An Intelligent Agent for Home Heating Management (Demonstration)

Alex Rogers, Sasan Maleki, Siddhartha Ghosh and Nicholas R. Jennings
Electronics and Computer Science
University of Southampton
Southampton, SO17 1BJ, UK
{acr,sm9g09,sg2,nrj}@ecs.soton.ac.uk

ABSTRACT

Intelligent software agents are increasingly being applied within the smart grid; a future vision of an electricity distribution network where information flows in both ways between between consumers and suppliers, and where electricity prices change in real-time in response to the current balance of supply and demand across the grid. In this demonstration, we show a home heating management agent that can learn the thermal characteristics of a home and predict local weather conditions, in order to provide home owners with real-time information about their daily heating costs. Furthermore, we demonstrate how the agent can then optimise heating use to minimise cost and carbon emissions whilst satisfying the home owners preferences for comfort.

Categories and Subject Descriptors

I.2.11 [**Computing Methodologies**]: Distributed Artificial Intelligence

General Terms

Design, Algorithms, Experimentation, Theory

Keywords

Agent, smart grid, electricity, heating optimisation

1. INTRODUCTION

The creation of a smart electricity grid has been posed as one of the greatest engineering challenges of this century, as countries face dwindling non-renewable energy sources and work to minimise the adverse effects of climate change due to carbon emissions [1]. To this end, the UK government has committed to reducing carbon emissions by 80% by 2050, and central to achieving this aim is the mandated roll-out of smart meters to all 26M UK homes by 2020, and support for the electrification of heating through the installation of air and ground source heat pumps [2, 3]. However, this vision of a smart grid, in which electricity prices change in real-time to reflect the current balance of supply and demand across the grid, presupposes that the grid's users are also capable of responding in real-time to reduce loads [4]. In the case of domestic users, and particularly for electric heating loads which involve a significant time lag between cause and effect, this is currently not the case. Thus, the Intelligent Decentralised Energy-Aware Systems (iDEaS) (`www.ideasproject.info`) and the Intelligent Agents for Home Energy Management (`www.homeenergyagents.info`) projects at the University of Southampton are developing and demonstrating intelligent agents, to be deployed within these homes, to manage energy use within them. These agents can learn the thermal characteristics of a home, and predict local weather conditions, in order to provide home owners with real-time information about their daily heating costs. Furthermore, these agents can then optimise heating use, taking full account of real-time pricing signals, to minimise cost and carbon emissions whilst satisfying the home owner's preferences for comfort [5, 6].

Appears in: *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2012)*, Conitzer, Winikoff, Padgham, and van der Hoek (eds.), 4-8 June 2012, Valencia, Spain.

2. HOME HEATING MANAGEMENT

Our home heating management agent learns the thermal characteristics of the home in which it is installed, and the environment in which it operates. In more detail:

- Using internal and external temperature sensors, and by monitoring the activity of the home's heating system, the agent is able to learn the thermal characteristics of the home. More specifically, it models the thermal characteristics of the home through a coupled set of differential equations that describe the flow of heat from the heater, into the internal air, and then out to the structure of the home, and the external environment. A regression process then fits the parameters of this model to the temperature data observed, in order to define (amongst other things) the heat output of the heating system and the thermal leakage rate of the home.

- Using a computationally efficient implementation of multi-output Gaussian processes, the agent then predicts the local external temperature over the next 24 hours by combining local measurements from an external sensor with predictions from an online weather forecast. In doing so, it creates a *site-specific* forecast for the next 24 hours, by explicitly considering both the period nature of its own 24 hour sensor data, and the likely correlation with the online forecast data.

Using these factors the agent is able to predict the consequences, in terms of cost and carbon, of any thermostat setting and provide this information to the home owner through the agent's graphical user interface, informing them of the predicted daily cost and carbon consequences of their current thermostat and time settings. Going further, the agent is then able to fully optimise the use of heating (using either an optimal CPLEX implementation or a computationally efficient greedy heuristic). In doing so, it provides the same level of comfort as a standard thermostat operating at the same set-point temperature (evaluated using a comfort model based on the

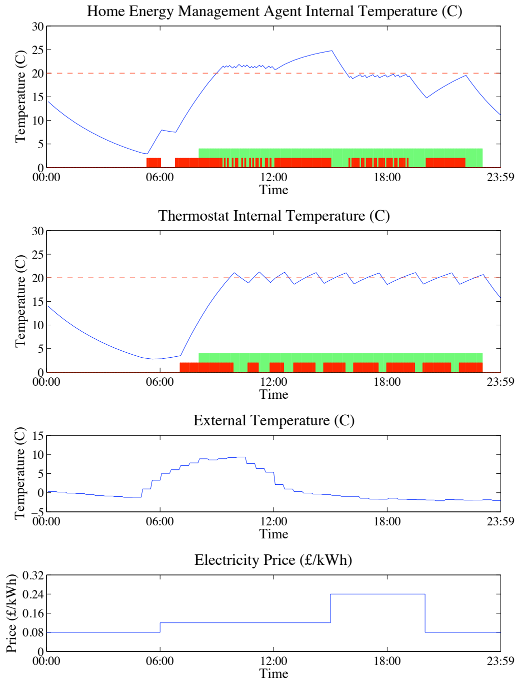

Figure 1: Example setting showing the home heating agent optimising heating use to maintain comfort whilst avoiding a critical pricing period.

ASHRAE thermal comfort standard — ANSI/ASHRAE Standard 55-2010) whilst also minimising either cost or carbon.

Figure 1 shows simulation results for an example setting where the home heating management agent optimises heating to avoid a critical pricing period (i.e. the time period 15:00 to 20:00 where the price of electricity is £0.24 per kWh). In this case, we compare the internal temperature of the home when the heating is controlled by both a standard thermostat and the home heating management agent. In both cases, the green shaded area represents the time interval over which heating is required, and the red shaded area represents when the heating system is actually producing heat. Note that the agent applies heat before the critical pricing period, allowing the temperature to increase, and then allows this heat to leak away over this period (the effect is exaggerated here for clarity). In contrast, the standard thermostat applies heat uniformly across this period. Similarly, note that the agent also exploits the low price of electricity before 06:00 and supplies heat even though it is not immediately required. In both cases, the agent is effectively storing cheap electricity in the form of hot air, so that this stored energy can be used when electricity is more expensive. This provides an alternative to the use of more costly electrical storage batteries, and in this setting, reduces heating costs over the day by 20%.

3. SOFTWARE IMPLEMENTATION

The home heating management agent described here has been implemented within a Java software simulation (see Figures 2 and 3). The simulation represents the physical environment of the home, and is driven by real sensor and weather data for January 2010. A touch sensitive display provides a graphical user interface for the agent that displays the cost and carbon emissions corresponding to any thermostat setting, and allows the both the thermostat setting and mode of operation to be adjusted. A video of the simulator and agent in operation is available online (see `http://www.ideasproject.info/research.php/`).

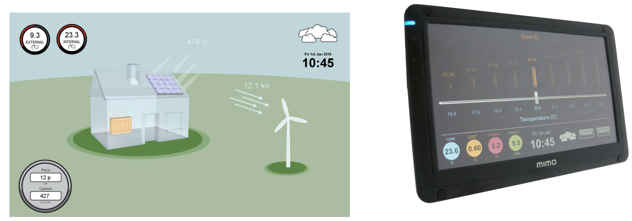

Figure 2: Software implementation of the simulated environment and the graphical user interface to the home heating management agent.

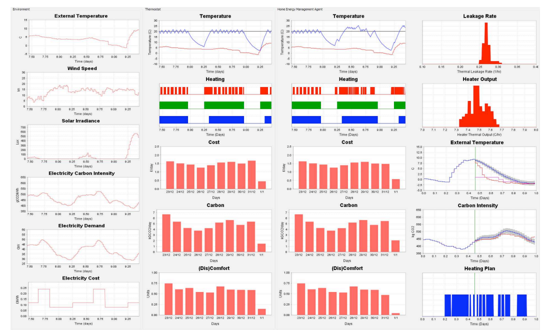

Figure 3: Graphical view of the software agent in operation learning environmental parameters and optimising heating use.

4. CONCLUSIONS

The work demonstrated here shows that a home heating management agent deployed within a home can yield significant cost and carbon savings whilst also facilitating the type of demand response envisaged within the smart grid (i.e. the ability to reduce electricity demand at peak times through real-time pricing). Our future work is focused on developing the currently simulated system into a real-world deployment in conjunction with industrial partners, and to this end, we are currently working to close the control loop and trial the complete controller on a number of instrumented homes owned by the University.

5. REFERENCES

[1] United States of America Department of Energy, *Grid 2030: A National Vision For Electricity's Second 100 Years*, 2003.

[2] HM Government Department of Energy and Climate Change, *Smarter grids: The opportunity*, 2009.

[3] D. MacKay. *Sustainable energy: Without the hot air*. UIT, Cambridge, 2009.

[4] F. Schweppe, B. Daryanian, and R. Tabors. Algorithms for a spot price responding residential load controller. *IEEE Power Engineering Review*, 9(5):49-50, 1989.

[5] A. Rogers, S. Maleki, S. Ghosh and N. R. Jennings. Adaptive Home Heating Control Through Gaussian Process Prediction and Mathematical Programming. *Proc. of the 2nd Int. Workshop on Agent Technology for Energy Systems*, Taipei, Taiwan. pp. 71-78, 2011.

[6] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings. Decentralised control for decentralised demand side management in the smart grid. *Proc. of the 10th Int. Conf. on Autonomous Agents and Multiagent Systems*, Taipei, Taiwan. pages 5-12, 2011