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ACTIVE CONTROL OF INDOOR ENVIRONMENTAL QUALITY

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ABSTRACT

This paper presents a methodology for the integrated control of Indoor Environmental Quality. The most important aspect of the methodology is the treatment of the task as a multi-objective optimization problem. Appropriate control actions that achieve reasonable tradeoffs among conflicting objectives are selected through multi-objective optimization in which predictive models are trained using machine learning techniques. The methodology is currently being implemented and tested in the Field Environmental Chambers (FEC) of the Department of Building, National University of Singapore.

KEYWORDS

Building Automation, Control, Multi-Objective Optimization, Indoor Environmental Quality

1. INTRODUCTION

Automatic controllers promise to improve energy efficiency and reduce maintenance costs. For example, a system called NEUROBAT (Morel et al., 2001) obtained energy savings of 13% (compared to conventional open loop controllers) in two occupied rooms during a complete heating season. Other examples of the use of automatic controllers for thermal comfort can be found in Chen (2001), Kummert (2000) and Chow et al. (2002). Guillemin and Morel (2002) developed a prototype that simultaneously controlled heating and lighting. Since such systems are still being tested in laboratories, they have not penetrated the industry. Commercial Heating Ventilating and Air-Conditioning (HVAC) systems operate through taking actions sequentially in order to meet targets related to individual parameters. Integrated control of diverse indoor environmental quality (IEQ) parameters such as temperature, lighting level, relative humidity and carbon dioxide (CO_2) do not exist as commercial products.

In most of the systems described above, control is treated as a single objective optimization problem. Parameters that influence indoor environmental quality such as temperature, humidity, level of CO_2 and lighting can be adjusted through operating individual devices. But it is not easy to obtain the right combinations of values of these parameters since operating a single device might have several effects. For example, suppose that the objective is to improve the level of lighting in a room. When other objectives are ignored, the most economic solution will be to draw open the window blinds. However, this brings more radiant heat into the room and consequently, the cooling load increases. When there are multiple objectives, we need to search for solutions that make compromises among conflicting objectives.

There are many researchers who have studied the influence of interacting parameters on the indoor environment quality, for example, Suter et. al. (2007); and Mahdavi and Unzeitig (2005). In these works, multiple parameters are modelled for the purpose of simulation and performance evaluation, but not for adaptive control. Multi-objective optimization approaches such as Pareto optimization have never been investigated for the control of IEQ. These techniques have been successfully applied to other domains such as structural control (Adam and Smith, 2005). Recent theoretical advances in the area of multi-objective control make it possible to identify solutions that achieve reasonable trade-offs amongst conflicting objectives such as minimizing energy and maximizing comfort.

This paper presents a methodology for integrated control of IEQ parameters through multi-objective optimization. The primary contribution of this paper is in the area of building automation and control. A new control strategy that maximizes building performance has been developed. The most important aspect of the methodology is the treatment of the task as a global optimization problem. The methodology is currently being implemented and tested in the Field Environmental Chambers (FEC) of the Department of Building, National University of Singapore. This paper reports work that is in progress and focuses mainly on the theoretical framework.

2. INTEGRATED CONTROL OF IEQ

The perception of indoor environment quality is influenced by many aspects such as thermal comfort, air quality, and lighting. Air quality may be measured through a number of parameters such as relative humidity (RH), level of CO_2, velocity of air movement, etc. Traditionally, HVAC systems control the air quality and thermal comfort using parameters set by users. In most cases, the only parameter that the end-user can set is the temperature. The air conditioning system provides adequate supply of cold air into the room such that the required temperature is attained. The amount of cold air supplied to a room is regulated by opening and closing of dampers to various levels that are determined by the control algorithm. The supply of cold air indirectly influences other parameters such as RH and CO_2. Accurate simultaneous control of these parameters is not possible through this approach. In fact, these parameters are not even measured in the conventional systems.

In the present work, all the important IEQ parameters are measured by appropriate sensors. Measured IEQ parameters include temperature, RH, CO_2 and lux. In addition, energy consumption of individual subsystems are also measured using power meters.

The room is equipped with a number of actuators that perform different functions. These include dampers that let in cold air into the room, dampers that control the in-take of fresh air from outside, switches that control lighting illuminance and position regulators of blinds.

Data from sensors is used to identify the most appropriate control action through multi-objective optimization. The complete feedback loop is shown in Figure 1.

3. MULTIOBJECTIVE OPTIMIZATION

The control task is treated as a multi-objective optimization problem. Instead of optimizing a single objective, multiple objectives are considered simultaneously. There are objectives related to attaining desirable values of IEQ parameters as well as minimization of energy. The goal of active control is to achieve the objectives to the maximum extent possible. Since objectives frequently conflict with each other, multi-objective optimization should aim at achieving reasonable trade offs. For example, it may not be possible to attain the set values for both the temperature and RH, since excess humidity is usually removed by cooling the air which tends to lower the temperature below the set values. In such situations, the optimization algorithm has to identify the best control action that will achieve reasonable compromises. This is not an easy task.

There are several approaches to multi-objective optimization. One popular approach is called Pareto optimization and is adopted here. In this approach, a population of solutions known as the Pareto set is generated (Raphael and Smith, 2003a). The Pareto set (front) consists of a set of solutions that satisfy what is known as the Pareto optimality criterion. According to this criterion, a solution point P (Figure 2) is accepted only if there are no solutions better than P with respect to all the objectives. For example, even if P is worse than another solution P1 with respect to one objective, P is accepted provided that it is better than P1 in at least one objective. Thus each Pareto optimal solution is good in some respect. The set of all Pareto optimal solutions form the Pareto set or Pareto front.

Many techniques for generating the Pareto front are found in the literature. These include multi-

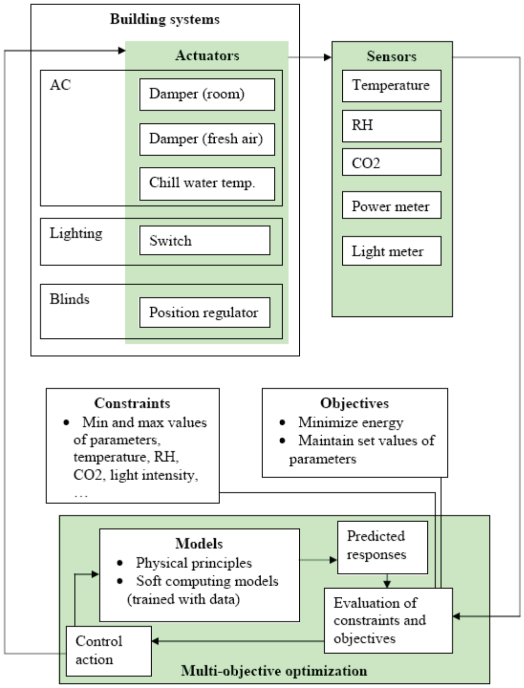

Figure 1 System Architecture

objective versions of genetic algorithms (Haralampidis et al., 2005, Deb and Tiwari, 2005, Grierson and Khajehpour, 2002), simulated annealing (Czyzak and Jaszkiewicz, 1998, Ulungu et al., 1999), weighting methods (Kim and Weck, 2006), and multi-start methods (Jaszkiewicz 2002). In this work, a newly developed algorithm (Raphael 2006) is used to generate the Pareto front. This algorithm divides a multi-objective optimization problem into a series of single objective optimization problems that are easier to solve. This is done by selecting one objective at a time and treating remaining objectives as

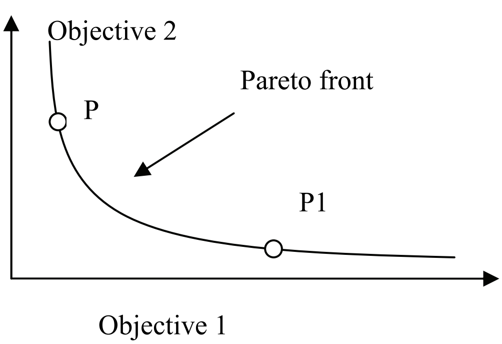

Figure 2 Pareto Front

constraints. It has been shown that this algorithm is able to generate good quality Pareto fronts. Another attractive feature of this algorithm is that it has a mathematical proof of convergence.

Once the Pareto front is generated, a suitable solution point can be selected using a number of heuristics. A simple heuristic is to select the point on the normalised Pareto surface where the slope is close to 45 degrees. This is the point where the relative gain in one objective is compensated by an equivalent loss in the other objective.

4. MACHINE LEARNING

The objective functions that are used in the optimization compute the difference between desired states and the predicted states after the application of a control action. This requires an accurate prediction of the effects of control actions. In general, the effects of control actions cannot be predicted accurately since closed form equations are not available and theoretical models involve many parameters whose values are not known precisely. In these circumstances, machine learning techniques are used to train models to be used for prediction. Two types of models are used. The first type is based on physical principles, but contains parameters whose values are not known precisely. The values of parameters are determined through a process known as model updating in which the best combination of values of parameters is found through the minimization of prediction error. The second type of models is purely empirical and is obtained through training artificial neural networks.

An example of the first type of model is the energy balance equation which predicts the change in the average temperature of the room due to the opening of the damper by a unit amount. Parameters in the model whose values are unknown include the heat influx into the room, temperature and velocity of incoming air, etc.

An example of an empirical model is the computation of air velocity at a specific location of room. Accurate determination of air velocity requires complex analysis using computational fluid dynamics. However, a reasonable approximation might be obtained in a given setting through empirical observations, including previous observations where air velocities have been determined.

A model updating procedure similar to Robert-Nicoud et. al. (2005) has been adopted in this project. In this approach, the error between model predictions and measurements is minimized using a global search algorithm called PGSL (Raphael and Smith, 2003). The procedure results in the identification of a population of candidate models. The characteristics of this population are studied in order to evaluate the reliability of identification and to determine whether a unique model explains the data.

Conventionally, model identification is treated as an optimization problem. The model whose prediction has the minimum error with respect to measurements is chosen as the best model. I has been shown in Robert-Nicoud et. al. (2005) that this procedure results in the identification of wrong models in the presence of modelling and measurement errors. This is because different types of errors might compensate for each other such that the next error is very small. In order to avoid this problem, it is important to compute the error threshold through an estimate of modelling errors and sensor precision. All the models whose predictions lie below this threshold are chosen as candidate models. An examination of the variation in the values of model parameters will reveal whether a unique identification is possible. For example, if model parameters show wide variation, it means that many different models match observations within the error threshold. In such a situation, we need to install more sensors or increase the precision of sensors.

5. CURRENT STATUS

Two field environmental chambers (FEC) are currently being equipped with sensors and actuators using the European Installation Bus (EIB) technology. EIB is a building automation system founded in the late eighties with the support of a number of major European manufacturers such as Siemens, Gira, Jung, Merten, and ABB. It is being widely used in Europe and is increasingly being used in other parts of the world. Even though it is currently used mainly for controlling home appliances such as lighting, water heaters and security cameras, the flexibility offered by this technology makes it possible to control any type of electrical device. The EIB system consist a bus control cable installed in addition to and parallel to the power supply cable. EIB devices such as switches and sensors are connected to the bus. The bus is the common communication medium. Readings from sensors can be obtained through a computer connected to EIB. Control commands to actuators can also be sent from the computer through the bus. This makes it possible to develop customised control applications that operate on these devices. Existing HVAC components in the FEC are in the process of being interfaced with EIB devices.

The multi-objective optimization routine has been fully developed and has been tested on a number of benchmark problems. However, the control strategy needs to be fine tuned and it cannot be evaluated at this stage since reliable data has not been obtained yet. Model development and testing are still in progress. Preliminary results are expected in the coming months.

6. CONCLUDING REMARKS

The main contribution of this paper is a methodology for the integrated control of IEQ. Instead of making decisions using the values of individual parameters, control is treated as a multi-objective optimization problem. Control actions are selected such that there are reasonable trade-offs among conflicting objectives. This is achieved through Pareto optimization. The selected actions are applied by sending commands to appropriate actuators. Responses to these actions are recorded by sensors and are input into the optimization module to complete the loop. It is an innovative feedback control system that simultaneously takes into account multiple objectives.

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8. REFERENCES

[1] Adam, B. and Smith, I.F.C. Tensegrity Active Control: a Multi-Objective Approach, Journal

of Computing in Civil Engineering, Volume 21, Issue 1, 2007, pp. 3-10.

[2] Chen T., Real-time predictive supervisory operation of building thermal systems with thermal mass, Energy and Buildings, 33(2), 2001, pp. 141-150.

[3] Chow T., Zhang G., Lin Z., and Song C., Global optimization of absorption chiller system by genetic algorithm and neural network, Energy and Buildings, 34(1), 2002, pp. 103-109.

[4] Czyzak P. and A. Jaszkiewicz. (1998). "Pareto Simulated Annealing – A Metaheuristic Technique for Multiple-Objective Combinatorial Optimisation." Journal of Multi-Criteria Decision Analysis 7, 34–47.

[5] D. E. Grierson, and S. Khajehpour, A method for conceptual design applied to office buildings, ASCE Journal of Computing in Civil Engineering, Vol. 16, No. 2, April 2002, pp 83-103.

[6] Guillemin A., and Morel N., Experimental results of a self-adaptive integrated control system in buildings: a pilot study, Solar Energy, 72(5), 2002, pp. 397-403.

[7] Haralampidis Y., Papadimitriou C. and Pavlidou M., Multi-objective framework for structural model identification, Earthquake Engng Struct. Dyn,. 34, 2005, pp. 665–685.

[8] Jaszkiewicz, A.. Genetic Local Search for Multiple Objective Combinatorial Optimization, European Journal of Operational Research 137(1), 50–71, 2002.

[9] Kim I. Y., Weck O. L., Adaptive weighted sum method for multiobjective optimization: a new method for Pareto front generation, Struct Multidisc Optim, 31, 2006, pp. 105–116.

[10] Kummert M., Andre P., and Nicolas J., Optimal heating control in a passive solar commercial building, In proceedings of the eurosun 2000 Congress, Copenhagen, Denmark, 2000.

[11] Mahdavi, A., Unzeitig, U., Occupancy implications of spatial, indoor-environmental, and organizational features of office spaces, *Building and Environment* 40 (1), pp. 113-123, 2005.

[12] Morel N., Bauer M., El-Khoury M., and Krauss J., Neurobat, a predictive and adaptive heating control system using artificial neural networks, International journal of solar energy, 21, 2001, pp. 161-201.

[13] Y. Robert-Nicoud, B. Raphael and I.F.C. Smith, System identification through model composition and stochastic search, ASCE journal of Computing in Civil Engineering, (JCCE), Vol 19, No 3, 2005, pp. 239-247.

[14] B. Raphael and I.F.C. Smith, Fundamentals of computer aided engineering, John Wiley and sons, Ltd, 2003a (306 pages).

[15] B. Raphael and I.F.C. Smith, A direct stochastic algorithm for global search, J of Applied Mathematics and Computation, Vol 146, No 2-3, 2003b, pp 729-758.

[16] Raphael, B., A new approach to multi-objective optimization. IT solutions for the design and managment of infrastructure construction projects, ed. B. Kumar and P.R. Swarup (2006) CIDC. (ICITE/ITCSED, 15 - 17 Nov 2006, New Delhi 2006.

[17] Suter, G., Brunner, K., Mahdavi, A., Building model reconstruction based on sensed object location information, Automation in Construction 16 (1), pp. 2-12, 2007.