of DR on a complete residential load system. Gathering real data regarding the utility functions of different households will also enrich our model. In the context of human behavior modeling, bounded rationality may also be used in the future in conjunction with heuristic optimization. Finally, considering industrial users in our future simulation will enable us to tradeoff between residential and industrial needs.

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