STOCHASTIC SIMULATIONS VERSUS DETERMINISTIC ONES: ADVANTAGES AND DRAWBACKS

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Abstract

The fundamentals of a probabilistic approximation in thermal buildings analysis is here briefly presented. However, the principal aim of this paper is to show the advantages of such simulation approach in many applications requiring massive simulations. Several examples are presented to illustrate the relevance of the proposed method as an alternative to deterministic simulations, and to show how it is a powerful tool for analysis. The developed simulation approach appears; as an extremely helpful method for comfort analysis in free-floating buildings. It has also been used to derive powerful methods for generating and evaluating typical meteorological. years.

1 Introduction

Stochastic simulations have been made for a long time by different teams for many purposes. The research closest to our field and which inspired our work was done by the EPFL (see e.g. [Botazzi, 1991]). They base their approach on a direct stochastic description of the "natural" climatic data and on the use of nodal models to represent the thermal behaviour of the building. This approximation assumes some strong hypothesis including the stationarity and the statistical independency of the weather inputs as the more important ones. In this method, the stochastic processes involved are modelled as Markov chains, and the stochastic integration through the building model is then carried out by numerical procedures. The method forces a discretization of the weather input variables and the range of possible values of the outputs of the thermal model, and, consequently, it must handle vary large matrices. A work was undertaken to take advantage of the modal formalism in order to reduce the size of the data structures, to increase the accuracy of the building representation, and to accelerate simulations [Iskandarani, 1988]. But this last work relied too on the assumed stationarity of the "natural" weather data, and it has the same numerical problems that the previous one. However, the approach adopted here [Palomo, 1993a, 1993b] was on the contrary developed on the basis of three fundamental observations: the natural weather data are not stationary processes; the thermal behaviour of buildings seems to be a time-dependent Gaussian process; and, both, solar radiation and outdoor temperature time series could be adequatly described as time-dependent cross-correlated Orstein-Uhlenbeck processes. The main practical advantages of this approximation are that no discretization of the input-outputs variables is required, the stochastic integration is done by quasi-analytical procedures, simulations are really accelerated, and results are more informative and accurate than the ones provided by the other two approaches. As it will be shown here this "probabilistic" approch is based on the use of dynamic continuous models describing the time evolution of the statistical regularities (e.g. mean values, variances, and probability functions) of the output building's variables as a direct function of the statistical regularities describing the climate (mean values, variances, autocorrelations and cross-correlations). The main remarkable characteristics of such "probabilistic" models are:

- Weather data inputs are supplied not as long time series but as a reduced set of statistical parameters.
- Similarly, after integration, the evolution of the building's outputs is described by means of their corresponding mean values, variances and probability functions (postprocessing is not required).
- Buildings are represented by means of modal models. The main advantage of such a representation is that the order of the model can be strongly reduced (e.g. models of order 3 are good enough to simulate the time evolution of the indoor temperature). The information required concerning the building is hence reduced to a small set of parameters.

All these characteristics will significantly contribute to reduce the amount of information and the computation time required in applications concerning the long-term thermal behaviour of buildings. On the other hand, it will be shown that probabilistic models are specially pertinent for analyzing and understanding the coupling between the climate and buildings.

2 Fundamentals for a probabilistic approximation to the thermal building analysis

2.1 Dynamic models describing the instantaneous thermal evolution of buildings

When modelling thermal building behaviour, the fundamental equations of transport are usually discretized (finite difference, finite elements or finite volumes methods) on a mesh to lead to a system of non-linear ordinary differential equations in the general form:

$$C(T,t)\dot{T}(t) = A(T,t)T(t) + E(T,t)U(t) \quad (1)$$

where C is the matrix of "capacitances", A is the "heat exchange" matrix, E is the "excitation" matrix, T is the vector containing the temperature field, and U is the vector containing the excitation variables (inputs).

When doing the hypothesis of linearity of the previous equation, that has been proved to be a good approximation for many applications, a mathematical transformation (see e.g. [Lefebvre, 1990]) applied on equation (1) leads to the following system, called a modal model:

$$\dot{X}(t) = FX(t) + B\dot{U}(t) \quad (2)$$
$$Y(t) = HX(t) + SU(t)$$

where X is the modal state vector, F is a diagonal matrix containing the eingenvalues of the system and Y is a vector containing some observation variables (e.g. indoor air temperature). S is a matrix containing the static parameters of the system.

The main properties of a modal model can be summarized as follows:

- It is demonstrated that the evolution of each modal state is solution of an equation decoupled from the other ones (which is not true for all other methods) and requires the use of smaller matrices.

- It has been observed that only a reduced number of modes are significant to explain the response of the system. Different, more or less sophisticated, techniques to strongly reduce the order of a modal model (e.g. reduction techniques consisting in keeping only the more dominant modes) can be applied preserving a very good accuracy of the outputs (see e.g. [Oulefki, 1993]). On the other hand, only pure dynamic behaviour is modified by the reduction techniques, due to the fact that the static and dynamic parameters of the model are contained in separated matrices.

For applications requiring a large amount of simulations, the above properties are essential aspects to take into account when choosing a model to describe the thermal behaviour of a building.

2.2 Predictive models for weather data

The components of the vector $U(t)$ are usually the outdoor temperature, T_{out}, the solar energy incident on different building's surfaces, φ_i, and the heating/cooling power. In the following, only free-floating buildings (no heating or cooling devices) will be considered. $U(t)$ will be then the vector of the meteorological inputs.

$$U(t) = [T_{out}(t), \varphi_1(t), \varphi_2(t), ...]^T \quad (3)$$

Outdoor temperature and solar radiation time series are usualy assumed to be a special kind of markovian stochastic process, whose main properties can be summarized in a reduced set of statistical regularities (e.g. means, variances, autocorrelations, cross-correlations, ...). From such descriptions a strong reduction of the weather data information required for building simulations is achieved. On the other hand, very simple but accurate meteorological predictive models can also be built from it. The predictive model that will be used here is of the general form:

$$U(t) = \mu_u(t) + \sigma_u(t)z(t) \quad (4)$$
$$\dot{z}(t) = \rho(t)z(t) + \epsilon(t)$$

where $\mu_u(t)$ is the time-dependent vector of inputs mean values, $\sigma_u(t)$ is a diagonal time-dependent matrix containing the standard deviation values of the inputs, $z(t)$ is a vector containing the stochastic part of the inputs time evolution, $\rho(t)$ is a time-dependent diagonal matrix of autorregresive coefficients, and $\epsilon(t)$ is a Gaussian white noise.

The "deterministic" part of the weather inputs is described by their time-dependent mean and standard deviation values. The stochatic part, $z(t)$, corresponds then to the fluctuations of the inputs around the mean evolution, normalized by the standard deviation. It is modelled as a time-dependent Ornstein-Uhlenbeck process (see e.g. [Arnold, 1974]).

It has been proved in [Palomo, 1993] that the model (4) is a good approximation to describe weather data for building simulation purposes. The vector $\mu_u(t)$, the matrices $\sigma_u(t)$ and $\rho(t)$, and the covariance matrix of $\epsilon(t)$ can be estimated by simple procedures from historical hourly weather data.

2.3 Probabilistic models describing the long term thermal behaviour of buildings

Due to the stochastic nature of weather inputs, the thermal building response can be also seen as a stochastic process. It has been shown [Palomo, 1993] that such a process behaves as a time-dependent Gaussian process. At any time, the probability density function, $\pi(T,t)$, and the cumulative distribution function, $\Pi(T,t)$, of the process $T(t)$ only depend on its time-dependent mean, $\mu_T(t)$, and its standard deviation, $\sigma_T(t)$.

$$\pi(T,t) \in \mathcal{N}(\mu_T(t), \sigma_T(t)) \tag{5}$$

It can be also demonstrated (see [Palomo, 1993]) that the joint process $W(t) = [X(t), z(t)]^T$ - {state variables, weather stochastic component} - is a linear diffusion process. The time evolution of the mean values of the process $T(t)$ is then given by

$$\dot{\mu}_x(t) = F\mu_x(t) + B\dot{\mu}_u(t) \tag{6}$$
$$\mu_T(t) = H\mu_x(t) + S\mu_u(t)$$

and the time evolution of its covariance matrix by

$$\dot{K}_{ww}(t) = A(t)K_{ww}(t) + K_{ww}(t)A^T(t) + D(t)$$
$$K_{TT}(t) = Q(t)K_{ww}(t)Q^T(t)$$

$K_{ww}(t)$ is the covariance matrix of the process $W(t)$ Its time-evolution is determined by a dynamic Lyapunov equation. $A(t)$ is the so called "drift matrix" of the process $W(t)$:

$$A(t) \doteq \begin{bmatrix} F & B\{\dot{\sigma}_u(t) + \sigma_u(t)\rho(t)\} \\ 0 & \rho(t) \end{bmatrix} \tag{8}$$

and $D(t)$ the corresponding "diffusion matrix"

$$D(t) = \begin{bmatrix} B\sigma_u(t) \\ I \end{bmatrix} E\{\epsilon(t)\epsilon^T(t)\} \quad \sigma_u^T(t)B^T \tag{9}$$

$K_{TT}(t)$ is the covariance matrix for the process $T(t)$, whose diagonal contains the time-dependent variances. The matrix $Q(t)$ is given by:

$$Q(t) = \quad H \quad S\sigma_u(t \tag{10}$$

Equations (5) through (10) represent the "probabilistic model" describing the long-term thermal building behavior. It must be noticed that:

- It is continuous in time and in the input-output system variable space. The problem of discretization of buildings outputs, that affect the other existing stochastic approximations to building simulation, and that strongly limits their use, has been eliminated.
- Climatic inputs to this model hqve to be supplied, not as long time series, but as a reduced set of statistical parameters: the vector $\mu_u(t)$ of inputs mean values, the matrix $\sigma_u(t)$ of standard deviations, the matrix $\rho(t)$ of autorregresive coefficients, and the covariance matrix $E\{\epsilon(t)\epsilon T(t)\}$.
- Buildings are represented in the "probabilistic model" by means of the matrices F, B, H and S of a (reduced or not) building modal model.
- After integration, outputs from the "probabilistic model" are a set of statistics (time-dependent mean values and covariances) describing the thermal evolution of the buildings in terms of probability.

To integrate equations (6) and (7), we can assume (see [Palomo, 1993]) that the variables in the vectors $U(t)$ and $Y(t)$ (inputs and outputs) are 24-hour stochastic processes. This hypothesis is not strictly necessary, but it contributes to acelerate the integration process and to reduce the information (climatic inputs, building outputs) to be manipulated.

3 Application to the analysis of thermal comfort in buildings

3.1 Statement of the problem

Many variables (e.g. air temperature, humidity, air speed, ...) contribute to the energy balance in the human body, and many indices have been proposed to evaluate their effect on the hygrothermal comfort. One of the most popular is the PMV (Predicted Mean Vote)[Fanger, 1970]. When fixing some values such as the activity level, the humidity and the air velocity, the PMV is related to the indoor resultant temperature through a linear equation:

$$PMV = a + bT_{in} \tag{11}$$

where a and b depend on the values of the fixed parameters. Another interesting comfort index is the PPD (Percentage of Persons Disatisfied), which is related to the PMV through the following equation:

$$PPD = f(PMV) = 1.0 - 0.95e^{-(0.03353PMV^4 + 0.2179PMV} \tag{12}$$

The equations above can be used to define the instantaneous level of comfort. However comfort assesment in buildings implies long-term comfort evaluation. A "standard" procedure for such evaluations is:

a thermal model for the building is built, and historical records of hourly weather data (e.g. 10-15 years) are available;

2) the building thermal evolution is then simulated; outputs are long hourly series (e.g. indoor resultant temperature) that could be then translated into e.g. PMV or PPD time series;

3) finally, the information contained in such time series must be in someway synthetized; the WPMV (Weighted PMV) could be used here:

$$WPM \quad = f^{-1}(WPPD)$$

where WPPD (Weighted PPD) is the mean value of the observed PPDs.

3.2 Using "probabilistic" models for comfort assessment

Instead of using the above standard procedure, the following probabilistic approach is suggested:

1) build a modal model for the building (output = resultant temperature), and reduce it as much as possible (minimum ordre with a good accuracy);

2) use historical records of hourly weather data to build a model of type (4); in other words, estimate the hourly (1-24) mean values, the hourly variances, the autocorrelations at lag 1, and the cross-correlations at lag 0, for the variables in the sollicitations vector;

3) from the results of 1) and 2), build the probabilistic model (equations 5-10; in discrete time version), and integrate it; outputs from this model are the hourly (1-24) probability density functions for the resultant temperature process, $\pi(T_{in}, t); t = 1, 2, ...24$, and the global probability function, $\Pi(T_{in})$;

4) assuming that the parameters a and b in equation (11) could depend on the hour of the day ($t = 1, 2, ..., 24$), estimate the hourly probability density functions of the PMV index as

$$\pi(PMV = pmv, t) = \pi(T_{in} = \frac{(pmv - a(t))}{b(t)}$$

and then calculate the WPMV index as

$$WPPD(t) = \int f(PMV)\pi(PMV, t)dPMV$$

$$WPPD = \frac{1}{24}\sum_{t=1}^{24} WPPD(t)$$

$$WPMV = f^{-1}(WPPD)$$

The validation of this approximation to comfort assesment have been performed by comparing the results from deterministic simulations (standard procedure) with the results from probabilistic models. A very good agreement between both has been found in the analyzed cases - buildings oriented mainly towards south (see [Palomo, 1993]).

On the other hand, the computing time required is strongly reduced when using the probabilistic models. This advantage comes from the adopted climate and building representations, and from the fact that the statistics usually employed to describe the long-term building behaviour are directly obtained (post-processing is not required).

3.3 Example

The above advantage makes probabilistic models a specially pertinent approach to guide buildings design. For instance, sensitivity analysis measuring the effect of different design parameters on the WPMV value can be quickly and easily performed. The results of the sensitivity study carried out in summer, Almeria (Spain), are gathered in figure 1. Three inertial levels (basic, heavy and light) and four orientations (E, N, S and W) have been tested. For each couple {inertia level, orientation}, two shading levels and three ventilation strategies have been considered (see table 1). The main conclusions from this analysis are: a) the inertia level has a secondary effect on comfort; b) the effect of the orientation is only relevant in the case of buildings with low shading and ventilation levels; c) the shading level has a strong influence on the comfort; d) the effect of the ventilation strategy is weighted by the shading level (for greater shading levels, the effect of increasing ventilation is less significant).

Shading	Ventilation strategy 1/1 ACH	1/6 ACH	6/6 ACH
Low	Curve 1	Curve 2	Curve 3
High	Curve 4	Curve 5	Curve 6

Table 1: Shading and ventilation parameters. x/y ACH: x= ACH value during day; y=ACH value during night.

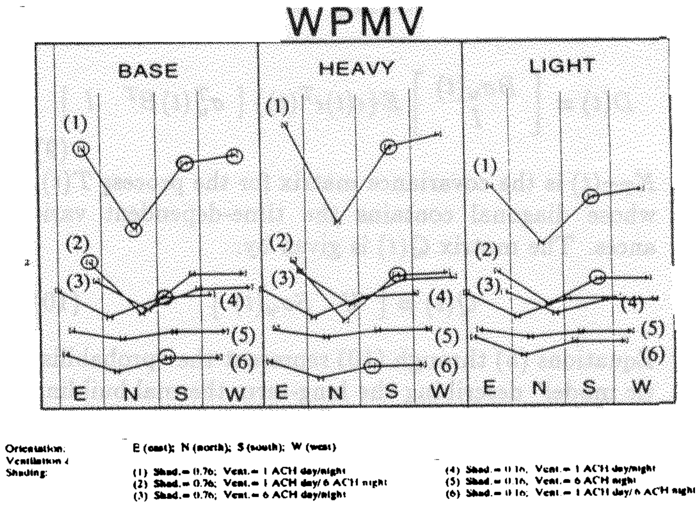

Figure 1: Effect of different design parameters on the WPMV value. Summer, Almeria (Spain).

If more detailed information is required, the cummulative distribution functions (CDF) of the resultant temperature can be analysed. Figure 2 shows the effect of shading and ventilation on the long-term thermal behaviour of the base-inertia south-oriented building. A high level of shading combined with a 1/6 ACH strategy for ventilation, gives the better results from a thermal comfort point of view.

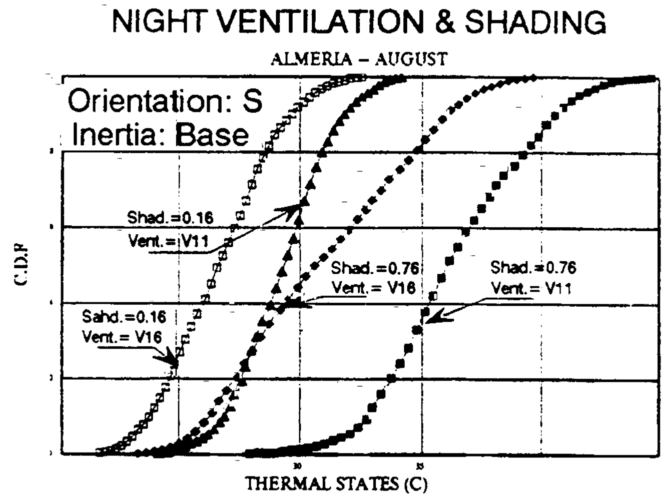

Figure 2: Effect of ventilation (V11= 1/1 ACH; V16= 1/6 ACH) and shading (low=0.76; high=0.16) on the cummulated distribution function of the resultant temperature.

4 Application to the problem of TMYs generation and qualification

4.1 Statement of the problem

Hourly simulations using long (e.g. 10-15 years) weather data time series are usually required to define the long-term thermal building behaviour. Typical Meteorological Years (TMYs) are generally used to replace such a long time series. They must therefor preserve the most important characteristics of actual weather data in order to lead to typical output sequences when simulating.

Different methods exist to generate TMYs (see e.g. [CEC, 1985] and [Petrakis, 1995]). In most of them, called "empirical methods", the TMY is formed linking together actual months (from january to december) of different years. A TMY can include observations from january 1987, february 1991, ... and so on. Actual months in the TMY are selected by statistical procedures. The whole set of observations available (e.g. 10-15 years for january) is characterized by means of different statistics (e.g. means, variances, correlations, distribution functions, ...). These statistics are also estimated for each one of the months in the data base (e.g. each january 1987, 88, ...). Finally the month (e.g. january 1987) that statistically was closest to the set of months, is selected as typical month. Different statistical criteria, will usually lead to different TMYs. What statistical criteria should therefor be used? The response to this question is not obvious. If TMYs will be used for buildings simulations, it is clear that the response will be a function of the buildings characteristics (thermal inertia, insulation level, solar performance, ...) and of the simulations purposes (output variables of interest, and statistics to be used to synthetize the time-evolution of the output variables).

A related problem is the evaluation of a TMY. The quality of a TMY will also depend on the building characteristics and on the simulation purposes. Evaluating a TMY is thus a hard task requiring many simulations. A "standard" procedure for TMY evaluation can be the following one:

1) define a large enough set of significative buildings, covering a wide range of inertia levels, insulation, solar performance, ..., and build the corresponding thermal models;

2) simulate the thermal response (e.g. indoor air temperature evolution, heating requirements, ...) of such buildings using the available historical weather data (e.g. 10-15 years);

3) simulate the thermal building behaviour using this time the TMY to be evaluated;

- compare results from 2) and 3) using pertinent statistics (e.g. means, variances, probability functions, ...)

This procedure requires a considerable amount of simulations and the manipulation of a large amount of data (weather data and output variables time series).

Both problems, TMYs generation and TMYs evaluation, will be treated in sections 4.2 and 4.3 using the "probabilistic" approach described in section 2.

4.2 Guidelines for generating TMYs

The question above: *which statistical criteria must be used for selecting typical months?*, could be translated into the following one: *what statistics, among the ones describing the climate, have a greater influence on the long-term thermal behaviour of buildings?*, or, in other words, *what is the effect of perturbating the statistics describing the climate on the statistic describing the long-term buildings behaviour.* Solving this problem by "standard" procedures (based on deterministic simulations) is almost impossible. However, the solution is trivial using the "probabilistic" models described in section 2. The procedure to follow is:

- After selecting a large enought set of representative buildings, a detailed thermal model is built for each one of them. These models are then transformated in modal models and reduced up to order 3. The resulting reduced models are finally introduced in a library accesible to the users. When required, a set of buildings could be built by taking a pertinent subensemble of buildings from the library, or given different weights to each one of the models in the library. A more easy procedure could be followed if we are only interested on conventional monozone buildings. In this case, first order modal models can be directly built from the following global building's parameters ([Lefebvre, 1987]): τ = the first time constant (measure of the building's inertia level); A_s = the solar aperture (measure of the solar performance of the building); and UA = the global thermal losses coefficient (measure of the building's thermal insulation). In this case, the definition of the set of buildings is made as follows:

- a pertinent domain of variation for the parameters τ, A_s and UA is defined giving their corresponding maximum and minimum values (notice that for free-floating buildings these parameters could be reduced to 2: τ and A_s/UA);
- the above domain is discretized subdividing the intervals of variation of the above parameters in a given number of subintervals.
- a probability law is superimposed on the resulting mesh.

Each point in the discrete domain of parameters represent a building, $\mathcal{B}_i$, with a probability, p_i, of appearence.

- From the hourly data of solar radiation and outdoor temperature available, the corresponding hourly means, standard deviations, first autocorrelations and cross-correlations values are estimated.
- For each building $\mathcal{B}_i$ in the set, the cummulative distribution function for the resultant temperature process, $P_i(T_r)$, is estimated by integration of the corresponding "probabilistic model" (equation 5 to 10)
- Each one of the statistics describing the climate (means, standard deviations, ...) has been sequentially pertubated (e.g. variation of a 1%), and the resulting cumulative distribution functions $\tilde{P}_i(T_r)$ estimated.
- The effect of perturbating one of the statistics describing the climate is finally measured by means of

$$D_{max,i} = max\left|P_i - \tilde{P}_i\right|$$

Figures 3 and 4 show the sensitivity analysis carried out on a set of 121 buildings using the data available for august in Athens (13 years). Among the performed analysis, these figures illustrate quite well what is a typical pattern of sensitivity for summer. The main general conclusions from figure 3 are:

- the long-term thermal behaviour of buildings is very sensitive to the hourly mean values of the outdoor temperature (points on the vertical $x = 1$);
- its sensitivity to the mean hourly values of solar radiation (points on the vertical $x = 2$) and to the sequential properties of the outdoor temperature time series (points on the vertical $x = 5$) is also important;
- however, it is practically insensitive to the perturbations of the hourly standard deviation values (points in the verticals $x = 3$ and $x = 4$), on the sequential properties of solar radiation series (points in the vertical $x = 6$), and on the cross-correlation between solar radiation and outdoor temperature time series (points on the vertical $x = 7$)

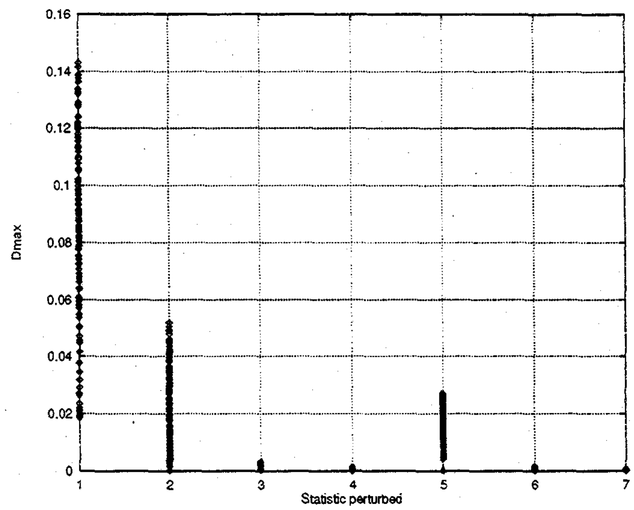

Figure 3: Sensitivity of the long-term thermal behaviour of buildings to the statistics describing the climate: 1= temperature mean values; 2= solar radiation mean values; 3= temperature standard deviation values; 4= solar radiation standard deviation values; 5= temperature first-autocorrelation values; 6= solar radiation first-autocorrelation values; 7= cross-correlation values at lag 0

In figure 4 a total of 11x3 curves are presented, each one containing 11 points. Curves with the legend "T-mean" represent the values of the criterium $D_{max,i}$ achieved when the hourly mean values of the outdoor temperature time series have been modified. Curves with the legend "R-mean" represent the values of the criterium $D_{max,i}$ achieved when modifying the hourly mean values of the solar radiation time series. Finally, curves with the legend "T-autocorr" represent the values of $D_{max,i}$ obtained when hourly first-autocorrelation values of the outdoor temperature are perturbated. These curves are grouped in 11 groups having the same value of the parameter A_s/UA (solar aperture/global thermal coefficient): from 0 (on the left) to 0.05 (on the right). Whithin an isolated curve, the different points (11) represented are associated with different values of the parameter τ (first time constant), from $0h$ (on the left) to $250h$ (on the right). It can be seen that:

- As greater the inertia level of the building is, greater is the sensitivity of the long-term thermal behaviour of the building to the statistics defining the climate.

- The sensitivity of the thermal building behaviour to the mean values of the outdoor temperature decreases when the value of the parameter A_s/UA increases. The contrary is observed for the mean values of the solar radiation time series.

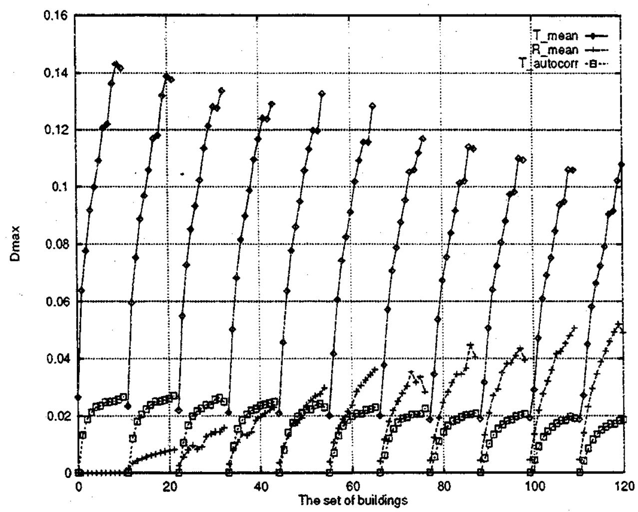

Figure 4: Sensitivity of the long-term thermal behaviour of buildings to the statistics describing the climate. Variation with the building's parameters τ and A_s/UA.

The results of this analysis has been used to guide the selection of the "weighting factor" required by the "empirical" procedure for generating TMYs proposed in ([Petrakis, 1995]). They also suggest another interesting procedure for TMY's generation (see [Palomo, 1995]). A typical e.g. January is formed by the following procedure:

a the hourly first autocorrelation values of the whole outdoor temperature time series available (e.g. 10-15 years) are estimated;

b such statistics are also estimated for the outdoor temperature time series associated to each month in the data base (e.g. January 1987, January 1988, ...);

c the month (e.g. January 1990) so that the differences observed between the statistics calculated in a) and b) were smaller is selected;

d the weather data registered in the month above are normalized by the following standard procedure

$$z_i(d,h) = \frac{u_i^k(d,h) - \mu_i^k(h)}{\sigma_i^k(h)}$$

where $u_i^k(d,h)$ is the observed value for the variable u_i at hour h in the day d of year k, $\mu_i^k(h)$ are the corresponding hourly mean values, and $\sigma_i^k(h)$ the estimated standard deviation values;

e the 'typical month" is finally generated by transforming the sequences above according to

$$\tilde{u}_i(d,h) = z_i(d,h)\sigma_i(h) + \mu_i(h)$$

where $\mu_i(h)$ and $\sigma_i(h)$ are the hourly mean values and the hourly standard deviations corresponding to the whole set of u_i observations (k=1,2,.....).

"Typical Months" from this method have the same hourly mean and standard deviation values than the whole set of weather data available. On the other hand, they have the same sequential properties as one of the years in the data base. Because this procedure leads to "Typical Months" that are not "actual months", it was called "semi-empirical" method.

4.3 A method to compare and to evaluate TMYs

Instead of the "standard" procedure described in 4.1, the following method based on the use of probabilistic models is proposed:

- a set of buildings (and models of buildings) is generated (or selected) by the procedure described in 4.2.
- for each building in the set, $\mathcal{B}_i$, the probabilistic model is integrated using the statistical description of the historical weather data. Results are then manipulated to get the whole cummulative distribution function of the resultant temperature process, $P_i(T_r)$.
- for each building in the set, $\mathcal{B}_i$, the probabilistic model is integrated using the statistical description of the TMY. Results are then manipulated to get $\tilde{P}_i(T_r)$.
- for each building in the set, the maximum difference between the cummulative distribution functions estimated above is calculated

$$D_{max,i} = max \left| P_i - \tilde{P}_i \right|$$

- the TMY's quality is then measured by weighting the above results using the probability values, p_i, associated to each building in the set

$$\sum_i D_{max,i} p_i$$

Such a procedure is used here to compare different procedures to generate TMYs. Figure 5 shows the results achieved when comparing typical August in Athens (TMM) built from the "semi-empirical" method and from the "empirical" methods mentioned above. It can be seen in this figure that the first method ("semi-empirical" procedure) is substantially better than the second one. Whatever may be the inertia level, the solar performance or the insulation level of the building (121 different buildings have been used), the TMM generated by the "semi-empirical" procedure leads always to very good results. On the contrary, the better "natural month" in terms of the test of pertinence leads to pertinent results only in a 30% of the cases. This kind of results were also achieved for the others months in Athens.

The "semi-empirical" method seems to be a better approach for generating TMYs that any "empirical method". The reasons are that it preserves the hourly mean values of the historical weather data and the sequential properties of the year closest to the ensemble in terms of outdoor temperature autocorrelations values.

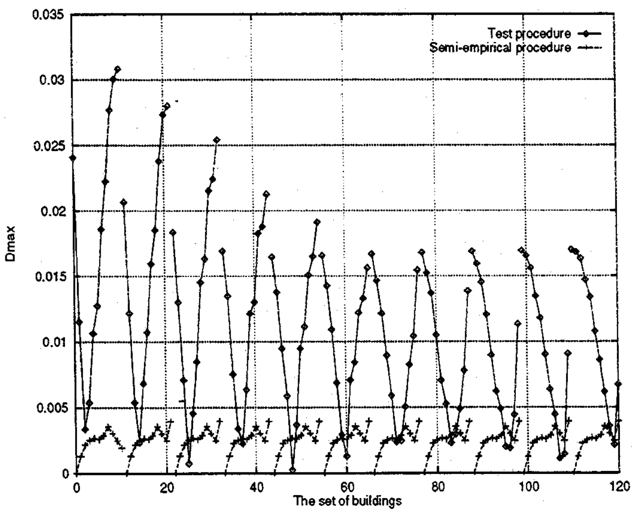

Figure 5: Results of the "test of pertinence" when used to compare two different methods for generating TMMs.

5 Conclusions and future works

The fundamentals of a probabilistic approximation to the thermal buildings analysis have been briefly presented. There are based on the use of dynamic continuous models describing the time evolution of the statistical regularities (e.g. mean values, variances, and probability functions) of the output building's variables as a direct function of the statistical regularities describing the climate (mean values, variances, autocorrelations and cross-correlations). The main advantages of this approximation, over the other existing ones, are that no discretization of the input-outputs variables is required, the stochastic integration is done by quasi-analytical procedures, simulations are accelerated, and results are more informative and accurate than the ones provided by the other approaches.

However, the principal aims of this paper were to show the advantages of such a simulation approach in many applications requiring massive simulations: weather data inputs are supplied, not as long time series, but as a reduced set of statistical parameters; similarly, after integration, the evolution of the building's outputs is described by means of their corresponding mean values, variances and probability functions (postprocessing is not required); and buildings are represented by means of modal models that can be strongly reduced (e.g. models of order 3 are good enougth to simulate the time evolution of the indoor temperature). To illustrate the relevance of the proposed method as an alternative to deterministic simulations, and to show how it is a powerful tool for analysis, several examples have been presented. It has been shown that the developped simulation approach is an extremely helpful method for comfort analysis in free-floating buildings, and it has also been used to derive powerful methods for generating and evaluating typical meteorological years.

Future developpements will concern the generation of the weather predictive model in order to include new variables (e.g. humidity, wind velocity, ...), and the extension of the probabilistic approach to the case of non-linear models for buildings.

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