Automated Energy Usage Optimization for the Residential Sector: Impact of Price Tariffs

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1 Introduction

Energy consumption in the residential sector accounts for a significant proportion of national usage. For example, in Ireland this sector accounted for 32% of total electricity usage in 2008, and over 44% of thermal energy usage [1]. The electricity demand in this sector is expected to increase significantly in the coming years due to the influx of plug-in electric vehicles (PEVs) [2].

A number of methods have been proposed to improve the energy efficiency of homes, or enable the user to improve their energy efficiency, such as smart metering and better building insulation. The pricing strategy used by the utility can also affect user behavior. In particular, time-variable tariffs such as Time-of-Use Pricing (TOUP) and Real Time Pricing (RTP) encourage load shifting on the part of the user from peak to off-peak times.

TOUP is a fixed strategy where cheaper rates are charged for expected off-peak times (e.g. during the night) and higher rates are charged for expected peak times (e.g. 17:00-19:00). RTP charges the user at a rate based on the actual market price at that time. However, it is often impractical for the user to manage their energy usage in reaction to constantly changing price information.

A Home Energy Management System (*HEMS*) is an energy efficiency tool which can be used to address this issue, automating energy usage of certain home appliances with respect to time-varying prices. The HEMS provides set points for the controllable energy consumers in a home over a fixed horizon, subject to certain constraints.

Optimization of energy usage in the home can then be mutually beneficial to the homeowner, the electricity provider, and the environment. The homeowners benefit by a reduction in their electricity costs through optimization of energy usage where applicable. The flexible energy users in the home which we consider in our problem are the heating system; the charging of an electric vehicle; and schedulable appliances (e.g. washing machine / dishwasher).

Although reductions in an individual homeowner's energy usage will have little bearing on the network load, the aggregated use of such optimization tools across homes can result in a large reduction in the peak energy usage. This is beneficial to both the electricity companies and to the environment as largescale, carbon-intensive, generators are required less, and investment in new fossil fuel based generators can be postponed or even avoided.

2 Problem Description

The HEMS problem can be simply stated as follows: given a price forecast over a fixed horizon discretized into N time intervals (e.g. 15/30 minutes), $t = \{1, \ldots, N\}$, minimize the electricity cost of the home while maximizing the user comfort. This involves scheduling the following three components: heating/cooling of the home in each time interval, charging/discharging of the EV battery in each available time interval, and the start time for the schedulable appliances (dishwasher, washing machine, etc.). These are scheduled subject to the electricity price per time interval and user preferences; e.g. the ambient temperature in the home should be 21°C from 18:00-23:00, the EV battery state-of-charge (SOC) should be 80% at 08:00, the washing machine should start at 21:00.

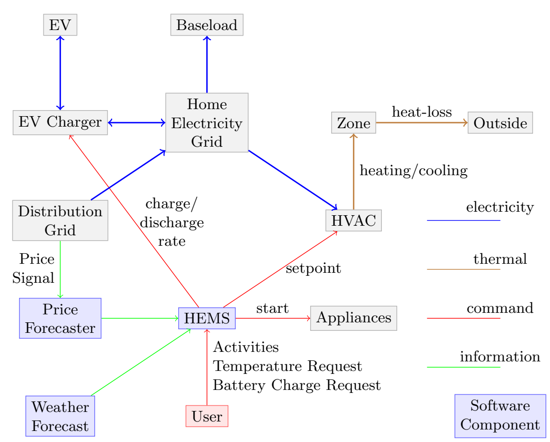

Fig. 1: Home Energy Management System

The EV requirement is considered to be a hard constraint, provided it is physically possible to charge the battery from the SOC upon arrival to the requested departure SOC. The user requirements for temperature and appliance start time are incorporated into a user comfort function of the form:

$$a * max(0, x_{actual} - x_{user}) + b * max(0, x_{user} - x_{actual})$$

where x refers to the temperature / appliance starting time, and a/b are fixed constants depending on whether the temperature set point is below/above the user preference or the appliance is scheduled to start earlier/later than the user preference. We model the HEMS problem as a Mixed Integer Programming (MIP) problem.

3 Price Tariff Comparison

We investigated the behavior of our algorithm under different pricing schemes. In particular, we assessed the savings possible with real-time price data from a number of energy markets in Europe [3–5] and North America [6, 7], and similarly TOUP data from a number of European and North American utilities [8–11]. We do not currently consider combining real time prices with an inclining block rate, as performed in [12], where the price is a function both of the real time price and the user's energy usage in the time period. For each location, we gathered price and weather ([13]) data for four winter weekdays which, although a relatively small sample, was sufficient to illustrate the points of interest. The standard MIP solver CPLEX 12.2 [14] was used to find the optimal solution for each day.

Simulations were performed investigating savings achievable compared to a baseline where no price information is considered when scheduling the components. Our results revealed a number of interesting points, due to space restrictions we merely summarize these here (further details can be found in the accompanying slides).

Firstly both RTP and TOUP often lead to considerable daily savings, with the results for TOUP being more consistent. The lack of savings with RTP for the Swedish and Canadian markets (a similar result was observed in [15]) can be explained by a lack of variance in the price across each 24 hour period. Indeed we found a high correlation between the daily savings and the ratio of minimum to maximum price over the day.

The range in daily RTPs was insufficient in certain cases to overcome the tradeoff in shifting an energy consumer to a cheaper time interval with larger energy losses. For example, to ensure that the ambient temperature is at the required level at the specified time, pre-heating the home in cheaper periods will require more energy to account for subsequent heat losses. This will only be viable if there is a sufficient price differential between the time periods, as illustrated in Figure 2 for heating and for charging/discharging the EV battery.

Secondly, since RTP data is not known in advance, we tested three forecasts for the Irish market over 40 days of data. The results showed that significant daily savings of 20-24% on average can still be achieved when using forecasts, compared to 29% if the actual price was known in advance. Finally, we tested the impact of V2G capabilities on the same set of data with both RTP and forecasts. Our findings were that this capability accounted for over 5% of daily savings when RTP was used, but only a maximum of 2% when forecasts were used.

4 Conclusions

In this work, we have investigated the impact of price tariffs when automating the energy usage in the home. Our comparison of real time market price with time-of-use price tariffs revealed that TOUP tariffs were more consistent in providing savings to the user. For some markets the daily variation in the real time prices was too small to warrant load shifting due to energy losses incurred.

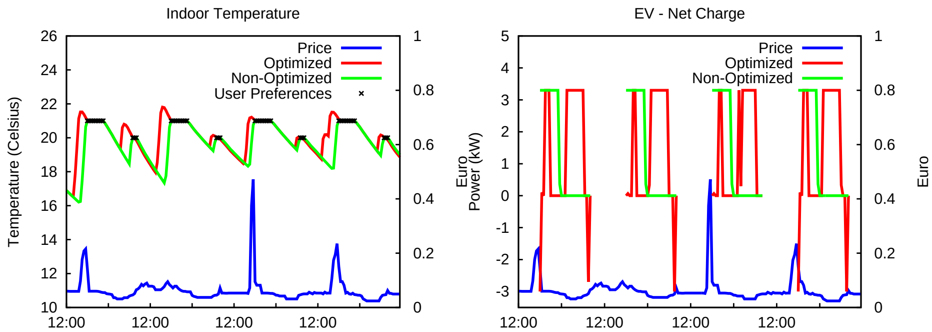

Fig. 2: Temperature and EV state of charge, optimized for Irish RTP data. Average daily savings due to HVAC accounted for 48.4% (€0.68) of total daily savings, similarly smart charging of EV accounted for 42.4% (€0.59 of daily savings.

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