ADDING SUB-HOURLY OCCUPANCY PREDICTION, OCCUPANCY-SENSING CONTROL AND MANUAL ENVIRONMENTAL CONTROL TO ESP-r

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ABSTRACT

A wide range of events in buildings occur at sub-hourly frequencies. Notable examples include daylight-sensing control and manual adjustment of blinds and lights in response to sub-hourly illuminance variations. Such short-term changes can produce notable shifts in instantaneous solar and equipment loads, in turn affecting electrical energy demand. Although sub-hourly time discretization is currently available in several whole building energy simulation programs, it remains challenging to model this level of complexity as traditional hourly *utilization* or *diversity* profiles describing occupancy, lighting and equipment loads remain the basic input data model. This paper provides a background review of various models predicting occupancy, occupancy-sensing control and manual environmental control, and outlines their current addition to whole building energy simulation, in particular ESP-r. This should be taken as an outlook on current work; as such, no simulation results are presented within the scope of this paper.

INTRODUCTION

Sub-hourly time discretization presents an opportunity to reconsider several existing assumptions in building energy simulation. An example is the use of hourly meteorological input data. Walkenhorst et al. (2002) demonstrate that the predicted annual artificial lighting demand can be underestimated by up to 27% if daylighting simulations are based on 1-hour means instead of 1-min means of measured beam and diffuse irradiances. To this end, an adapted Skartveit and Olseth (1992) stochastic model, deriving short-term fluctuations from hourly time series irradiance data, is found in DAYSIM (Reinhart 2001), a RADIANCE-based (Ward 1994; Ward Larson et al. 1998) dynamic daylight simulation method. Similar work is described in Janak and Macdonald (1999). Analogous work on stochastic modelling of short term wind velocity fluctuations is presented by Marques da Silva and Saraiva (2002). A number of these models should likely find their way in larger whole building energy simulation programs in the near future.

This paper deals with another assumption that may need revising in the light of sub-hourly time discretization: how occupancy-related input data models are defined and used in energy simulation. Although whole building energy simulation programs such as ESP-r (ESRU 1999; Clarke 2001) or EnergyPlus (Crawley et al. 2001) offer sub-hourly simulation time-steps, diversity profiles of occupancy and related internal gains, such as lighting and equipment, constitute the main input data model; a solution passed down from the previous generation of hourly simulation programs. It is nevertheless possible in ESP-r to access sub-hourly input data through external files or databases, but this approach is usually deemed appropriate for short, detailed test cell studies with measured data. There are at least three major impediments to extending the use of this approach to annual energy simulations:

(1) the approach would require pre-configuring data for many variables (various casual gains, optical sets for multiple window/blind configurations, etc.) for multiple zones, a risky and time-consuming exercise (i.e. requires good book-keeping);

(2) the approach is essentially limited to input of meteorological, casual gain and mass flow data, i.e. other external variable input is simply not possible

without major changes to the source code; and most importantly,

(3) the approach does not allow control over input, a potentially desirable option notably in cases where control might depend on the state of certain variables known only at run-time, e.g. room air temperature. As sub-hourly discretization increasingly becomes the norm, a more robust and integrated solution seems desirable.

BACKGROUND

Dynamic building energy simulation customarily requires input of casual gain loads, typically comprising metabolic heat discharged from occupants, as well as from lighting and equipment receptacle loads. Absenteeism, occupant environmental preference and energy management features of various office equipment, are well-known factors that influence casual gain variations. Output variability is ordinarily defined by associating different sets of 24-hour *diversity factors* for weekdays, weekends, holidays, etc. to the maximum load of each *end-use* (occupants, lighting, equipment, etc.).

Diversity factors are numbers between zero and one, and are used as multipliers of some user-defined maximum. Certain simulation programs use variants of this widely-used technique: ESP-r for instance requires profiles of *actual* loads expressed in W or W/m², instead of diversity factors of some nominal load. Many energy standards and codes either provide, or refer to, *typical* diversity profiles for performance-based compliance demonstrations (MNECB 1997; ASHRAE 90.1 2001). Abushakra et al. (2004) provide an overview of existing methods for deriving diversity profiles.

Diversity profiles are often adequate as average input data models for large thermal zones containing multiple spaces. Using sub-hourly occupancy input loads (i.e. metabolic heat discharged by occupants), rather than hourly loads, would typically have little outcome on annual energy simulation results, given the thermal lag of building mass and mechanical systems. If daily patterns of lighting and office equipment use in a given building follow a *typical* trend for a given set of day-types (e.g. if lights and office equipment are solicited independently of weather patterns), then the impact of using sub-hourly input data would likely remain quite trivial on annual energy requirements.

Recent developments in this area include findings from the ASHRAE Research Project 1093 (Abushakra et al. 2001). The goal of ASHRAE RP-1093 was to compile a library of schedules and diversity factors based on *measured* electricity consumption data for use in energy simulations and peak cooling load calculations in office buildings. This research project derived multiple sets of diversity factors from measured lighting and receptacle loads in 32 office buildings (Claridge et al. 2004). Occupancy was not monitored under RP-1093, yet another study from Claridge et al. (2001) established a strong correlation between observed occupancy levels and lighting loads, suggesting that valid occupancy diversity profiles may be derived from lighting diversity profiles using linear regression.

One significant shortcoming of the RP-1093 diversity profiles, or any other similarly-derived profiles for that matter, is that they are derived independently of weather data. This may be a valid assumption when considering *core* zones, but hardly so for *perimeter* zones with either manual or daylighting controls, or a mix of both: for given occupancy levels and daylight illuminances, two differently-oriented *perimeter* zones will clearly possess very distinct lighting loads if daylighting and/or manual control are available. Correlating occupancy from these lighting profiles would lead to obvious errors.

Yet as many North American buildings have very low envelope-to-floor area ratios, these errors may be considered by some to be minor and applying diversity profiles (including occupancy) derived from monitored *core* zone lighting consumption may be considered acceptable. However, in cases where greater envelope-to-floor area ratios are found, or even in some cases where there are no *core* zones, the use of general diversity profiles may be difficult to justify. This would certainly be the case for building designs aiming at high daylight autonomy levels and/or offering outside views to most occupants, such as suggested by certain daylighting design guides or required by similar standards (DIN 5034 1999; DGCCB 2002).

Other studies have shown that the use of hourly diversity profiles can lead to considerable errors when applying control strategies that are quite sensible to short-term variations in occupancy. Degelman (1999) suggests that fixed lighting profiles generate misleading information regarding electric demand charges when occupancy-sensing lighting controls are used, and puts forth a Monte Carlo approach to space occupancy prediction based on survey statistics, enhancing the accuracy of electrical energy demand estimation.

Keith (1997) demonstrates how average profiles lead to overestimations of electrical energy savings and demand reduction through occupancy-sensing controls, which in turn lead to underestimations of heating loads for various U.S. locations. Keith proposes an on-line, field-based tool that modifies standard DOE-2.1E (Winkelmann et al. 1993) weekly profiles to introduce *peakdays*, thereby enhancing monthly peak demand estimations without increasing simulated energy consumption.

Newsham et al. (1995) describe a first version of the LIGHTSWITCH stochastic occupancy model, based on field data, to predict arrival, departure and temporary absence probabilities of individual occupants in office environments at 5-minute intervals. The short time-step accuracy of LIGHTSWITCH provides more realistic artificial lighting use as a function of daylighting and occupancy-sensing controls. Newsham et al. suggest carrying out multiple runs of LIGHTSWITCH to produce average lighting diversity profiles for DOE-2.1E.

Another misleading occupancy-related assumption in building energy simulation is that occupants are often considered as "fixed metabolic heat generators passively experiencing the indoor environment" (Newsham 1994). Occupants instead respond to various environmental stimuli, triggering sudden manual changes in window blind settings and artificial light use, in turn affecting electrical energy use and demand. This consideration fuelled the original development of the field-based LIGHTSWITCH manual control algorithms in the 1990s, which have been further validated and extended by Reinhart (2001), before their integration within DAYSIM. The current version of LIGHTSWITCH (Reinhart 2004) integrates several, now well-established, field-based occupant response probabilistic control laws for specific combinations of blind settings, daylighting controls and lighting control systems. Assumptions underlying the model are currently being validated and refined through a series of field studies which are carried out within the International Energy Agency's Task 31, *Daylighting Buildings in the 21st Century.*

http://www.iea-shc.org/task31/index.html

LIGHTSWITCH evidently provides DAYSIM with more realistic predictions of electrical energy savings and demand reduction. Yet even such an integrated approach has its drawbacks: the annual performance assessment of daylighting solutions and advanced lighting controls in DAYSIM is done in isolation from other related building and system domains. Manual changes in window blind settings for glare control, as well as manual adjustments in electric light use, will produce notable short-term changes in solar and internal gains, and eventually indoor climate control. Behavioural models predicting operable window use and eventually task-ambient conditioning systems (Morrow 1995; Arens et al. 1998) are also dependent on occupancy patterns and their control may prove to be as significant in whole building energy assessments.

SCOPE OF WORK

The current development consists of a suite of occupancy-based predictive models (i.e. child processes) to be accessed at run-time by whole-building energy simulation programs (i.e. parent process). At the core is an occupancy predictive model, capable of tracking individual occupants within individual spaces. The LIGHTSWITCH occupancy model will be used in the current development as the default occupancy prediction model. Instead of defining diversity profiles for occupancy, individual occupancies (i.e. *in*/*out*) are defined through probabilistic calculations of arrival, departure and intermediate absenteeism.

The second set of models called at run-time adjusts occupancy-sensing casual gains (e.g. occupancy-sensing lighting, task lighting, personal computers (PCs), etc.). Delay periods and multi-stage power down profiles, as defined in most PCs (Roberson et al. 2002), are available. Individual loads are either controlled based on *any* occupancy levels in a given room (e.g. as with occupancy-sensing lighting) or *individual* occupancies (e.g. as with PCs).

The last set of models accessed at run-time consists of field-based algorithms predicting occupant response and control over various environmental settings, namely window blind and artificial lighting use (Reinhart 2001; 2004). A similar operable window control model is added within the scope of the first author's PhD thesis.

A modular *plug-and-play* approach is favoured to facilitate future code updating, as model assumptions are continually revised over time: future researchers/developers well-versed in coding behavioural models would likely feel more comfortable adding future facilities (i.e. child processes), without the requirement of mastering whole-building energy simulation programs. Notable contributions in building behavioural models include research from the Low Energy Architecture Research Unit (LEARN) (Nicol 2001).

HOW IT WORKS IN ESP-r

As previously mentioned, ESP-r is the chosen whole-building energy simulation program for the current development: a program currently based on user-defined hourly diversity profiles of various casual gain input, e.g. occupancy, lighting and equipment loads.

Lighting gains are optionally controlled at run-time in ESP-r, based on several available daylighting models (e.g. daylight factors, RADIANCE-based daylight coefficients or direct coupling, etc.) and a number of related control laws. It is worth mentioning however that lighting output would evidently remain unchanged during the course of an hour if controls are based on traditional input parameters (e.g. hourly solar irradiance time series data). As suggested previously, sub-hourly control of lighting is possible if sub-hourly irradiance data are available and used as input in direct ESP-r/RADIANCE daylight coefficient or direct coupling approaches (Janak 1997). To correct this for hourly climate time series data, the ongoing development includes the addition of the Skartveit and Olseth (1992) stochastic model for deriving short-time fluctuations, as found in DAYSIM (Reinhart 2001).

Figure 1 provides a flow chart representation of the occupancy-related models that update short-term casual gain input and environmental control at run-time, and in the case of manual blind and light control, interact with ESP-r's daylighting models. Fields in grey indicate on-going developments, while fields in white represent potential future alternatives. Most loads found in individual office environments may be predicted using this technique. If certain load variations are difficult to describe based on simple occupancy patterns (i.e. vacant or occupied) such as the output of local pumps or fans or even standard office equipment such as photocopiers (the relationship between output and occupancies is likely to be more complex), then one may fall back on traditional diversity profiles.

At run-time, various subroutine calls are carried out within the ESP-r integrated simulator to load future time-row casual gain input data in common data structures. A more detailed presentation of ESP-r simulation is found at the Energy Systems Research Unit (ESRU) main web page:

http://www.esru.strath.ac.uk/

The current development introduces new object-type data structures to store future time-row occupancy-specific data for every zone, such as occupancy levels (e.g. the current number of individuals within individual thermal zones); the state of occupancy-sensing controls (e.g. on/off for lighting, ratios of maximum power for office equipment, etc.); the state of blinds (e.g. settings 1, 2, 3, etc.); lights (e.g. ratios of maximum power); windows (e.g. ratios of maximum free area); and finally counters for future events (e.g. the number of time-steps before forthcoming arrivals or departures, delay times for occupancy-sensing controls, etc.).

At each time step, the ESP-r integrated simulator first checks if occupancy-related control is required within the simulation and then occupancy levels are subsequently updated, followed by adjustments to occupancy-sensing controlled equipment and fixtures, if required. The state of blinds, lights and windows are in turn updated, again if required. The ESP-r integrated simulator continues with simulation operations and uses the generated occupancy-specific data, as either multipliers or flags, to control the state of predefined casual gains or adjust various controls. The process is repeated at each time step.

CONTRIBUTION

The purpose of the current development is to explicitly take into account the *whole-building energy simulation* impact of short term occupancy variations and user preferences of various environmental settings. This impact may be more significant in certain cases than in others: as the influence of external boundary conditions is more greatly felt in buildings with high envelope-to-floor area ratios, the impact of manual control of blinds, lights and operable windows affecting energy and mass flows across building envelopes will clearly be more significant.

Not only are savings in energy requirements more reliably predicted by taking into account the *human variable*, but monthly peak power demand estimation is greatly enhanced. This is opportunistic, as ESP-r currently offers detailed network electrical power flow modeling (Kelly 1998). Monthly peak demands are significant factors to consider, not only in regards to energy cost estimation, but in environmental terms as well.

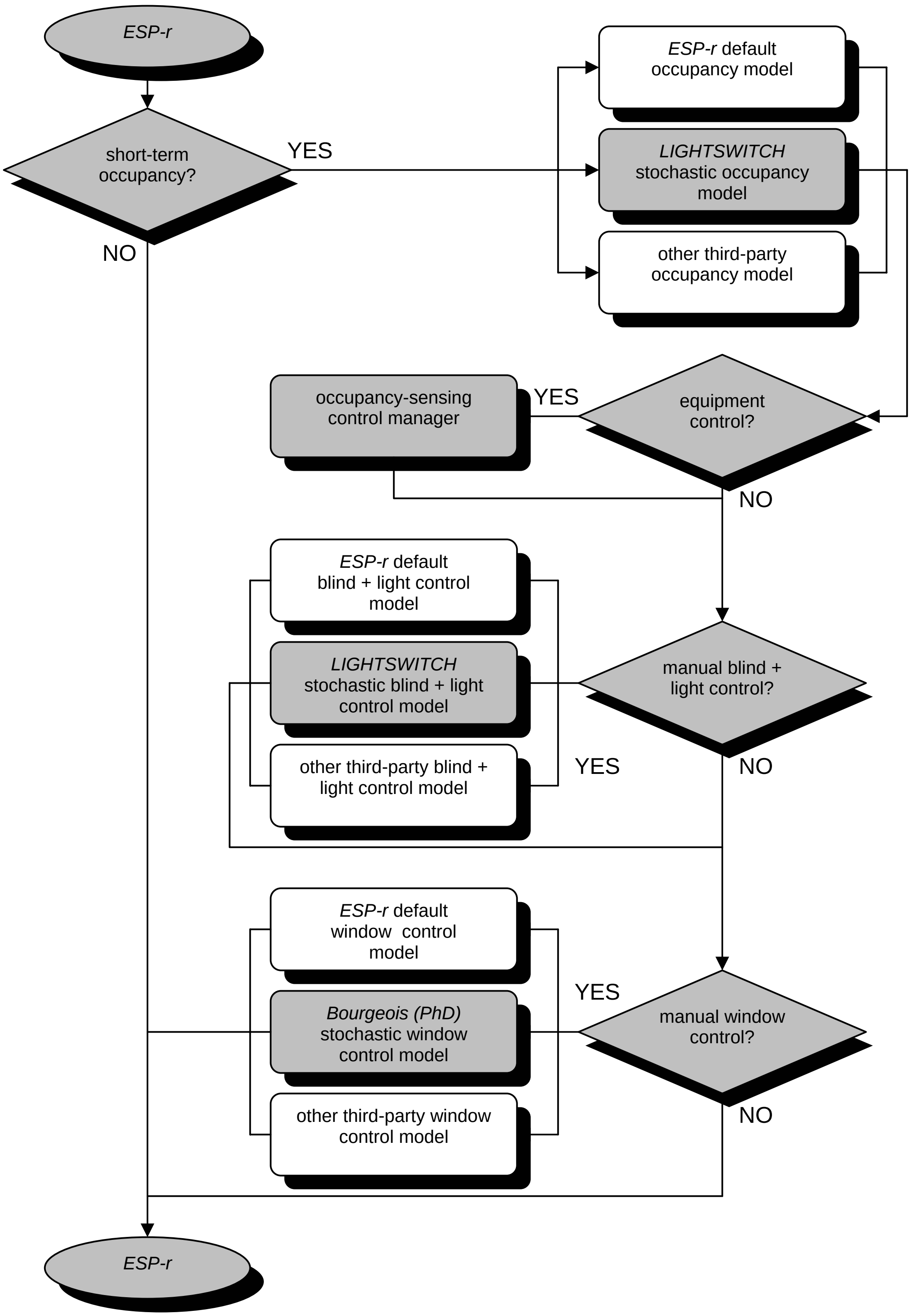

Figure 1
Flow chart representation of sub-hourly occupancy-related models that update casual gain input and environmental control at run-time.

The addition of the LIGHTSWITCH stochastic manual blind and lighting model to ESP-r in particular offers a more realistic input of occupant behaviour in regards to daylighting glare. Prediction of glare and the subsequent manual blind adjustments to remedy the situation would be quite helpful, constituting a practical yardstick for distinguishing *good* from *poor* daylighting designs, as well as passive solar energy harvesting concepts within occupied environments: a present shortcoming of existing tools. Furthermore, the stochastic operable window model would be useful for investigating the potential contribution of adaptive comfort models (de Dear et al. 1998; Humphreys et al. 1998; Hensen et al. 2001).

FUTURE ENHANCEMENTS

One of the shortcomings of the current research described in this paper is the limited occupancy prediction capabilities. As indicated earlier, all previous occupancy-related control models are dependent on sub-hourly occupancy prediction. Previous field studies have amassed a collection of databases on occupancy patterns in office environments (Newsham et al. 1995; Keith 1997; Degelman 1999; Reinhart 2001), yet it is unclear for the moment how all or some of the data may, or should, be integrated within a single predictive model.

Although the proposed suite of tools is capable of integrating several probabilistic calculation methods for predicting occupancy, a simpler version of the LIGHTSWITCH stochastic occupancy model, requiring minimum input, is defined as the default model in ESP-r.

The wish list of future developments, i.e. beyond the scope of the current research presented here, includes addressing the increasingly complex occupancy patterns found in office environments. Occupants tend to stray away from the traditional 9-to-5/five-day work week. They have flexible work hours, come in earlier or later in the day, and even work on weekends. They equally have the option of occasionally working outside their usual office environment, typically at home. Certain worker profiles have never shared the pattern of routine office occupancy to start with: salespeople, university faculty and research personnel are known for their mobility and their daily use of multiple spaces (e.g. a university professor is likely to spend as much time in the office, in classrooms, in laboratories, in the field, on the conference circuit, etc.).

If short-term predictive occupancy models are to constitute the general basis for future short-term occupancy-based controls in whole building energy simulation, additional modelling facilities will be required for tracking project-specific intra- and inter-building population movement, providing in turn zone-specific occupancy probabilities at run-time. *Discrete event simulation* is an interesting avenue for future development in this area (Nassar et al. 2003).

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REFERENCES

MNECB (1997), 'Model National Energy Code of Canada for Buildings', Ottawa: National Research Council of Canada, Institute of Research in Construction, Canadian Commission on Building and Fire Codes.

DIN 5034 (1999), 'Tageslicht in Innenräumen', Deutsches Institut für Normung.

ASHRAE 90.1 (2001), 'Energy Standard for Buildings Except Low-Rise Residential Buildings (IESNA cosponsored; ANSI approved; Continuous Maintenance Standard), SI Edition', American Society of Heating, Refrigerating, and Air-conditioning Engineers, Inc.

DGCCB (2002), 'Daylighting guide for Canadian commercial buildings', Public Works and Government Services Canada (PWGSC).

Abushakra B., Haberl J. and Claridge D.E. (2004), 'Overview of existing literature on diversity factors and schedules for energy and cooling load calculations (1093-RP)', *ASHRAE Transactions*, 110.

Abushakra B., Sreshthaputra A., Haberl J. and Claridge D.E. (2001), 'Compilation of diversity factors and schedules for energy and cooling load calculations', RP-1093, American Society of Heating, Refrigerating and Air-conditioning Engineers 485.

Arens E.A., Tengfang X., Miura K., Zhang H., Fountain M. and Bauman F.S. (1998), 'A study of occupant cooling by personally controlled air movement', *Energy and Buildings*, 27 45-59.

Claridge D.E. and Abushakra B. (2001), 'Accounting for the occupancy variable in inverse building energy baselining models', *Proceedings of the International Conference for Enhanced Building Operations (ICEBO)*, Austin.

Claridge D.E., Abushakra B., Haberl J. and Sreshthaputra A. (2004), 'Electricity Diversity Profiles for Energy Simulation of Office Buildings', *ASHRAE Transactions*, 110.

Clarke J.A. (2001), *Energy Simulation in Building Design*, Butterworth-Heinemann.

Crawley D.B., Lawrie L.K., Winkelmann F., Buhl W.F., Huang Y.J., Pedersen C.O., Strand R.K., Liesen R.J., Fisher D.E., Witte M.J. and Glazer J. (2001), 'EnergyPlus: creating a new-generation building energy simulation program', *Energy and Buildings*, 33 319-331.

de Dear R.J. and Brager G.S. (1998), 'Developing an Adaptive Model of Thermal Comfort and Preference', *ASHRAE Transactions*, 104 145-167.

Degelman L.O. (1999), 'A model for simulation of daylighting and occupancy sensors as an energy control strategy for office buildings', *Proceedings of Building Simulation ’99, an IBPSA Conference*, Kyoto, 571-578.

ESRU (1999), 'The ESP-r system for building energy simulations, user guide version 9 series. ESRU Manual U99/1', University of Strathclyde.

Hensen J.L.M. and Centnerova L. (2001), 'Energy simulation of traditional vs. adaptive thermal comfort for two moderate climate regions', *Proceedings of the Windsor Conference 2001: Moving Thermal Comfort Standards into the 21st Century*, Windsor, 78-91.

Humphreys M.A. and Nicol J.F. (1998), 'Understanding the adaptive approach to thermal comfort', *ASHRAE Transactions*, 104 991-1004.

Janak M. (1997), 'Coupling building energy and lighting simulation', *Proceedings of the 5th International IBPSA Conference*, Prague, 313-319.

Janak M. and Macdonald I. (1999), 'Current state-of-the-art of integrated thermal and lighting simulation and future issues', *Proceedings of Building Simulation '99, an IBPSA Conference*, Kyoto.

Keith D.M. (1997), 'Use of peak occupancy data to model the effects of occupancy-sensing lighting controls', MSc thesis, Faculty of the Graduate School/Civil Engineering, University of Colorado.

Kelly N.J. (1998), 'Towards a design environment for buildings integrated energy systems: The integration of electrical power flow modelling with building simulation', PhD thesis, Department of Mechanical Engineering, Energy Systems Research Unit (ESRU), University of Strathclyde.

Marques da Silva F. and Saraiva J.G. (2002), 'Natural ventilation air change rates considering atmospheric turbulence. Estimates and measurements', *Proceedings of Roomvent 2002, the 8th International Conference on Air Distribution in Rooms*, Copenhagen.

Morrow W. (1995), 'Personal environments and productivity in the intelligent building', *Ergonomics*, June.

Nassar K. and Nada M. (2003), 'Discrete-event activity simulation for predicting occupants’ movements in buildings', *Towards a Vision for Information Technology in Civil Engineering, Proceedings of the 4th Joint International Symposium On Information Technology In Civil Engineering*, Nashville, Flood I. ed.

Newsham G.R. (1994), 'Manual control of window blinds and electric lighting: Implications for comfort and energy consumption', *Indoor Environment*, 135-144.

Newsham G.R., Mahdavi A. and Beausoleil-Morrison I. (1995), 'Lightswitch: a stochastic model for predicting office lighting energy consumption', *Proceedings of Right Light Three, the 3rd European Conference on Energy Efficient Lighting*, Newcastle-upon-Tyne, 60-66.

Nicol J.F. (2001), 'Characterising occupant behaviour in buildings: towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans', *Proceedings of the 7th International IBPSA Conference*, Rio, 1073-1078.

Reinhart C.F. (2001), 'Daylight availability and manual lighting control in office buildings - Simulation studies and analysis of measurement', PhD thesis, Department of Architecture, Technical University of Karlsruhe.

Reinhart C.F. (2004), 'Lightswitch 2002: A model for manual control of electric lighting and blinds', *Solar Energy*, (in press).

Roberson J.A., Homan G.K., Mahajan A., Nordman B., Webber C.A., Brown R.E., McWhinney M. and Koomey J.G. (2002), 'Energy use and power levels in new monitors and personal computers', LBNL-48581, Energy Analysis Department, Environmental Energy Technologies Division, Ernest Orlando Lawrence Berkeley National Laboratory, University of California 32.

Skartveit A. and Olseth J.A. (1992), 'The probability density and autocorrelation of short-term global and beam irradiance', *Solar Energy*, 49 477-487.

Walkenhorst O., Luther J., Reinhart C.F. and Timmer J. (2002), 'Dynamic annual daylight simulations based on one-hour and one-minute means of irradiance data', *Solar Energy*, 72 385-395.

Ward G. (1994), *The RADIANCE 2.4 Synthetic Imaging System*, University of California.

Ward Larson G. and Shakespeare R. (1998), *Rendering with RADIANCE. The Art and Science of Lighting Visualization*, Morgan Kaufmann.

Winkelmann F., Birdsall B.E., Buhl W.F., Elllington K.L., Erdem A.E., Hirsch J.J. and Gates S. (1993), 'DOE-2 Supplement, Version 2.1E', Lawrence Berkeley National Laboratory.