PERVASIVE SENSING AS A MECHANISM FOR THE EFFECTIVE CONTROL OF CHP PLANT IN COMMERCIAL BUILDINGS

Joe Clarke[1], Jon Hand[1], Jae-min Kim[1], Cassim Ladha[3],
Karim Ladha[3], Patrick Olivier[3], Tony Roskilly[2],
Mohammad Royapoor[2], Aizaz Samuel[1] and Dawei Wu[2]
[1]Energy Systems Research Unit, University of Strathclyde, Glasgow, UK
[2]Sustainable Energy and Power Group, Newcastle University, Newcastle, UK
[3]Culture Lab, Newcastle University, Newcastle, UK

ABSTRACT

A recently completed, EPSRC-funded project researched the use of low cost, pervasive sensing to monitor building environmental conditions and occupant interactions as a means to reduce the uncertainties associated with the creation of a building model for refurbishment options and smarter control appraisal.

This paper gives a brief introduction to the pervasive sensing system as established within the project and describes its use to enable simulations of the multi-input, multi-output (MIMO) control of a combined heat and power (CHP) unit in a commercial building context. Within the project, data from pervasive sensing was used to calibrate a simulation model of an office building and impose occupant-related inputs at the time step level as a means to reduce modelling uncertainty. The MIMO input parameters considered include space temperatures, heat store temperatures, electricity demand and electricity tariff, while the output parameters include space heat supply, heat stored, electricity utilised locally or exported, and CHP unit fuel use. The simulation model was used to compare performance when the CHP unit is subjected to conventional and MIMO control. It is demonstrated that the pervasive sensing approach enables control that delivers enhanced energy performance.

INTRODUCTION

Low cost, pervasive sensing of environment conditions and occupant interactions can be used to provide detailed information on the use of building spaces. Within the reported project, a pervasive sensing system, termed BuildAx, was developed comprising physical and virtual sensors.

A physical device encapsulates sensors for temperature, relative humidity, noise, illuminance and movement was constructed and deployed within several trial buildings, along with virtual sensors that provide information on room and IT equipment usage. The device, as shown in Figure 1, utilises the IEEE 802.15.4 compliant, 2.4 GHz Zigby protocol to transmit wirelessly to a central communicator via a self-healing MESH network, which can be extended via routers. Its dimensions are 77x53x33 mm and it is battery powered. Sampling is at 4 Hz for movement (Murata IRS-B210ST01 sensor) and audio (Wolfson WM7120 sensor) and 6 seconds for illuminance (Avago APDS-9007 sensor), temperature and humidity (Honeywell H1H6131 sensor for both). The communicator is linked via USB to a computer where logging software integrates the data and passes it to downstream applications. In the present project a Raspberry Pi with a Linux operating system was employed. Both the monitoring devices and software are available under an Open Source license.

Figure 1: a pervasive sensing BuildAx device.

Within the project monitored data were obtained from a BuildAx coordinator via FTP transfer, post-processed, transferred to a MySQL database and employed within a service that supports facilities management established using the EnTrak ‘e-service’ definition program (2014). As reported here, these data were also passed to a building energy model to define the time varying occupant effects within simulations, aiming to optimise the economic dispatch of a CHP unit. Previous research in this field has employed search algorithms based on multi-objective constraints (e.g. Song *et al* 1999 and Vasebia *et al* 2007). The present approach complements these efforts by employing building use data in real time.

To support CHP control system appraisal, a BuildAx pervasive sensing network was deployed within the Kingsgate office building at Newcastle University. This comprised 150 devices deployed as depicted in Figure 2, along with virtual sensors extracting information on IT equipment and room usage.

The building is a typical commercial development comprising open plan and cellular offices with a central air conditioning system and gas-fired boiler.

The proposal investigated was the replacement of the latter by a CHP unit based on a gas-fired engine.

MODEL CREATION/CALIBRATION

A high resolution ESP-r (2001) model comprising 82 thermal zones was established to represent the building, with an air flow network superimposed to represent infiltration and mechanical ventilation. Façade shading devices were explicitly modelled using ESP-r's insolation ray tracing method. Model geometry, construction and HVAC system details were based on information obtained from design documents and site visits. Significantly in the present context, the ESP-r system was modified at the source code level to utilise outputs from the pervasive sensing environment in order to impose actual variations in occupant presence and space interactions on simulations. Figure 3 shows a wire-frame and Radiance (2014) rendered image of the established model.

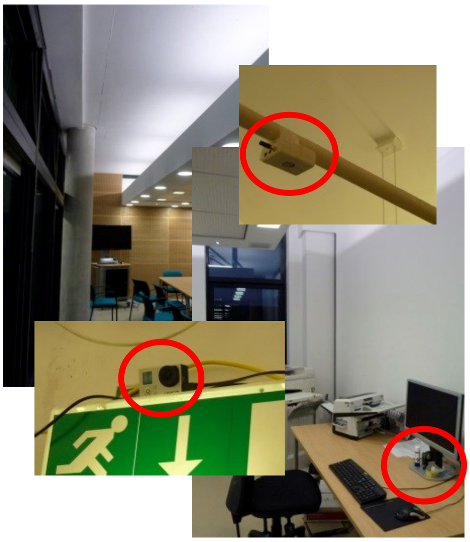


Figure 2: deployment of pervasive sensing within the Kingsgate building.

The model was calibrated against monitored data, with judicious parameter adjustments made on the basis of sensitivity analyses. The most significant parameters, excluding occupancy effects, were the supply rate of fresh air and infiltration. It should be noted that occupancy-related data, as inferred from pervasive sensors and imposed on the ESP-r model were significantly different from assumptions made at the design stage to demonstrate compliance with building regulations.

The calibration process was terminated when simulation outputs gave a satisfactory match with monitored data as judged by statistical goodness of fit parameters suggested by Williamson (1995). A typical winter week based on degree-day averaging was selected for calibration purposes and energy use data for heating and electricity were compared. Table 1 shows results for electrical energy use for the initial and final calibration runs; both results were obtained with greater than 95% confidence. For this period the measured mean and standard deviation were 81 kWh and 62 kWh respectively, which compares favourably with the final predictions as evidenced by the improvement by a third in the normalised error. Correlation coefficients show slight improvement but the inequality coefficient is reduced by a quarter. The marked improvement in the occupant-related aspect of the ESP-r model contributed greatly to the exceptional final agreement.

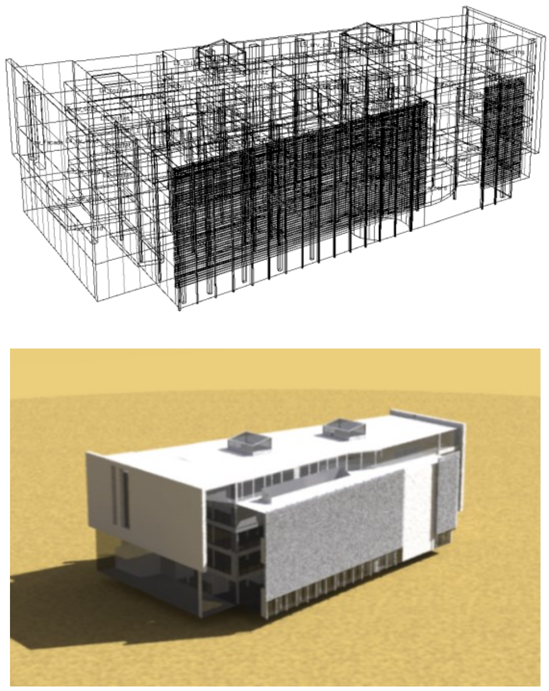


Figure 3: model wireframe and rendered image.

Figure 4 provides a visual comparison of the electrical energy demand over a single day as obtained from initial and final simulation models.

Table 1: goodness of fit parameters for predicted electrical energy use.

	Initial model	Final model
Mean	77 kWh	80 kWh
Standard deviation	57	64
RMS error	1.93	1.64
Normalised RMS error	0.0288	0.0194
Pearson's correlation coefficient	0.929	0.938
Spearman's rank correlation coefficient	0.847	0.883
Williamson's inequality coefficient	0.141	0.107

CHP UNIT MODEL

In practice it is difficult to optimise for the fuel use cost of a CHP unit because of demand dynamics and the complexity of part-load operation, the characteristics of which may not be fully known (Konstantakos *et al* 2009). Within the present study this difficulty was overcome by using a dynamic CHP model based on a laboratory-derived performance map. This model is able to predict unit heat and electricity outputs against consideration of part-load efficiency and time varying heat-to-power ratio.

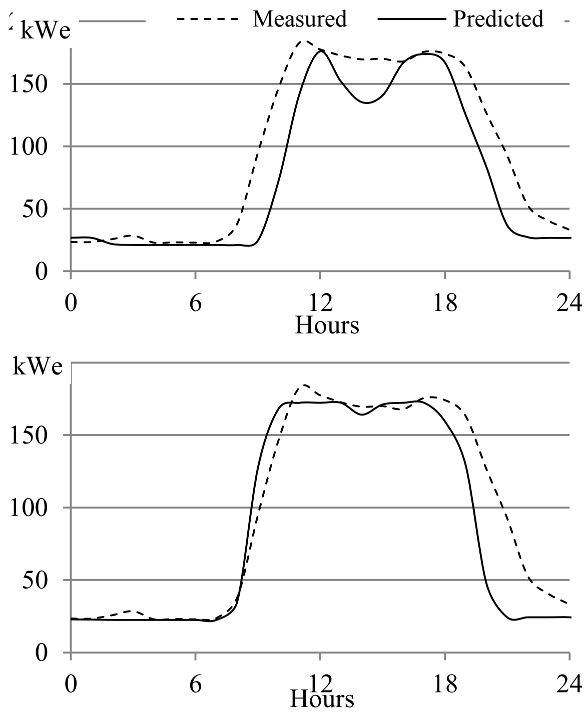


Figure 4: measured and simulated electrical loads initially (top) and finally (bottom).

The major prime mover technologies for building CHP are gas turbines and gas engines (Wu and Wang 2006). In relation to the heat and electricity demands of the Kingsgate building, a prime mover technology that can accommodate part-load operation is required. Since the gas engine responds better to a fluctuating load while delivering a high electrical efficiency in the range of 30-45% (Carbon Trust 2010), a unit from Caterpillar was chosen with 160 kW_e rated electrical power (200 kVA at a power factor of 0.8) and an electrical efficiency of 30%. Part-load behaviour is shown in Figure 5: the unit can modulate down to 80 kW_e.

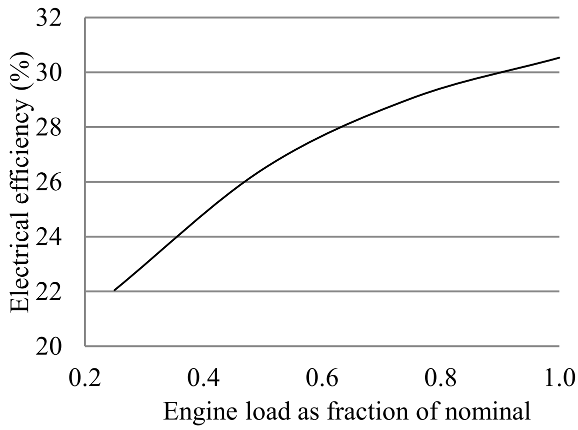


Figure 5: electrical efficiency of CHP engine.

The unit is intended to be easily modified for building application, with the waste heat from the exhaust gases and coolant water recovered via heat exchangers. At full capacity, the recovered heat content from coolant water at 99°C is 174 kW_t, while exhaust heat recovery is about 97 kW_t when recovered at 120°C. Given a heat exchanger effectiveness of 0.88, the maximum heat recovery can reach 240 kW_t at rated electrical output. This reduces to 96 kW_t at the lower limit of unit modulation. The part-load behaviour of the tested unit is shown in Figure 6.

PERVASIVE SENSING FOR CHP CONTROL

The possibilities for MIMO control considered in the project included combinations of 5 input control parameters as follows.

P_1 - space heat demand

This parameter determines whether there is demand for heating within each serviced space at any time. For a building with pervasive sensing this input is provided from temperature sensing of each thermal zone along with information about whether the space is occupied or will be occupied in the near future. Within the simulations, the space heat demands are predicted on the basis of the time step updates of occupant behaviour as delivered by the pervasive sensors.

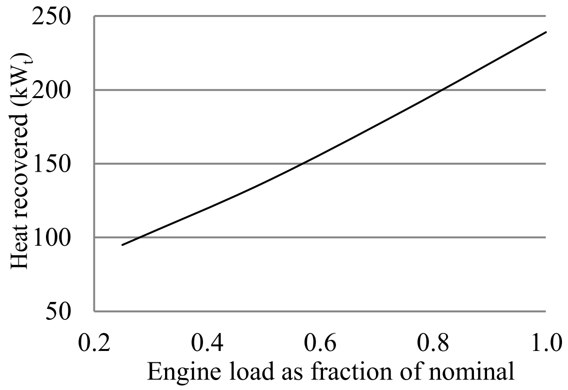


Figure 6: heat recovery from CHP engine.

P_2 - heat store demand

This parameter determines whether there is current capacity within a heat store. For a building with pervasive sensing this input may be estimated from the sensed store temperature. Within the simulations the thermal store is modelled in terms of its thermal capacity and passive losses.

P_3 - space electricity demand

This parameter determines the electrical power requirement of each occupied space. For a building with pervasive sensing it is determined from the sensor returns defining equipment usage, lighting states and grid/CHP power factors. Within the simulations this information is updated at each time step.

P_4 - electricity grid export potential

This parameter defines the ability to 'store' electricity within the grid and reflects the practical constraints that may be imposed by utility providers such that grid export is not available at all times. It corresponds to a virtual sensor that would in practice receive a grid availability signal from the utility. Within the simulations various scenarios were imposed.

P_5 - financial incentive

The potential advantage of CHP is the improved operational efficiency. This parameter defines the differential between CHP fuel costs, including any feed-in tariff incentive, and the cost of fuel when supplying energy by conventional means. The cost of energy was taken from data provided by the Energy Savings Trust (EST, 2014):

Electricity = 10.58 p/kWh from 6 a.m. – 11 p.m.

Electricity = 5.91 p/kWh from 11 p.m. – 6 a.m.

Feed-in tariff = 4.64 p/kWh at all times

Gas = 11.3 p/kWh

CHP CONTROL ALGORITHM

Typically, a CHP unit will be controlled in heat following mode, perhaps with heat storage for future use. Ambient temperature compensation might also be included in the control algorithm. CHP units are difficult to control optimally because of the dynamic variation in the heat and electricity demands, the limits imposed on unit regulation, and the feasibility of exporting to the electricity grid.

Table 2 shows a control 'truth' table that captures possible states of the 5 input control parameters described above and those combinations for which the CHP unit would be switched ON or OFF. Instances where the financial incentive is zero represent times when CHP will be switched OFF and have not been shown for brevity. Note that in the present study the unit was operated in heat-following mode, only being activated when there is a space heat demand or where the thermal store (where available) is not full; and in both cases where the heat demand is greater that the minimum limit of the CHP unit. This means that the generated elecricity is always an unregulated by-product.

The control algorithm imposed on the unit was as follows.

1. Demand from zones = heat required to bring all zones up to their set-point temperature (simulation output).
2. Demand from store = maximum store capacity – current store capacity – losses over previous time step.
3. Total heat demand = demand from store + demand from zones. Assume CHP unit is ON.
4. Demand CHP can meet = total heat demand but constrained within maximum and minimum CHP capacity limits. Establish unit efficiency and cost of gas from performance map.
5. CHP unit heat to zones = minimum of 1 and 4
6. CHP unit heat to store = heat demand at 4 – heat delivered at 5.
7. Thermal store heat to zones = heat demand at 1 – heat delivered at 5 when limited by heat flow rate from store to zones.
8. Auxiliary heat to zones = heat demand at 1 – heat delivered at 5 and 7 (with a lower bound of 0).
9. Total heat supplied = heat delivered at 5/η_{CHP} + heat delivered at 6/η_{CHP} + heat delivered at 8/η_{AUX} where η_{CHP} and η_{AUX} are CHP and conventional heating system efficiencies.
10. Cost of heat = heat supplied at 9 x gas tariff.
11. Electricity demand from zones = electricity required to satisfy plug loads and equipment.
12. Determine electricity produced by CHP from performance map based on heat delivered.
13. CHP electricity to zones = maximum of electricity at 11 and electricity at 12.
14. Electricity exported = electricity at 12 – electricity at 11 (lower bound of 0).
15. Electricity imported = electricity at 11 –electricity at 13 (lower bound of 0).
16. Total cost of electricity = electricity at 15 x electricity tariff – electricity at 14 x feed-in tariff – electricity at 12 x generation tariff.
17. Total conventional energy cost = (heat at 1/η_{AUX}) x gas tariff + electricity at 11 x electricity tariff.
18. Total CHP energy cost = cost at 10 + cost at 16.
19. Switch CHP OFF if energy cost at 18 > energy cost at 17.

SIMULATION RESULTS

Within the simulation study conventional control is compared with smart control based on pervasive sensing.

Case 0 (the base case) assumes that the CHP unit provides space heating via conventional control based on ambient and return air temperature sensing. Electricity export to the gird is enabled. Subsequent cases apply progressively more comprehensive control based on the presence of pervasive sensing. Case 1 is as Case 0 but with multiple temperature sensed points to enable zone control.

Case 2 is as Case 1 but assumes the availability of a thermal store large enough to accommodate 20% of the design-day heat demand.

Cases 3 is as Case 2 but makes use of virtual sensors relating to grid export and building electricity demand. This case represents the scenario where export to grid is not always feasible (perhaps because of power quality issues or a low broadcast tariff in a future smart grid). This situation (grid unavailability) can result in one of two possibilities when there is excess electrical power from the CHP unit: the excess power is sent to a dump load (e.g. hot water or battery storage), or the unit is switched OFF. The first situation is represented by Case 3.

Case 4 is as Case 3 but where the CHP unit is switched OFF in preference to power dumping.

Case 5 is as Case 4 but with control on the basis of an attempt to minimise the overall cost for heat and power, i.e. on the basis of economic feasibility. Table 3 summarises the cases simulated along with the total cost of energy over the heating season.

Table 3: Simulation case and total energy cost over the heating season.

Case	Description	Total cost (£)
0	Base case (no pervasive sensors).	1,603,000
1	Zone temperature sensing.	1,378,000
2	As 1 with store and electricity export to grid always available.	1,359,000
3	As 2 with electrical power sensors (export not always available, excess electricity dumped).	1,458,000
4	As 3 with CHP unit switch off when excess electricity produced.	1,366,000
5	As 4 with control based on economics.	1,344,000

Supplementary heating was assumed to be present in all cases so that temperature set-points would always be attained to support a fair comparison. This supplementary heating was activated when heat demand exceeds CHP supply or when demand is lower than the minimum CHP output. Note that the heat demand profile for Case 0 equates to more energy than Case 1. The reason for this is that with Case 0 there is no provision for pervasive temperature sensing of each thermal zone and only one sensor is employed in the return air stream per floor (as now). Heating to individual zones cannot therefore be switched OFF and consequently several zones overheat.

Figure 7 shows the predicted heat and electricity demands for the building based on idealised control, i.e. the exact amount of heat required to keep the space at the set-point temperature is delivered regardless of how this heat is generated. These demand profiles are applicable to all cases except Case 0 for which the heat demand is similar but greater in magnitude. These results correspond to a typical winter day selected on the basis of degree-day averaging over the heating season. While detailed comparisons were made for this 'design' day, simulations to compare control regime performance were carried out over the full heating season.

Figure 8 shows how demand was met for Case 1: this represents a 14% energy saving over Case 0. In the morning, demand exceeds CHP capacity by about $60kW_t$ but for most of the remainder of the day is lower than the low limit of CHP modulation ($96kW_t$). Auxiliary heating is required for these periods except during the evening when the unit operates at part-load and with lower electrical efficiency.

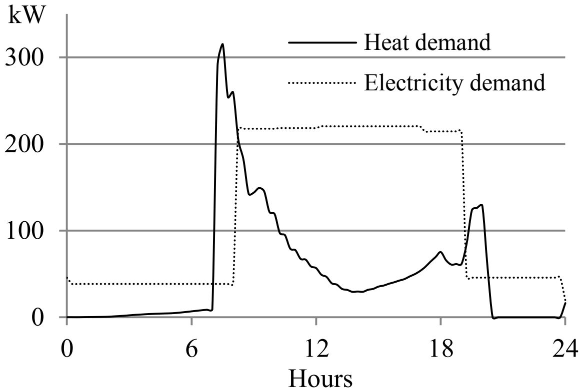
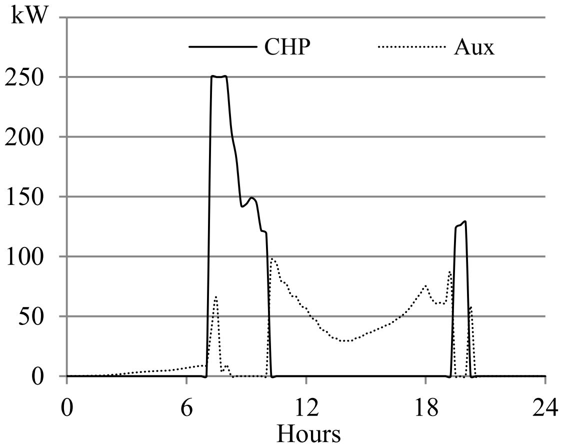


Figure 7: heat and electricity demand for a 'design' day.



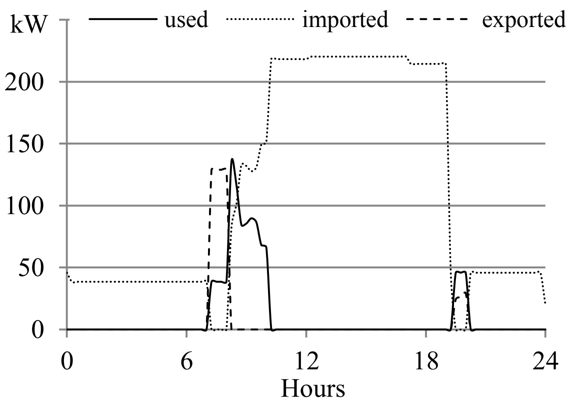


Figure 8: Case 1 heat delivered to zones (above) and electricity used/generated (below).

In order to operate the CHP unit at or around full capacity more often, a heat store was incorporated (Case 2). This was sized to provide heat at peak hours and when the demand was beyond the CHP unit's capacity. The capacity chosen was 250 kWh_t, which is 20% of the daily heat demand of Figure 7. Figure 9 shows the situation when the heat store is activated. Electricity is exported in the morning and late evening as before but regular switching of the CHP unit is observed during the period of low heat demand – this rapid switching may not be acceptable in practice. The overall cost is reduced by 1.2%.

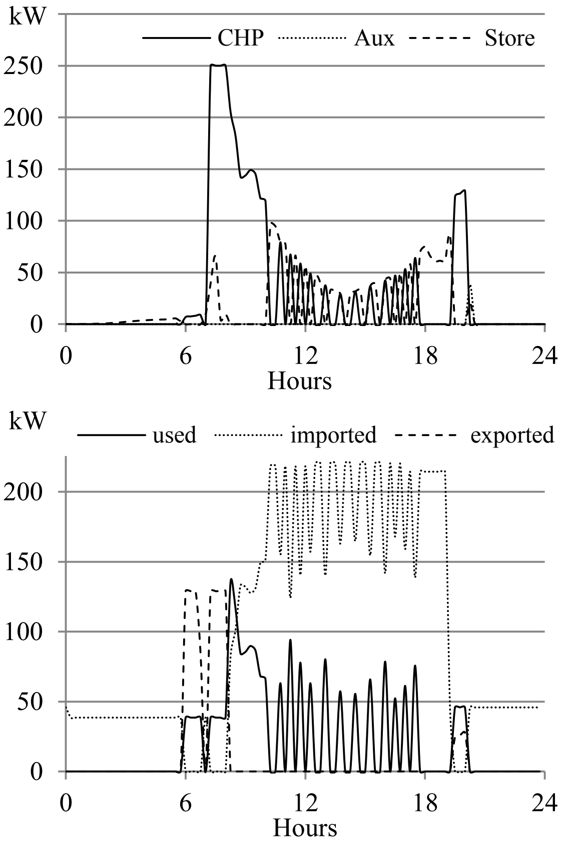


Figure 9: Case 2 heat delivered to zones (above) and electricity used/generated (below).

With Case 2 it is interesting to note that when the thermal store size was subsequently increased no significant further savings were made. This is due to ther increased passive losses from the larger store and indicates that in practice it may not be advantageous to have a heat store, especially with oversized CHP units. A better operational regime would be to use a lower capacity CHP unit with a heat store. This was investigated via a parametric analysis and the results are reported in the next section.

The effect of changes as imposed in Cases 3 and 4 on the design day profiles is not significant when compared with Case 2. The effects do however accumulate over the heating season and for Case 3 (excess electricity dumped) the overall cost is reduced by 9% relative to Case 0. For Case 4 (CHP unit switched OFF) the cost saving is 15%, which is similar to Case 1 (at 14%). Unit switching is similar to Figure 9 but slightly less frequent. This suggests that in practice higher cost saving can be realised because unit startup losses will be less.

Finally, in Case 5 the CHP unit is subjected to full MIMO control based on a financial incentive to switch ON. As might be expected, the cost function is lowest for this case, with a reduction of 16% relative to Case 0. This cost was further reduced by 20% of Case 0 when optimum plant sizes were assumed as described in the next section. Switching profiles were similar to Figure 9.

From the results of Table 3 it is observed that the cost of energy required to provide heat and electricity decreased as the level of pervasive sensing increased.

PARAMETRIC INVESTIGATION

The capacity of the CHP unit is 80% of the design day peak heat demand. For the remainder of the day, heat demand is low principally due to internal heat gains. Because of this, the CHP unit is not active for much of the time in cases without a thermal store and switches regularly in cases with a store. Parametric simulations were commissioned to investigate how thermal store and CHP unit size affect operating cost. Both were varied and the findings are shown in Figure 10, which assignes the cost of Case 1 to be 100%. The results suggest that there is an optimal CHP unit and heat store size – here 150 kW_t and 200 kW_t respectively for the demand profile in question.

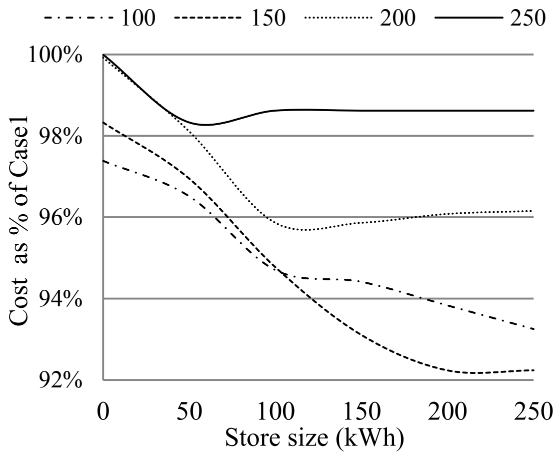


Figure 10: proportional cost of supplying heat and power as a function of the indicated CHP unit capacity (kW_t).

CONCLUSION

An office building was subjected to pervasive sensing of environmental conditions and space use at high temporal resolution. This information was fed to a detailed simulation model in order to inform MIMO control of a proposed CHP unit. The controller was then systematically enhanced by making available progressive levels of context information. The results indicated that decisions based on pervasive control are likely to be more economically feasible than those based on conventional control utilising parameters representing heating demand only.

ACKNOWLEDGEMENT

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Table 2: Control truth table for controlling CHP unit.

P_5 **financial incentive**	P_4 **export available**	P_3 **electricity load**	P_2 **storage capacity**	P_1 **heating load**	**State of CHP unit**
1	0	0	0	0	0
1	0	0	0	1	1
1	0	0	1	0	1
1	0	0	1	1	1
1	0	1	0	0	0
1	0	1	0	1	1
1	0	1	1	0	1
1	0	1	1	1	1
1	1	0	0	0	0
1	1	0	0	1	1
1	1	0	1	0	1
1	1	0	1	1	1
1	1	1	0	0	0
1	1	1	0	1	1
1	1	1	1	0	1
1	1	1	1	1	1