Transfer

Mark McLeod

I. Paper Section

A. Problem outline

Preamble about government energy targets, carbon, orchid, and the impending rise of the smart grid.

Short overview of electricity generation and distribution that motivates influencing the shape of the daily load profile.

The aim of this work is to develop a method for setting time varying tariffs in a way that allows the shape of the load profile due to domestic space heating to be controlled.

B. The home model

To form a realistic model of the response to variation in tariff a realistic model of the home is required. [1] divides domestic loads into these that are and are not suitable candidates for influence via pricing. The later are devices that are used directly by the residents such as lighting, cooking and entertainment, the former devices such as washing machines, refrigerators and heaters. This category is further split into shiftable static load (those that could start at a selection of times but once started will run a fixed profile) and thermal loads. A model for thermal loads is developed and it is these devices that are the focus of this paper. In 2012 $77.6TWh$ of electricity was used for domestic purposes, of which $16.5TWh$ was used for space heating [2] so thermal loads represent a significant fraction of electricity use. They also have the advantage over other devices that they are likely to be always on as a background process, and are already the subject of research to produce more intelligent versions [3] [4] with some currently available models having features such as individual room control [5], highly configurable schedules [6] and occupancy detection [7]

Multiple studies have

Thermostats are getting more intelligent, internet pricing publishing has already been proposed. RT pricing has laready been proposed. Advance publishing allows the thermostats to plan ahead and has already been proposed, but as market price not as control signal. cite adaptivehome

C. Thermal agent maths

The smart thermostat model presented here is based on the model proposed in and in that it uses a quadratic utility cost for deviation from a target temperature during times when the thermostat is active and sums this with the cost of the power used to form the objective function. The most notable difference is that rather than requiring the heating to be either on or off the heating control is allowed to be any value between zero and one. This assumes a pulse width modulation scheme is present in the controller so that the control input multiplied by the heating system power gives the expectation of load, rather than the true load. By doing this the duration of each control period can be increased, and so the number of degrees of freedom is reduced leading to a reduced computation time. It is also assumed here that the temperature cycle is periodic over 24 hours, this removes the initial value from the problem.

A simple exponential cooling model is used, the home is defined by a thermal mass, cm, and insulation value, $\frac{1}{k}$, and a heater power P If the external temperature is $T^e(t)$ then the temperature is governed by the first order differential equation

$$\frac{dT(t)}{dt} = -\frac{k}{cm}(T(t) - T^e(t)) + \frac{P\delta(t)}{cm} \tag{1}$$

where $\delta(t) \in (0,1)$ determines the power setting of the heater. For a sufficiently small timestep Δt this can be approximated as an update rule

$$T_{n+1} = T_n - \frac{\Delta tk}{cm}(T_n - T_n^e) + \frac{\Delta tP\delta_n}{cm} \tag{2}$$

If the time period under consideration is discretized into N periods of Δt then T, T^e, δ can be represented as column vectors of size N and the update rule can be expressed as a matrix equation

$$\left(\mathbf{I}_{N+1\times N\times 1} - (1 - \frac{\Delta tk}{cm})\mathbf{U}\right)\underline{T} = \frac{\Delta tk}{cm}\mathbf{U}\underline{T}^e + \frac{\Delta tP}{cm}\underline{\delta} \tag{3}$$

which is an affine relation between temperature and input that can be expressed as

$$\underline{T} = \blacksquare\underline{\delta} + \underline{\Psi} \tag{4}$$

where

$$\blacksquare = \frac{\Delta tP}{cm}\left(\mathbf{I}_{N+1\times N\times 1} - (1 - \frac{\Delta tk}{cm})\mathbf{U}\right)^{-1} \tag{5}$$

$$\underline{\Psi} = \left(\mathbf{I}_{N+1\times N\times 1} - (1 - \frac{\Delta tk}{cm})\mathbf{U}\right)^{-1}\left(\frac{\Delta tk}{cm}\mathbf{U}\underline{T}^e\right) \tag{6}$$

and

$$\mathbf{U} = \left[\begin{array}{c|c} \underline{0}_{1\times N} & 1 \\ \hline \mathbf{I}_N & \underline{0}_{N\times 1} \end{array}\right] \tag{7}$$

The quantity that the home controller needs to minimise is the sum of the cost of deviation from the target temperature profile $\underline{T}^s$ and the cost of heating. The temperature deviation is only relevant when the home is occupied. This is encoded in the matrix $\mathbf{Q} = q \times diag(\underline{o})$ where $\underline{o}$ is a vector of size N with ones in positions where the home is occupied and zeros otherwise and q is a scalar that relates the utility of temperature deviation to monetary cost. The cost of heating is given by $P\underline{\Lambda}^T\underline{\delta}$ where Λ is a vector of size N giving the unit cost of electricity over time. This gives an objective function

$$f = (\underline{T} - \underline{T}^s)^T \mathbf{Q}(\underline{T} - \underline{T}^s) + P\underline{\Lambda}^T\underline{\delta} \tag{8}$$

So that the dimensionality of the problem can be reduced to a lower number than that defined by the resolution of the temperature update equation $\underline{\delta}$ is defined to be

$$\underline{\delta} = \mathbf{D}\underline{u} \tag{9}$$

where $\underline{u}$ is the M dimensional column vector that will be optimised over and D is the $M \times N$ matrix

$$\mathbf{D} = \mathbf{I}_M \otimes \underline{1}_{J\times 1}, \qquad N = MJ \tag{10}$$

.

Making these substitutions leads to the new objective function

$$f' = \underline{u}^T\mathbf{R}\underline{u} + \underline{S}^T\underline{u} \tag{11}$$

which differs from the original objective by a constant and where

$$\mathbf{R} = \mathbf{D}^T\blacksquare^T\mathbf{Q}\blacksquare\mathbf{D} \tag{12}$$

and

$$\underline{S}^T = 2(\underline{\Psi} - \underline{T}^s)^T\mathbf{Q}\blacksquare\mathbf{D} + P\underline{\Lambda}^T\mathbf{D} \tag{13}$$

The only constraints strictly required are those that constrain the heater input to be set between zero and one.

$$0 \leq \delta_n \leq 1 \qquad \forall n \tag{14}$$

These are expressed in standard form as

$$\left[\begin{array}{c}\mathbf{I}_M\\ \hline -\mathbf{I}_M\end{array}\right]\underline{u} \leq \left[\begin{array}{c}\underline{1}_{M\times 1}\\ \hline \underline{0}_{M\times 1}\end{array}\right] \tag{15}$$

In the following results further constraints are also placed on the absolute maximum and minimum temperature over all time, and that the temperature may not deviate by more than two degrees from the target temperature.

This specifies the procedure an individual smart thermostat will undertake to form an optimum heating plan. To model the response of the full set of customers multiple agents are created using a generative process to determine individual parameters and the sum of their load is used.

D. thermal agent generative process

In order for the model to provide useful information it must have similar characteristics to the true demand system.

An occupancy profile is generated for each thermal agent according to the model proposed in [**?**] which proposes a Markov chain generative model based on survey data. The model provides transition matrices for the number of active occupants in a building every ten minutes throughout the day, with separate chains for buildings with between one and six occupants. The number of occupants to use is drawn from a discrete distribution according to the data in the CABE dwelling size survey [**?**]. For the thermal parameters of the home the floor area is drawn from an offset gamma distribution chosen to match the floor area results found by the CABE survey. Nominal values are used to convert floor area to surface area and from these values to derive insulation and thermal mass values which are drawn from log-normal distributions based on the nominal values given in The Governments Standard Assessment Procedure for Energy Rating of Dwellings [**?**]. Future improvements to this procedure are discussed in section REF

Analysis of the individual agent optimisation and QP solution.

Material from `https://github.com/markm541374/tariffset/blob/master/quadthermo.pdf`

Basic spec of the quadratic comfort cost and exponential cooling is a citation of [1]. Add a few more constraints, remove the asymmetry, make it cyclical to avoid initial conditions. Expectation of PWM rather than direct on-off input.

Constants. Markov model for occupancy, survey for floor area. Nominal SAP values for insulation. A few magic constants.

E. Optimization method

Since the function we with to optimize requires significant computing time to evaluate it is worthwhile to invest some additional computing time in selecting the next point to evaluate, rather than following grid-search or multi-start line-search algorithms. The method used is Gaussian Process Global Optimization (GPGO)[8] in which given a mean and kernel function a value for the expectation and variance can be obtained for any point in closed form given the points that have been evaluated. Specifically

$$definemean, kernel, domain, points, eqnformean, cov \tag{16}$$

. In implementation the Cholesky decomposition of K is used rather than the inverse in order to reduce coputing time and avoid numerical problems. The expectation and variance of the function at a given point can be combined to provide some metric for the utility of an evaluation at that point. The utility used is the expected improvement (EI) which is defined as

$$EI = integralwherebestis... \tag{17}$$

The choice of mean and kernel and utility functions and the hyperparameters of the kernel function and their prior of course have a major influence on the effectiveness of the optimization. In the results presented below a zero mean function and EI utility function have been used. For the kernel a squared exponential function has been used with independent Gaussian priors over the hyperparameter values. The hyperparameters are updated under to the maximum posterior values given the observed points between evaluations. Searching for the maximum EI location, and for the hyperparameter values is done using the DIRECT search algorithm [9]. Alternatives to these choices are discussed in section REF.

F. Results

hopefully showing that the load responds to the tariff and that GPGO makes good reductions in the objective fn of the load. Show that agents have reduced their daily fee while still fulfilling constraints so are better of under the scheme.

II. Review/Proposal

A. Review-optimisation

Surrogate surface techniques. GPs. different maximization options, EI, PI, Entropy. multistep lookahead. Sing the S

B. Review-tariffsetting

Smartgrid overview. Other proposals for load management. This method is new because it both publishes ahead of time (giving agents time to plan ahead and b more flexible) and is not a direct exposure of market prices so is a proper control signal. some use carbon value, not really very good.

C. Proposal-model

Form a defensible model of a home using gov. surveys, power company stats, dissagregation datasets. Correlations between insulation/occupancy/location/weather/season/day-to-day.

D. Proposal-optimisation

Fast two-step lookahead `http://www.robots.ox.ac.uk./~markm/MSGPGO.pdf`

Using previous result as information for next day, using true load each day to update the model.

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