LEARNING MODELS - A NEW APPROACH TO SIMULATION

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ABSTRACT

In conducting and teaching Building Simulation, we often find two main disadvantages of conventional models: inconsistency of simulation results obtained by different users of the same model, and long machine times required for annual simulations of relatively simple buildings.

In searching for better simulation methods, we decided to depart from the conventional method and to introduce machine learning into mathematical modelling of buildings. This resulted with a new model, based on learning of building energy properties from monitored data. The model was named LEARNSIM LEARNing SImulation Model. A comparative testing of LEARNSIM and of a conventional model confirmed higher accuracy and faster operation of the former.

The aim of the paper is to present the main features of learning simulation models, to demonstrate how they can be used at present, and in the future.

NOMENCLATURE

- A_h - effective aperture of the building to solar radiation on the horizontal surface [m^2]
- A_v - effective aperture of the building to solar radiation on the vertical wall [m^2]
- A_w - effective aperture of the building to wind [m^2]
- c - specific heat of air [J/(kg^{o}C)]
- C_e - effective thermal capacitance of the building [J/^{o}C]
- dt - time-step [s]
- dT - room temperature differential [^{o}C]
- dT/dt - room temperature time derivative [^{o}C/s]
- e - standard error = mean ± standard deviation
- f_i - status flag of i-th driving function [-]
- F_i - i-th driving function
- g_e - equipment heat gain control function [-]
- g_h - heating control function [-]
- g_l - lighting heat gain control function [-]
- g_p - occupancy heat gain control function [-]
- i - index denoting ordinal number of a driving function [-]
- j - number of hours after the beginning of learning [-]
- k_i - building energy fingerprint for i-th driving function
- n - number of driving functions [-]
- N - duration of the learning period [s]
- q_e - heat gain from equipment [W]
- q_l - heat gain from lighting [W]
- q_p - heat gain from people [W]
- r - density of air [kg/m^3]
- S_h - solar radiation on the horizontal surface [W/m^2]
- S_v - solar radiation on the total window surface [W/m^2]
- T - room air temperature of the building [^{o}C]
- T_a - external air temperature [^{o}C]
- T_j - predicted temperature of the j-th timestep [^{o}C]
- $T_{m,j}$ - measured room air temperature of the building in the j-th timestep [^{o}C]
- T_n - room air temperature of the unheated space [^{o}C]
- T_s - soil temperature [^{o}C]
- UA_e - effective overall conductance-area product of the building envelope [W/^{o}C]
- UA_h - effective overall conductance-area product between the heating system and building air [W/^{o}C]
- UA_n - overall conductance-area product of the wall between the building and unheated space [W/^{o}C]
- UA_s - overall conductance-area product of the ground floor slab [W/^{o}C]
- W - wind speed [m/s]

INTRODUCTION

While conventional models are becoming more comprehensive and powerful, they also demand more from the user and from the machine. Users are asked to describe the building in more detail, and machines must be faster and must have more memory. An annual hourly simulation of a ten zone office building, which we conducted recently using a conventional simulation program and a SUN workstation, lasted approximately 8 hours. Furthermore, in every instance when our students were given the same simulation task on the same machine, running the same simulation program, and with the same initial conditions, different results and different design recommendations were reached. We came across the above two problems of time inefficiency and inconsistency of conventional simulation models while using or teaching the use of more than one simulation program. We therefore think that the conventional modelling method is approaching the limits of its development, when the question can be raised: is there a better way to simulate buildings?

The conventional modelling method divides buildings into elements, describes the elements with mathematical models, combines the models of elements into a comprehensive model of a building, and it carries out the calculation of interactions between these elements coupled to the driving functions such as weather data, internal heat gains, heating system operation, etc.

The above helps to explain the two problems associated with the conventional models. The inconsistency of results obtained by different users of conventional models occurs due to a large number of parameters required to describe a large number of building elements. Developers of simulation models supply default parameters so that their programs do not crash if users do not enter all input parameters. Different users of simulation models may not have time, knowledge, or experience to understand all the defaults. They accept a different number of default parameters and hence the inconsistency of results.

The time inefficiency of conventional models occurs due to a large number of interactions between different building elements and a consequent large number of associated calculations. This explains the eight hours of machine time for annual simulation of a ten zone building which we mentioned earlier. That is a lot of time, and it means that several days are required to evaluate several design options. The designer is therefore forced either to reduce the number of options, or to abandon simulations and to use other means for evaluating design options and making design decisions.

The conventional modelling method would seem totally inadequate in nature. Suppose that a seagull sees a fish in water and wants to catch it. If the seagull used the conventional modelling method to control this process, the modelling could look like this: the seagull sees the fish in water, calculates the speed and direction of his body using wind velocity, aerodynamic resistance, force of gravity, intensity of wing movements and the resulting reaction force; he then calculates the speed and direction of movement of the fish, using hydrodynamic resistance, and the force of reaction due the movements of the fish; subsequently he uses the rules of vector dynamics in three dimensions in order to calculate where to go and when to go to catch the fish. The seagull cannot do that, but will still survive because of his experience which guides him through survival actions. This experience has been acquired through learning and correction of errors between actual and desired output, and is the essence of a fast, simple, and successful model.

This is how the idea of learning simulation models was conceived, and how LEARNSIM - the LEARNing SImulation Model was developed. This model compares the measured building performance with arbitrarily assumed building performance, and it reduces the error between the prediction and measurement through the learning process. The results of learning are parameters which comprise a condensed essence of building energy performance, used for fast, simple and accurate simulation.

The performance of LEARNSIM was compared with a conventional simulation model using data from several monitored buildings. The results showed that LEARNSIM was more accurate and approximately sixty times faster than the conventional model.

LEARNSIM has now become the basis of our research in building simulation, control, and design. The results of learning provided by LEARNSIM were used to devise control strategies in several office buildings, resulting with improvement of comfort and energy savings. LEARNSIM is the basis of development of our intelligent control system prototype for office buildings and retirement homes. An expert system for building energy management was also developed using this methodology.

Future research into application of LEARNSIM methodology to learning design inputs about particular buildings, and subsequent learning the extensive range of performance parameters of these buildings through a permanent feedback link, could potentially result with a powerful building simulation and design tool.

PREVIOUS WORK

The first steps towards learning simulation models were made in relation to dynamic heating tests of a building carried out by the author and co-workers (Jankovic et al. 1987). The tests were carried out in a three bedroom family house, in dull weather, with external insulating blinds lowered down. The building was unoccupied and the only heat input was from central heating and from additional heaters used during the test. From the results of these tests, the values of effective building thermal properties, such as conductance-area product, thermal capacitance, and time constant were calculated. These effective values were calculated on the basis of a simplified heat balance, similar to that used by LEARNSIM, as explained in the next section. The results of the dynamic heating tests showed that the effective building thermal properties obtained from the experiments were substantially different from the corresponding values calculated from tables of material properties and building geometry. A simple simulation program based on the experimental values of effective building thermal properties was developed (Jankovic 1988), but it had a limited use as the dynamic tests had been carried out with protective window blinds in position, under low solar radiation, and in the absence of casual gains.

The next step towards learning simulation models was the development of a simple resistance-capacitance (RC) model (Jankovic et al. 1989). The building internal air temperature was expressed as a Fourier series of external driving functions. The values of the effective building time lag and decrement factor were initially assumed, and were subsequently calculated from minimisation of errors between predicted and measured temperatures. On the basis of TRNSYS simulation program (Klein et al. 1988), a model of the same building was developed for comparison purposes (Jankovic 1988). The RC model simulated the building more accurately than TRNSYS, but because of the large number of calculations in the minimisation process, this was carried out separately from the simulation (Jankovic 1989).

In the following step in this development the automatic learning of building energy properties was introduced in the same piece of software used for simulation, and the program was named the 'Learning Model' (Jankovic 1991b). Learning was defined here as a minimisation of errors between arbitrary predictions and measured building performance, subsequent finding of the values of effective thermal properties, and retaining these for future use. This model had to be 'fed' initially with data from monitoring of buildings. Automatic learning was made possible by a changed building temperature model from that in the previous step to a simple rearranged heat balance model, exactly the same as in LEARNSIM. This allowed high flexibility of the model, as different terms of the heat balance equation dealing with different heat transfer mechanisms could be used. In this way the model was capable of handling different number of driving functions and was able to adjust to different buildings and to match different control systems by respecifying the number of parameters in the heat balance equation. The model allowed relatively simple minimisation of errors between the building performance assumptions and measurements. The minimisation was carried out by means of Downhill Simplex Method (Press et al. 1986), specially adjusted for this model. The minimisation routine demanded computing power of an average personal computer. Despite this, the learning period did not exceed about 1 minute per independent variable. However, this was not fully acceptable for control applications, where an increase of computing power requirement results with an increase of investment costs.

The next and the most recent step in this development is LEARNSIM - A LEARNing SImulation Model. Based largely on the Learning Model from the previous step, it has much faster learning algorithm, and can therefore run on low speed low cost computers, while providing higher accuracy than conventional simulation programs running on expensive work stations. LEARNSIM is explained in more detail in the next section.

Attempts by other authors to produce simplified and accurate simulation models are also worth mentioning (Virk et al. 1989; Penman 1990). The former used results from monitoring of a test cell to establish the relationship between inputs and outputs of a stochastic model, while the latter developed a five parameter model and established a relationship between inputs and outputs on the basis of short term monitoring of a building. And while the work of the former required high computing power for stochastic modelling, and the later lacked flexibility because of the fixed parameter set, both models did not recognise different heat transfer mechanisms of solar gains, casual gains, and gains from the heating system. These models therefore did not have the flexibility to adjust to different building types, and different control systems and strategies. The problems reported in relation to these models by their authors are mainly due to the fact that they have not been developed on the basis of data from long term monitoring of buildings.

LEARNSIM - A LEARNING SIMULATION MODEL

The Learning Simulation Model - LEARNSIM is based on a simple rearranged heat balance equation. The parameters of this equation - building thermal properties are determined through the learning process, which makes this equation an accurate expression of building dynamic thermal performance.

The flexibility of LEARNSIM to adjust to various building types, to various driving functions, and to various control parameters and strategies is achieved by a variable number of terms in the rearranged heat balance equation. The appropriate terms are

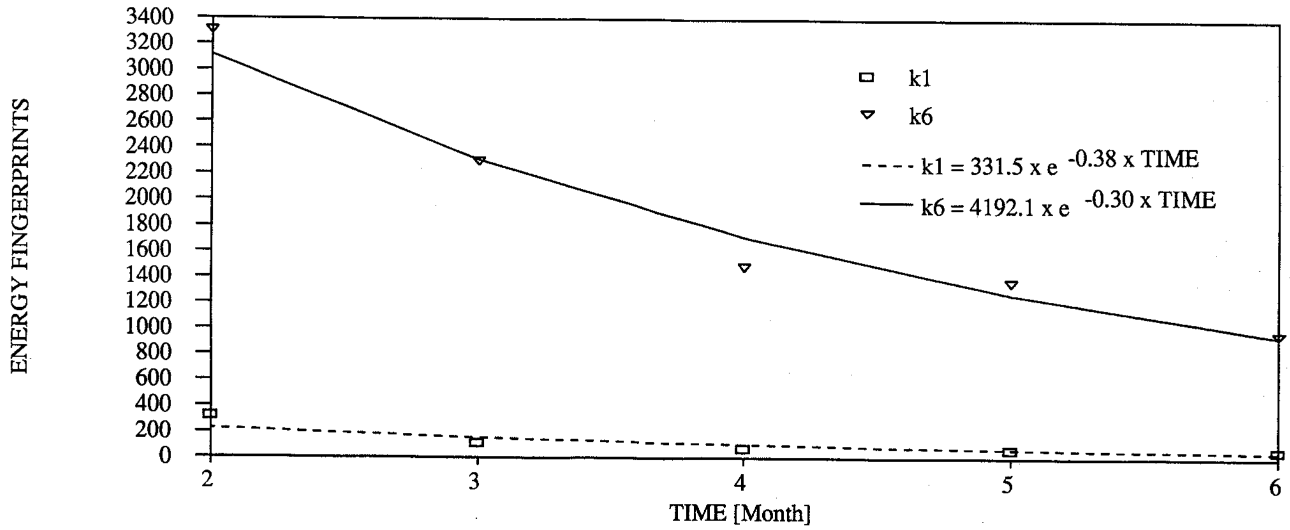

Figure 1. Seasonal Change of Energy Fingerprints

activated in the preparation of simulation by switching on status flags corresponding to the individual terms.

The equation governing the learning and simulation process of LEARNSIM has the following form:

$$C_e * dT/dt = \sum_{i=1}^{i=n} ((p_i) * F_i * f_i) \tag{1}$$

where

$$\begin{aligned} p_1 &= UA_e & F_1 &= -(T-T_a) \\ p_2 &= UA_n & F_2 &= (T_n-T) \\ p_3 &= UA_s & F_3 &= -(T-T_s) \\ p_4 &= UA_h & F_4 &= (T_h-T) * g_h \\ p_5 &= A_h & F_5 &= S_v \\ p_6 &= A_v & F_6 &= S_h \\ p_7 &= A_w * r * c & F_7 &= -W * (T-T_a) \\ p_8 &= q_l & F_8 &= g_l \\ p_9 &= q_p & F_9 &= g_p \\ p_{10} &= q_e & F_{10} &= g_e \end{aligned} \tag{2}$$

When the both sides of equation (1) are divided by C_e, the resulting rearranged equation is

$$dT/dt = \sum_{i=0}^{i=n} ((1/k_i) * F_i * f_i) \tag{3}$$

where

$$\begin{aligned} 1/k_1 &= UA_e/C_e \\ 1/k_2 &= UA_n/C_e \\ 1/k_3 &= UA_s/C_e \\ 1/k_4 &= UA_h/C_e \\ 1/k_5 &= A_h/C_e \\ 1/k_6 &= A_v/C_e \\ 1/k_7 &= A_w*r*c/C_e \\ 1/k_8 &= q_l/C_e \\ 1/k_9 &= q_p/C_e \\ 1/k_{10} &= q_e/C_e \end{aligned} \tag{4}$$

The room temperatures are then calculated in each timestep as

$$T_j = T_{j-1} + (dT/dt)_{j-1} * dt \tag{5}$$

Parameters k_1 to k_{10} are the results of learning. They are named building energy fingerprints (Jankovic 1991b) because of their one to one correspondence to individual buildings. These parameters are the essence of building energy performance. They make LEARNSIM, based on the above simple equations, more accurate than detailed conventional models, as it will be shown later in the text.

<u>The Learning Process</u>

The model prior to LEARNSIM, the Learning Model (Jankovic 1991b) carried out the learning process through minimisation of errors between the prediction and measurement, using the following equation as a criterion:

$$S = \sum_{j=2}^{j=N} | (T_j - T_{m,j}) | \tag{6}$$

The right hand side of equation (3) is a function of energy fingerprints during the learning period:

$$S = f(k_1, k_2, \ldots, k_n) \tag{7}$$

The above learning criterion required a standard multidimensional minimisation routine, which in the particular case was a specially adjusted Downhill Simplex Method routine (Press et al. 1986). The consequence of application of this method was the requirement for a personal computer hardware environment in order to carry out the learning process in a relatively short time.

The duration of an average learning process was approximately 1 minute per energy fingerprint. This meant that the learning process could not be repeated often during the simulation without slowing it down. On the other hand, it was found from several learning processes which were carried out at different time points in the monitored data, that building energy fingerprints change seasonally, following an exponential law (Figure 1). This indicated the necessity for updating the energy fingerprints continuously, especially in adaptive control applications.

The above problem was overcome in LEARNSIM with a newly developed method for continuous learning. The method

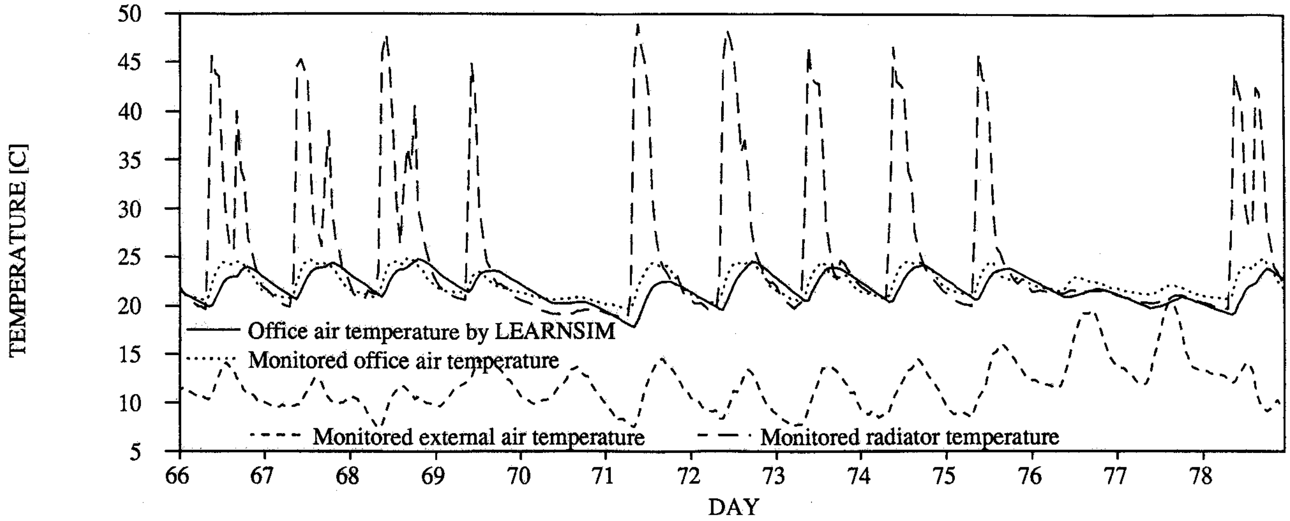

Figure 2. Simulation of the Office Building

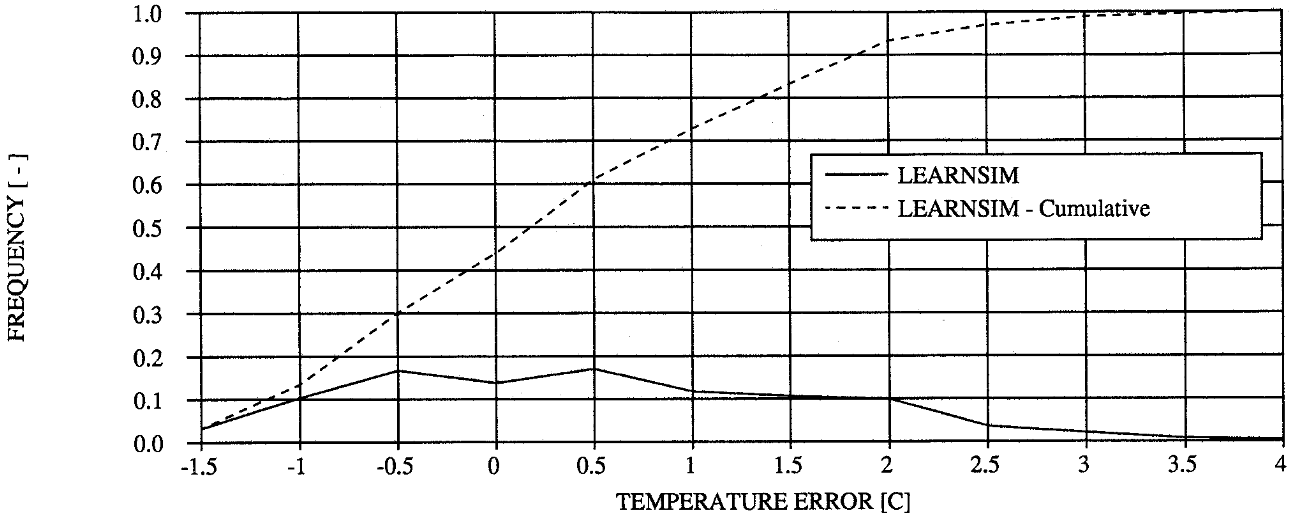

Figure 3. Accuracy of Simulations of the Office Building

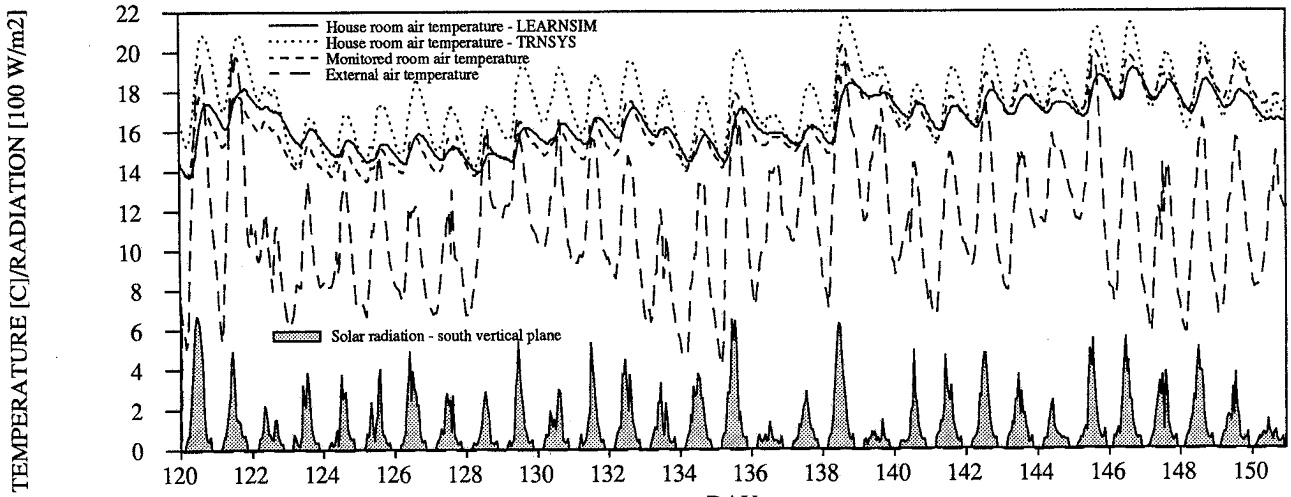

Figure 4. Simulation of the Family House

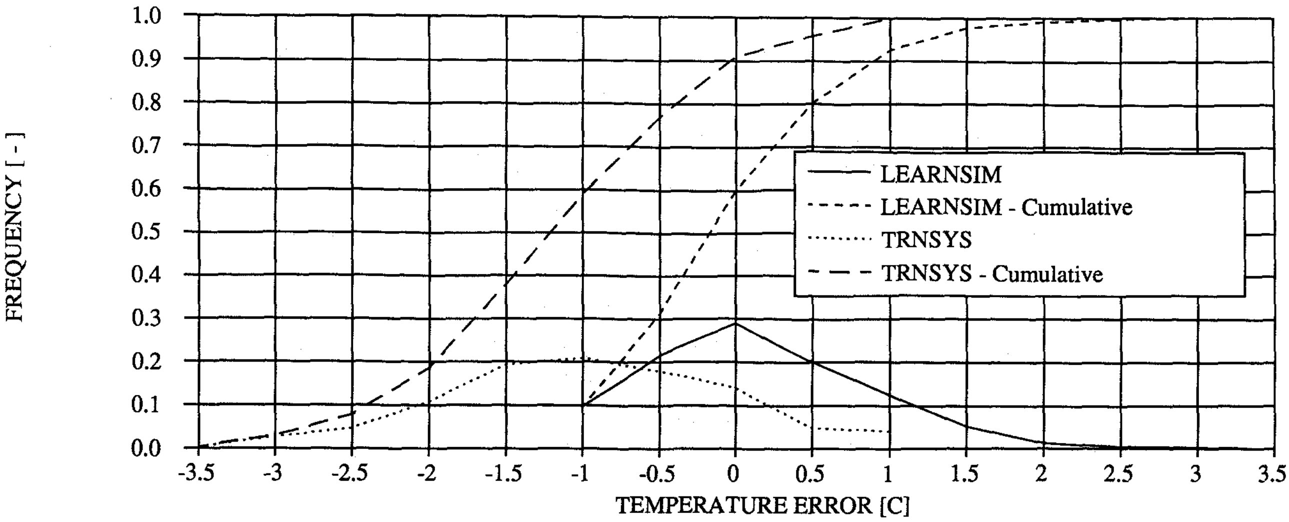

Figure 5. Accuracy of Simulations of the Family House

assumes that the temperature derivative from equation (3) depends only on one energy fingerprint at a time:

$$k_i = F_i / (dT/dt) \tag{8}$$

This enabled the application of the Reduced Memory Use Method, developed by the author earlier (Jankovic, 1988). In this way the speed of learning process was reduced approximately 4500 times. Due to this new learning method, LEARNSIM can now run on low cost computers, it can learn continuously without a substantial increase of machine time, and it can provide higher quality of simulation results than detailed conventional simulation models which run on expensive machines.

ACCURACY OF LEARNSIM

The testing of LEARNSIM was carried out using data from monitoring of buildings. The testing showed high accuracy and a good dynamic response of the model. We present here the results from two tests: a simulation of a five storey city building with 5000 m^2 office floor area, and a simulation of a three bedroom family house located in a suburban residential area.

Simulation of an Office BUilding

The comparison between the results of monitoring and the results of simulation of a five storey office building is shown in Figure 2. The monitoring data were acquired during the period of two weeks. The data were read and recorded in six minute intervals. The sequences of working days in Figure 2 are characterised with the radiator temperature raising substantially above the room air temperature in the morning and falling close to the room temperature in the evening. The two weekend periods can be recognised from continuously falling room air temperature, and the radiator temperature being close to the room air temperature.

The learning process in this case had to find the following unknown energy fingerprints: envelope fingerprint k_1, heating system coupling fingerprint k_4, and fingerprints k_8 to k_{10} dealing with coupling of internal gains from lights, people and equipment (see equations (4)). The objective of monitoring and simulation was to find the best control strategy for the building, using the existing controller (although the details of that exercise are beyond the scope of this paper, the stated objective explains the choice of independent variables relevant to this particular example). The energy fingerprints were chosen to represent the variables available to the controller, thus leaving out from the analysis some important variables, such as solar radiation. It also appeared that energy fingerprints related to internal gains from lights, people and equipment were occurring at the same time, and hence they were represented with a single parameter. In summary, the learning process had to find three energy fingerprints, and was therefore four dimensional.

After the simulation had been completed, the standard error of temperature prediction by LEARNSIM, compared with monitored temperatures for the period shown in Figure 2 was calculated as

$$e = 0.36 \pm 1.12\ ^oC.$$

Frequency of occurrence of actual simulation errors for this particular case is shown in Figure 3. Cumulative frequency curve shows that approximately 31% of simulated temperatures occur in the range of $\pm 0.5^oC$ around the monitored temperature, 59% of simulated temperatures occur in the range of $\pm 1.0^oC$ around the monitored temperature, and 80% of simulated temperatures occur in the range of $\pm 1.5^oC$ around the monitored temperature.

The results of this analysis show a relatively accurate simulation of building performance by LEARNSIM. It is believed that the accuracy would have been higher, had the solar radiation been taken into account, as the example below shows.

Simulation of a Family House

The monitoring and simulation results of a three bedroom family house are shown in Figure 4. The house was monitored during a period of five months while it was unoccupied. The data were collected in six minute intervals, and the presented analysis was done with hourly averages of recorded data. No internal gains or heating were supplied to the house during the monitoring period, and there was no control of solar gains. Hence, the house was in a free floating temperature mode. On this basis, the learning process had to find values of two energy fingerprints: the envelope fingerprint k_1, and the solar gain coupling fingerprint k_6. Hence, this problem had two independent variables and was three dimensional.

Unlike in the previous example, the simulations were also done using TRNSYS (Klein 1988), and the results by LEARNSIM and TRNSYS were compared with monitored data.

Before the analysis started, TRNSYS model had been fitted to the monitored data by means of a parametric optimisation. The model had been first assembled using data from material property tables, house geometry, and other known parameters.

Subsequently, significant parameters had been changed one at a time, the simulation had been repeated, and the results compared with monitored data. In this way over 50 simulations had been carried out until the accuracy of the TRNSYS model had stopped improving.

The comparative simulations by TRNSYS and LEARNSIM then followed (Figure 4). The standard errors of temperature predictions by TRNSYS and LEARNSIM, expressing the discrepancy from monitored data, were calculated for the period shown in Figure 4 as

$$\text{TRNSYS:} \quad e = -1.16 \pm 0.91\ ^{o}C.$$
$$\text{LEARNSIM:} \quad e = -0.05 \pm 0.72\ ^{o}C.$$

Hence, the standard error of simulation by LEARNSIM is much smaller, showing that LEARNSIM is more accurate. The results also show a substantial improvement of accuracy of LEARNSIM from the previous example. This improvement is believed to be the consequence of taking the solar radiation coupling fingerprint into account in this analysis.

Frequency of occurrence of actual errors of this simulation is shown in Figure 5. Cumulative frequency curves show that 83% of temperature predictions by LEARNSIM occur in the range of $\pm 1.0\ ^{o}C$ around the monitored temperature. Only about 41% of temperatures predicted by TRNSYS occur inside the same range.

LEARNSIM Time Efficiency

Elapsed times during the comparative simulations by TRNSYS and LEARNSIM were measured. And while TRNSYS simulation over five months of hourly input data lasted 2 hours, LEARNSIM completed the same task in about 2 minutes. It is quite possible that LEARNSIM was slowed down by the hard disk in the machine it was running on (a 286 personal computer), as there were no 'quiet' calculation intervals, but the hard disk was used continuously. On the other hand, the disk access speed did not seem critical in the TRNSYS case, as the 'quiet' calculation intervals step seemed longer than disk reading intervals.

In the particular case, LEARNSIM to TRNSYS speed ratio calculated from elapsed times is 60. Although this ratio is very high, it is likely that it would be even higher in a different hardware environment, for the reasons explained above.

PRESENT USE OF LEARNSIM

LEARNSIM is now being used in various aspects of our work. The development of our intelligent environmental controller is one of them. The controller learns the building energy fingerprints continuously, and provides the ideal match between the building and the environmental control system.

The same idea has been extended to monitoring and simulation of occupancy of homes. Activity pattern of occupants is monitored and modelled using the LEARNSIM method, and the interaction between the occupants activity pattern fingerprint and the building energy fingerprints results with even better match between the building and the control system. The prototype version of this controller has been undergoing field trials.

An expert system for building energy management has been developed on the basis of the same principles (Jankovic 1991a). This expert system is linked to an existing building energy management system (BEMS). On the basis of LEARNSIM, the expert system learns building energy fingerprints from up to 200 buildings, and it subsequently builds the model of normality of building performance. This enables the expert system to carry out diagnostic tasks and performance calculations using discrepancies of actual building performance from the model of normality.

Evaluation of long term building energy consumption from short term monitoring is one of useful services which LEARNSIM can provide. In conjunction with this, LEARNSIM was used in several instances for analyses of best control strategies for office buildings, and provided information for manual tuning of existing environmental control systems. This has already resulted with better use of energy and with the achievement of better comfort.

FUTURE USE OF LEARNING MODELS

Building design today is very much an 'open loop' process, with little and irregular feedback from existing buildings. However, it is likely that some form of a permanent feedback from existing buildings will be made possible in the near future. This is especially likely because of newly developed materials and instruments for temperature measurements using optical fibre. As optical fibre is gradually becoming the main telecommunication medium, it is likely that every building will be fitted with it in the future. Hence the permanent feedback is quite possible.

Another, perhaps more comprehensive type of feedback from buildings, can also be made available with advances of telecommunication technology. The building-in-use assessment of environmental quality (Vischer 1989) is at present conducted with building user questionnaires, and it gives as a result seven dimensions of environmental quality, as well as the assessment of productivity of building users, office workers morale, and building environmental health assessment. However, the information from questionnaires is infrequent, and if replaced with some means of online information of building user perception of their environment, it can become a valuable feedback from existing buildings.

Both of the above types of feedback can be provided to learning simulation models such as an extended future version of LEARNSIM.

The trend in development of a LEARNSIM based future model is expected to go towards learning of a wide range of building performance aspects from the permanent feedback from existing buildings. The performance fingerprints obtained from the model in this way will be cross-referenced with design information inputs for particular buildings, stored in the model database beforehand. After enough experience of relationship between the design input and performance feedback is acquired by the model, the later will become capable of simulating non-existing buildings and giving an invaluable design aid.

CONCLUSIONS

As an alternative to conventional simulation models, which are becoming inefficient due to a large number of operations and parameters, LEARNSIM - A LEARNing SImulation Model was developed.

This model learns building energy properties, named building energy fingerprints due to their identifying nature of different buildings. With the values of building energy fingerprints, LEARNSIM converts a rearranged heat balance equation into an accurate and fast simulation model.

The performance of LEARNSIM was tested and compared with monitored data, and with the performance of TRNSYS model. LEARNSIM appeared to be much faster and accurate than TRNSYS.

As a result of this, LEARNSIM has become a basis of development of an intelligent building environmental controller. The controller learns building energy fingerprints and building use patterns and provides the best possible match between the building and the environmental control system.

The ability to learn the actual building thermal properties made this model a very useful starting point for development of an expert system for building energy management. LEARNSIM provides the expert system with the model of normality of building performance, while departures from the normality are used by the system for diagnostic and performance calculation purposes.

Future research and application of a LEARNSIM based model is expected to go in the direction of comprehensive learning of many aspects of building performance, and relating that to design inputs stored in the model database in the past. The learning will be made easier by advances in telecommunication technology thus enabling permanent feedback from existing buildings in the future. In this way the LEARNSIM based model will ultimately gain sufficient experience of relationships between design input information and the building performance feedback. This will make it capable of providing an invaluable design aid.

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