UNIVERSITY OFFICE SIMULATOR FOR ENERGY AND COMFORT OPTIMISATION

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KEYWORDS

Intelligent Environments, Smart Offices, Ambient Intelligence, Intelligent Workplace

ABSTRACT

In this paper, the simulation of the environmental conditions in university offices is addressed. Based on the real data collected from the environment, a flexible simulator is developed which accepts different office worker profiles including expected office occupancy and computer usage. The simulator generates sensory signals which represents different activities and occupancy of the office environment. These signals will then be used to control heating, lighting and computer stand-by mode of operation. The validity of the simulator is verified by tuning the simulator parameters to occupancy data collected by sensory systems from real offices.

INTRODUCTION

The aim of our research is to model office worker behaviour in a university office environment in order to improve energy usage and user satisfaction with their working conditions. Activities are monitored using low level sensory devices to detect when they enter/leave the room, when they sit down at the desk, and when they use the computer. We also monitor when they switch the light on/off, when they adjust the heating or leave the room to get a drink.

The office environment can be a stressful place, and the stress can be increased when the conditions are not conducive to work. A room at the wrong temperature, a computer that has been shut down overnight and takes time to restart, inadequate lighting - all add stress to the workplace by reducing the workers' comfort. Moreover, if the office user attempts to alleviate these by leaving their computer, lights and heating permanently on, they are accused of being ecologically irresponsible. The workplace often includes reactive systems such as passive infra-red (PIR) activated lighting, but these can cause further stress, in that a worker quietly typing at their computer can find that the PIR decides they are absent, and switches off their office lighting. Heating systems often work on the assumption of a 9:00am to 5:00pm presence, five days a week, whereas an individual office worker may have a different schedule, including long periods out of the office.

The availability of modestly priced sensors and low cost computers lead us to consider that individualised control of the office environment would improve workers' sense of control and thus reduce their stress, since one of the major causes of stress cited by clerical workers is lack of control (Narayanan et al., 1999). In addition, if the power minimising functions were made more responsive to the user's habits and routines, there would be more acceptance of their use.

This paper is organised as follows: in the next section we summarise existing work on modelling the characteristics of an office or other building, modelling the behaviour of people within such an environment and quantifying and assessing the performance and comfort of workers. The proposed system of monitoring and controlling the conditions of office workers in the environment of a higher eduction establishment are explained after the related works section followed by some details on the proposed simulator which has been built to generate equivalent patterns to a human office worker, and which then allows more repeatable testing and assessment of algorithms. Some conclusions are drawn in the final section followed by some discussion on the direction in which the research needs to progress.

RELATED WORK

Automated control of the environment can be as simple as the home heating thermostat, and as complex as that which manages the growing conditions in a commercial glasshouse. Within the office environment, PIR control of lighting is commonplace and heating is tightly controlled. For the European Union (EU) this has become an area of concern, as buildings have become the fastest growing energy consuming sector (Li et al., 2009). Studies in (Doukas et al., 2009) found that energy efficiency measures could contribute to the reduction of current energy consumption by at least 20% within the EU, which is equivalent to the savings of 60 billion Euros annually. The related work in this area is presented in the following sections in three categories, namely; modelling the office or building, human behaviour modelling and comfort assessments.

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Proceedings 25th European Conference on Modelling and Simulation ©ECMS Tadeusz Burczynski, Joanna Kolodziej Aleksander Byrski, Marco Carvalho (Editors)
ISBN: 978-0-9564944-2-9 / ISBN: 978-0-9564944-3-6 (CD)

Looking into the future of residential and office buildings Mitsubishi Electric Research Labs (MERL) has collected motion sensor data from a network of over 200 sensors for two years in a 2-floor office environment (MERLSense, 2011). This data is the residual trace from the people working in a research laboratory. The dataset has been made publicly available as a benchmark to identify social and individual behaviour in an office environment. Similar datasets have been collected in a home environment as part of CASAS project (CASAA, 2011) where intelligent agents are utilised to perceive the environment through the use of sensors, and act upon the environment through the use of actuators.

Modelling the Office or Building

The authors in (Kazanasmaz et al., 2009) developed an office building prediction model to determine daylight luminance using artificial neural network (ANNs). The daylight's behaviour pattern depended on movement of sun, latitude of the building, climate condition, ambient temperature and sunshine availability (Wong et al., 2010). Although this work was aimed at designers to help predict illuminance within their buildings, the predictions could also be used once the building was in use to ensure that the artificial lighting was switched on/off before the occupants realised that they needed it (Ekici and Aksoy, 2009). Work by (Li et al., 2009) focused on the hourly cooling load in a building. They found that ANN and Support Vector Machine (SVM) can predict the hourly cooling load in a building with high accuracy. Such prediction is necessary in order to ensure that the building's heating system can be used optimally to maintain a consistent temperature for the workers.

Human Behaviour Modelling

The modelling of the thermal and illumination characteristics of buildings discussed earlier need to be linked with the way the building is used by its occupants, so as to improve the management of the environment for the occupants. Research by (Tabak and Vries, 2010) examined the intermittent activities that interrupt the planned "normal" activities of office workers. They found that probabilistic and S-curve methods could be used to predict activities (such as "smoking", "go to toilet") and these could be used in fine grained simulations of building performance. However, they cautioned that the results applied to typical Dutch office based organisations, and other office environments might need further experiments to generate data. Although Tabak and de Vries claim that predicting a single person's behaviour is "virtually impossible", they acknowledge that their method provides insight into the "average behaviour" including deviations from the mean. Akhlaghinia et al (Akhlaghinia et al., 2008a), (Akhlaghinia et al., 2008b) have shown that where a person is likely to have a more systematic pattern (e.g. an elderly person at home), then prediction of their behaviour is possible based on previous monitoring. Investigation by (Hong, et al.,2010) used wearable sensors for categorising activities within the office environment. They managed to identify 7 activities, including attending meetings and working at a computer, though the sensors were very obtrusive and thus purely for the purposes of the experiment.

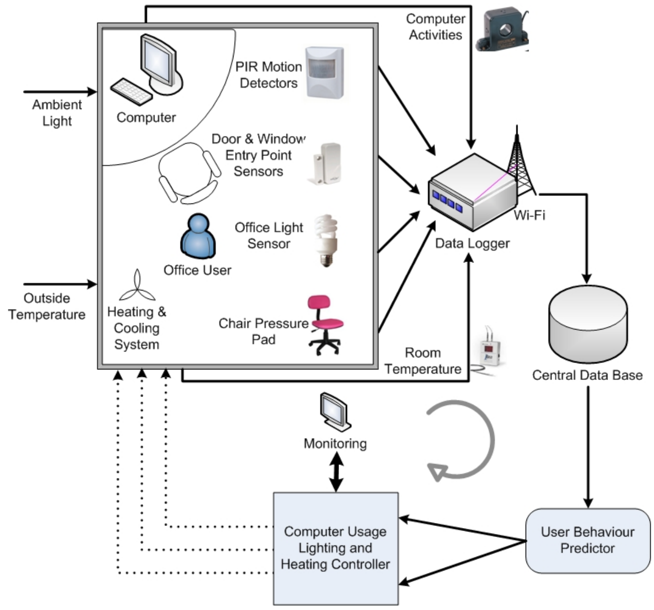

Figure 1: Proposed System Architecture for Intelligent Office Environment

Comfort and Performance Assessment

Investigation into the comfort levels of pupils by (Wong and Khoo, 2003) (Fischer, 2007) (Gaitani et al., 2010) showed that the wrong temperature in the classroom led to poorer learning performance. Similarly, performance studies of call centre workers in Sacramento (Heschong Mahone Group, 2003) showed that light levels, ventilation status and temperature all had significant effects on performance, though the effects were intertwined and complex. Seppanen et al (Seppanen et al., 2006) have collated studies on temperature and performance, and provide convincing evidence of the importance of maintaining the office temperature between 21-25$°C$ to optimise performance. Another study in (Aries et al., 2007), for example, used multiple survey items to assess worker discomfort, sleep quality and hindrance, in order to relate building aspects to any physical and/or psychological effects. However, Haynes (Haynes, 2008) points out that while there is sufficient evidence to support claims that office comfort affects productivity, there is no agreement as to how office comfort should be measured.

SYSTEM ARCHITECTURE AND SENSORS

As shown in the studies discussed above, office workers' performance and comfort can depend on temperature, ventilation and lighting. Their power use depends on the way they have adjusted their environment to optimise these characteristics, together with their use of Per-

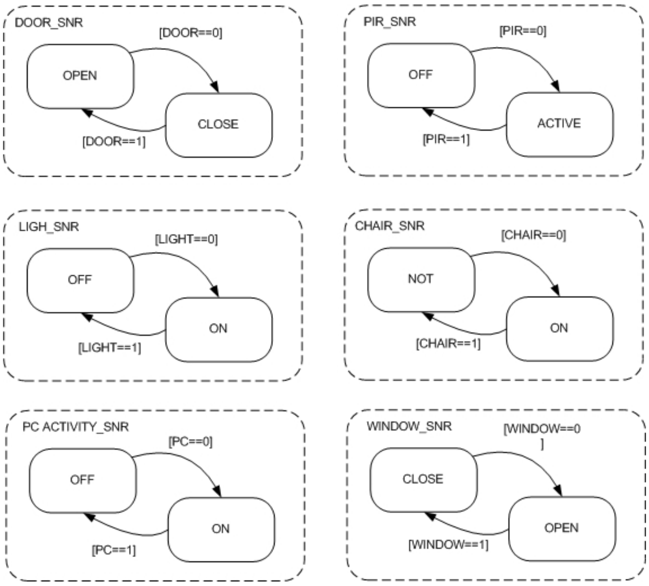

Figure 2: Individual State Models for Sensors

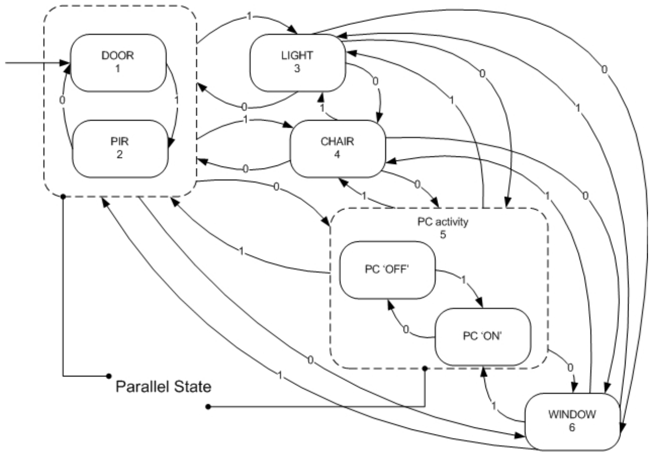

Figure 3: Finite State Machine for the Office Simulator

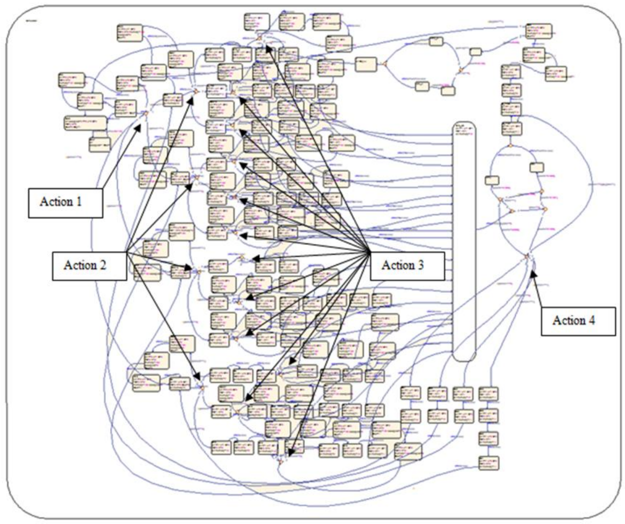

Figure 4: Transition from state to state with condition action.

sonal Computers (PCs). We must therefore consider the way in which one could monitor these characteristics (of both the worker and their environment) in order to log the data. The data capture and logging must be as unobtrusive as possible in order to avoid affecting the behaviour of the worker, and should not increase their stress.

We may classify the needs of our experimental system for an office as the ability to detect occupancy, record the ambient conditions (and any worker responses to them), and to identify activities. Occupancy detection may be considered to be covered by PIR motion sensors and door sensors. PIR motion sensors are low cost and readily available, though their typical activity thresholds mean that a worker quietly reading or writing a document would not cause them to signal. Door sensors are relatively unambiguous - a door generates a boolean open or shut signal. However, a visitor to an office would also trigger the open-shut sequence, so the office occupancy could not necessarily be deduced simply from the door. Thus occupancy needs to be deduced from a combination of these signals together with additional information provided by other sensors.

The ambient conditions can be recorded via temperature sensors (inside the office and external to the building) and light sensors. The response of the office worker can be captured via switches on the windows (as for doors) to detect when they have been opened or shut, and electricity usage monitors on desk lights and fan heaters. Identification of activities is a difficult task. It is possible to identify when a person is actually typing at a PC, or moving a mouse, by adding some background software. If a worker was at a desk reading a paper report, the PC activity might halt for a considerable time, and the PIR might not trigger. An additional boolean signal generated by a pressure sensor in the worker's seat could indicate when they are at their desk. These 'activity identification' sensors could also be used to support the occupancy deduction discussed earlier (Chen et al., 2010).

This leads to the system architecture proposed in Fig. 1. The full monitoring and control system would use the information provided by the sensor, together with rules and algorithms deduced from the data mining (Witten and Frank, 2005) to modify the environment such that the office worker found it optimal, while still achieving better energy consumption.

The office environment that we are using as the testbed for our experiment is the individual academic staff offices in the university campus.

OFFICE ENVIRONMENT SIMULATOR

Although we have set up a real room for monitoring office workers as part of this study, an important aspect of the research is the development of a simulator. This allows us to generate large data sets far faster than real time, and to set up specific patterns of behaviour. It

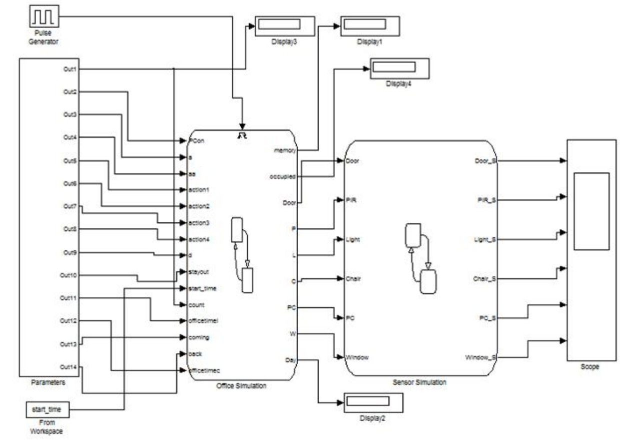

Figure 5: Block Diagram of the Office Environment Simulator

provides a test bed for the various algorithms which we need to assess and compare, and can be made increasingly more sophisticated. Moreover, unlike volunteer real office workers, who may not show the full range of behaviours, the simulator can be adjusted to cover the gamut from a reliable 9:00 to 5:00 worker who hardly moves from their desk, to the totally chaotic one, who hardly sits down for more than 30 minutes. Algorithms can be then assessed as to how well they work under this severe range of tests.

The simulator starts from the assumption of an office occupied by a single worker, who carries out a range of activities during the standard working day. It also starts by assuming that information is being generated by (virtual) sensors reporting on aspects of the behaviour. This is an important aspect of the realism, in that it allows the simulator to generate data that needs the same sort of interpretation as the real office. If the simulator simply produced records "Reading", "Typing at PC", "Out of Office" for example, it would have little value in helping to produce algorithms pertinent to the real environment, where activation, say, of the chair sensor could be used as an indicator of "Reading" only if it did not overlap with the data indicating that the mouse was being moved.

For this reason, each of the macro-states in the simulator has to be characterised by its name, allowed transitions, duration, and whether it overlap with others. The micro-states of the individual sensors are much simpler, and are as shown in Fig. 2. Combining the individual sensor models to take into account the possible overlapping of events and parallel activations of some of the sensors leads to the Finite State Machine of the office shown in Fig. 3.

In order to drive the behaviour of the simulator, it is necessary to create a model of human activities, with a simple set of actions characterised by a few parameters. This is to allow us to model a range of different workers' routines with differing degrees of chaos. The human model generates a sequence of 'actions' lasting for differing amounts of times. In order to create the behaviour of a person doing an activity that is as natural as possible, the values of the parameters are generated using random numbers based on a normal distribution. The actions, their start times, durations and transitions from one to another then feed into the office model, so that the individual sensor state machines are enacted - some in parallel and some in sequence, depending on the action being considered.

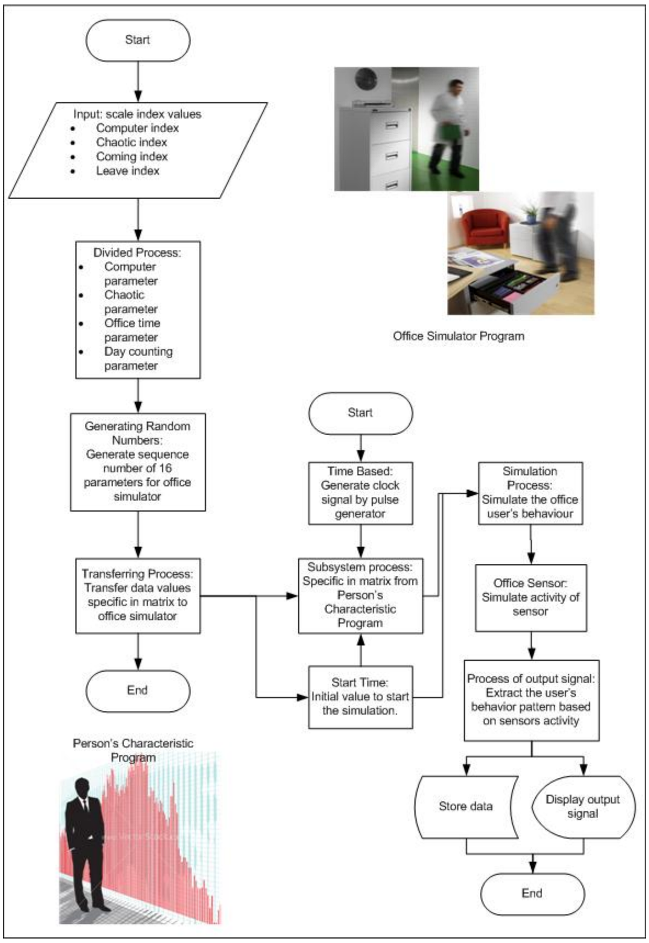

Figure 6: Processing flow within the Office Environment Simulator

The office environment simulator can thus be considered to be made of four parts: user parameterisation, office simulation,sensor simulation and output. The sequential structure allow the system run in AND and OR mode (see Fig. 2). To handle the complex number of states, the hierarchic structure is proposed as shown in Fig 4. All states of the sensors use logic 1 and 0 to represent the active and inactive states. Fig. 5 shows the block diagram of the office environment simulator. The output block of this simulator receives a trigger signal from the sensor simulation block, and all activity sensors depending on user activity are processed into the office simulation block. The office simulation block is controlled by the user parameterisation block. Fig. 6 shows the processing chain within the office environment simulator.

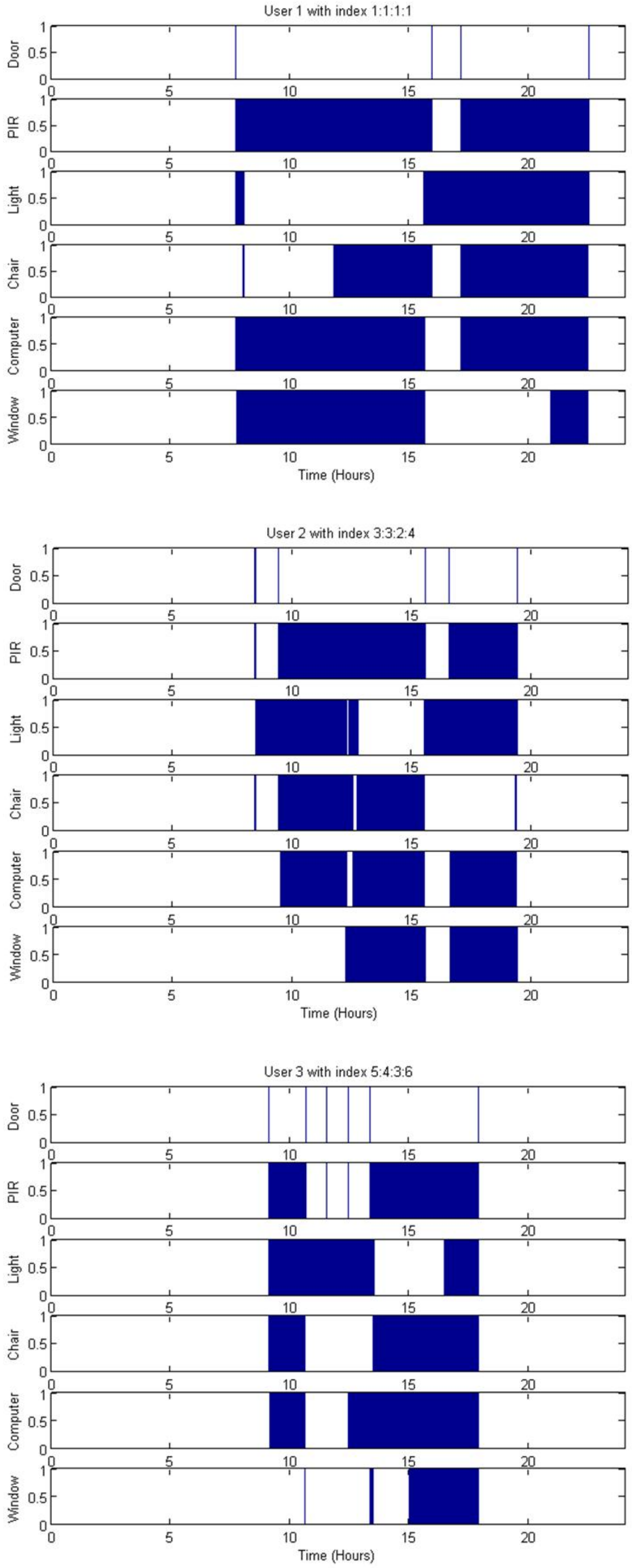

Figure 7: Simulated Data for 3 different user characterisations

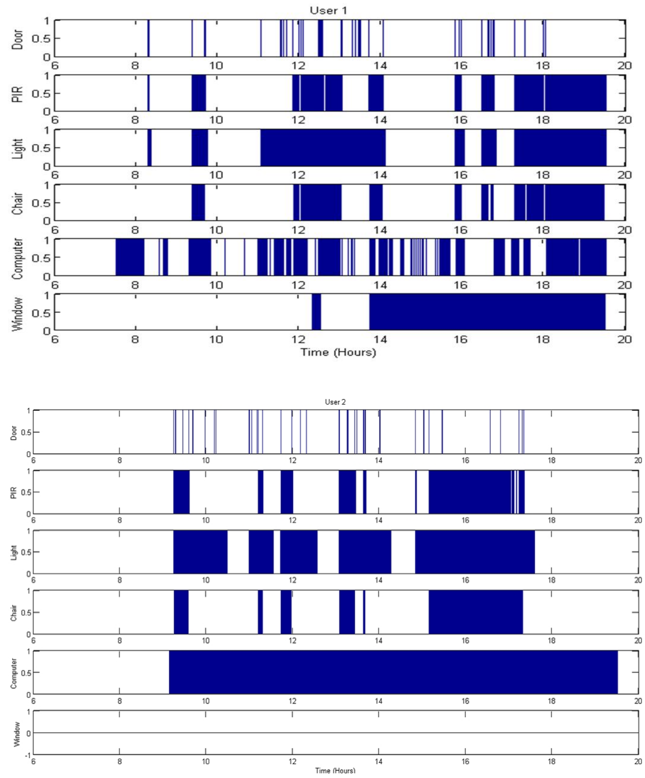

Figure 8: Real Data logged from two different users

To illustrate the complexity and difference in different user profiles, Fig. 7 shows a range of user profiles, where the occupancy of the office and behaviours within it are clearly differentiated. These were generated by using very few parameters to characterise the users.

The simulated data may be compared with the data logged from two offices monitored using a sensor system as described earlier. Fig. 8 shows initial data from these offices, and shows that the variation of the simulated office worker behaviour bears comparison with the real data recorded in terms of variety and pattern.

FUTURE WORK AND CONCLUSIONS

Initial use of the simulator has shown promise. Individual worker profiles can be characterised by a few parameters and appear to give us a wide range of behaviours, typical of the variation between academic staff. This allows us to generate a substantial amount of data much faster than real time.

Our experimental office has been set up as shown earlier. It now remains to run much longer logging sequences on this office with a few academic staff volunteers, and then compare the results with the simulator to ensure that the simulator results are relevant. This will lead to a more substantial period of data mining, both simulated and real data, in order to establish actions that are characteristic of reduced comfort. Prediction of these actions will then allow us to control the environment and, hopefully, reduce them to a minimum by pre-empting the need of the office worker. This would then give us a route to our goal - automated comfort management combined with optimal resource use.

ACKNOWLEDGEMENTS

The first author would like to acknowledge the support of the Ministry of Higher Education, Malaysia and Tun Hussein Onn University of Malaysia.

REFERENCES

Aries, M. B. C., Veitch, J. A., Newsham, G. R., “Physical and psychological discomfort in the office environment”, Light, Performance and Quality of Life – Light and Health Research Foundation (SOLG) Symposium, 2007.

Akhlaghinia M. J., Lotfi A., Langensiepen C. and Sherkat N., “Occupant Behaviour Prediction in Ambient Intelligence Computing Environment,” International Journal of Uncertain Systems, Vol. 2, No. 2, May 2008.

Akhlaghinia M. J., Lotfi A., Langensiepen C. and Sherkat N., “Single Occupancy Simulator for AmbientIntelligence Environment”, Journal of Internet Technology, Vol. 9, No. 4, pp. 333-338, October 2008.

CASAS Smart Home Project, Smart Home Datasets, Washington State University [online] Available: http://ailab.wsu.edu/casas/datasets.html

Chen C., Das B. and Cook D. J., “A data mining framework for activity recognition in smart environments”, in Proc. of the Sixth Int. Conf. on Intelligent Environments, pp. 80-83, 2010.

Doukas H., Nychtis C. and Psarras J., “Assessing energy-saving measures in buildings through an intelligent decision support model,” Build. Environ., vol. 44, pp. 290-298, 2009.

Ekici, B. B. and Aksoy, U. T., “Prediction of building energy consumption by using artificial neural networks,” Adv. Eng. Software, vol. 40, pp. 356-362, 2009.

Fischer J., Mescher K., Elkin B., McCune S. M. and Gresham J., “High-performance schools: High marks for energy efficiency, humidity control, indoor air quality first cost,” ASHRAE J., vol. 49, pp. 30-32+34+36-38+40-46, 2007.

Gaitani N., Lehmann C., Santamouris M., Mihalakakou G. and Patargias P., “Using principal component and cluster analysis in the heating evaluation of the school building sector,” Appl. Energy, vol. 87, pp. 2079-2086, 2010.

Haynes, B., “The impact of office comfort on productivity”, Journal of Facilities Management, Vol. 6 Iss: 1, pp.37 - 51, 2008.

Heschong Mahone Group, “Windows and Offices: A Study of Office Worker Performance and the Indoor Environment” California Energy Commission’s Public Interest Energy Research (CEC PIER) 2003.

Hong, Jin-Hyuk, Yang, Sung-Ihk , Cho, Sung-Bae, “ConaMSN: A context-aware messenger using dynamic Bayesian networks with wearable sensors”, Expert Systems with Applications 37 (2010) 4680-4686.

Kazanasmaz T., Gunaydin M. and Binol S., “Artificial neural networks to predict daylight illuminance in office buildings,” Build. Environ., vol. 44, pp. 1751-1757, 2009.

Li Q., Meng Q., Cai J., Yoshino H. and Mochida A., “Predicting hourly cooling load in the building: a comparison of support vector machine and different artificial neural networks,” Energy Conversion and Management, vol. 50, pp. 90-6, 01, 2009.

MERLSense, Two Years in a tar file, Mitsubishi Electric Research Laboratories [online] Available: http://www.merl.com/wmd/

Narayanan L., Menon S., Spector P. E., “Stress in the workplace: a comparison of gender and occupations” Journal of Organizational Behavior, Volume 20, Issue 1, pages 63-73, January 1999.

Seppanen, O., Fisk, W. J., Lei, Q.H., “Effect of temperature on task performance in office environment”, Lawrence Berkeley National Laboratory, 2006.

Tabak V. and B. de Vries, “Methods for the prediction of intermediate activities by office occupants,” Build. Environ., vol. 45, pp. 1366-1372, 2010.

Witten I. H. and Frank E., “Data Mining: Practical machine learning tools and techniques”, Morgan Kaufmann Pub., 2005.

Wong, S. L., Wan, K. K. W. and Lam, T. N. T., “Artificial neural networks for energy analysis of office buildings with daylighting,” Appl. Energy, vol. 87, pp. 551-7, 02, 2010.

Wong N. H., and Khoo S. S., “Thermal comfort in classrooms in the tropics,” Energy Build., vol. 35, pp. 337-351, 2003.