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POSTER 3

Stochastic model of inhabitant behavior in regard to ventilation

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Synopsis

Airflow rates are directly affected by the amount of open area and consequently by the inhabitant behavior with respect to window opening. In this paper, a stochastic model using Markov chains, developed at the LESO to generate time series of single-window opening angle is modified to generate multiple window openings. It is based on data measured by the TNO Delft on 80 identical, 16 openings dwellings located at Schiedam (NL). The model is then validated by a comparison of the real and generated data. The use of this model within building air infiltration design programmes should improve significantly the likelihood of the latter.

1. Introduction

1.1. Importance of the Inhabitant

The importance of airflow rates on heating cost and the elimination of pollutants within buildings is a fact and already many softwares are available to simulate them[1]. However, it must be pointed out that all these programmes run with unoccupied buildings, even though airflow rates are closely related to the amount of open area and therefore to the inhabitant behavior concerning window opening. For instance, measurements conducted in 25 Danish buildings shows that in average the increase in the airflow rate due to occupancy is more than 100%[2].

In order to improve future programmes a model simulating window opening during the winter has been developed and was presented elsewhere[3]. This model was based on measured data from four offices of the three storey's LESO experimental office building[4]. Using a method similar described by Fewkes & Ferris[5], the model generates time series of window opening angles with the same statistics (i.e. average opening angle, time correlation, temperature dependance, etc...) as the measured openings for the heating period.

1.2 Driving variables

From the work of IEA-ECB annex 8[2] (and since the 7th AIVC conference), it is well known that the inhabitant behavior concerning the openings depends on several variables. Some of these may drive the opening and closing, some others only one of this action (e.g. the occurrence of rain may enhance the probability of closing the windows). These driving variables are listed in Table 1

Table 1: Possible driving variables for window opening and closing[3].

External variables	Internal variables	"Human" parameters
Outdoor temperature Solar radiation Wind velocity Rain Noise Odors and pollutants	Indoor temperature Odors Contaminants Moisture	Time of the day Type of day Type of building Habits etc.

Several intercorrelations between the openings and some of these variables were examined. It was found that the most significant one is the outdoor temperature[3]. Only this variable is taken into account in the present work. This has moreover the advantage of linking the model to a data which is generally available all around the World in each meteorological station.

The indoor temperature was considered, but not retained as driving variable, the reason being that it is difficult to handle in multiroom infiltration programmes which are seldom combined with a thermal calculation code.

1.3 Basic principles of the model

A simple way of introducing inhabitant behavior in a computer code is to record the windows and doors openings in a dwelling, at a convenient time interval and during a statistically significant time period. These recorded data could then be introduced as input schedule in the computer code, which receives that way exact information on the inhabitant behavior of the monitored dwelling. However, this method presents several inconveniences:

1) The recorded data are valid only together with the meteorological data synchronously recorded on the same site. It is therefore not possible to translate the recorded information to other buildings under other climates.
2) Only the measured inhabitant is represented that way. Other behaviors could however be introduced by performing other measurements and storing other sets of data.
3) The many recorded data use much memory space. The basic data used within the framework of this paper filled fifteen 1.44 Megabyte disks, that is about 20 Megabyte for 80 dwellings.

The purpose of the model is to generate window opening sequences which are similar to the measured ones, but with a very small amount of input data. These input data are obtained by statistical treatment of measured data. The opening sequence is reconstructed by random generation according to some rules resulting from that statistical treatment.

The simplest generation is to close and open the windows following an independant stochastic process, according to frequency and opening time distributions. However, this method does not provide realistic sequences, since it is well known that the opening time depends on the outdoor temperature[2] and it was shown[3] that the opening angle of a window is autocorrelated, which means that the state at a given time depends on the preceding states.

The next step in complexity is the Markov chain, in which the state at one time step depends only on the preceding state. Markovian processes present a non-zero autocorrelation function, but a differential autocorrelation function† which is zero, except at the origin. The Markov chain has proven to be a suitable model for simulating window opening angles[3].

2. Data Used For The Model

The model developed here is based on measurements recorded every 10 minutes in 80 dwellings of a 10-floor building located at Schiedam (Netherlands)[6,7,8]. All the dwellings are similar (Figure 1) and there are 14 dwellings per floor. Each dwelling has 14 windows and two doors, located on both facades as shown on Figure 1.

Measurements of the window opening (using switches) were taken at very short time intervals (20 seconds). In order to discretize the time scale as required by the Markov chain, a time step of 10 minutes was adopted as a compromize, large enough to limit the number of data, and not too short in order not to loose too much accuracy. The opening time during these intervals was calculated for every window. When that opening time was larger than 5 minutes, the window was considered open during 10 minutes, and considered as closed if the open time was less than 5 minutes.

Each dwelling having 14 windows and 2 doors, the status of these was recorded as two bytes of 8 bits, that is 2 ASCII characters. Meteorological variables such as outdoor temperature, wind speed, solar radiation and rain as well as inside air temperature and inlet and outlet heating water temperatures were also recorded.

† The differential autocorrelation function is the autocorrelation function of the difference between two successive states.

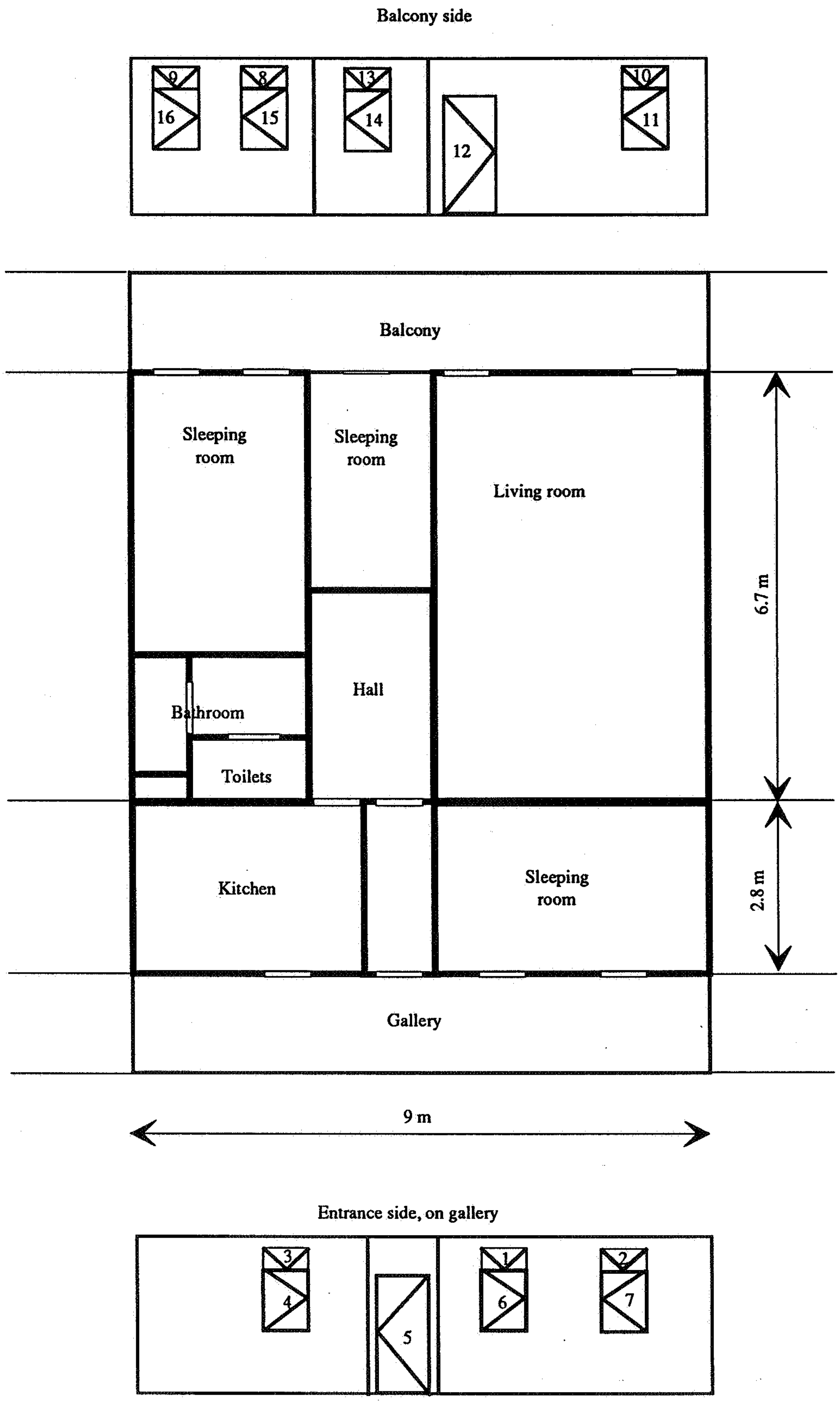

Figure 1: Floor plan of a dwelling and position of windows and doors in the facades and the corresponding numbers[6]

The measurements used for that study were taken during 118 days from winter to summer. These were taken out of longer files, using the following criteria:

- both meteorological data and window openings should be available at each time step,
- there should not be more than 20 minutes between two measurements, i.e. not more than one missing measurement. If one measurement was missing, the preceding data were taken without change.
- series of data with less than 100 measurements (that is shorter than 16.7 hours) were eliminated.

This resulted in a file of 17 043 measurements at 10 minutes interval, which is a pack of several smaller files. The transition between two files (i.e. during apparent time intervals larger than 10 minutes) were not taken into account in the analysis. The final number of valid transitions is then 16 976.

3. Setting up the Model

3.1 Existing model

The existing model[3] was developed to generate time series of window opening angles, which was divided into 6 classes: [0-1[(closed), [1-15[, [15-35[, [35-60[, [60-90[, [90-120] degree. Moreover, it was based on measurements performed in offices with a single openable window. The effect of the outdoor temperature was taken into account by dividing the domain of that variable into 4 classes: [-273-0[, [0-8[, [8-16[, [16-∞[°C. and four series of data were generated and used for each of these four temperature classes.

3.2 Reasons for modifications

The Schiedam measurements are window and door openings (that is either 0 for closed or 1 for open) and one dwelling has 14 windows and two doors, whose opening probabilities are likely to be correlated. The existing model should therefore be modified first to provide time series of openings instead of angles, but also to take account of the many windows in a dwelling.

The difference between the opening angle and the opening indicated by a switch is a trivial but important change: the 6 classes of opening angle of the preceding model are replaced by only two: closed or open. Since the air flow rates through a window depends on the opening angle[9], it is an important issue and maybe a dramatic approximation. However, there are, at our knowledge, no available data providing the opening angle for many windows in dwellings and this model should be based on existing measured data.

3.3 Which user should be simulated?

It is well known[2] that the inhabitant behaviors differ much from each other, and these differences give the basic reason to take them into account in the simulations. Since the measurements were performed on 80 dwellings, there is a large choice of behaviors. Whose of these should be chosen? Which criteria could be used for that choice?

The criteria could be the total opening time of all the windows and doors, the total number of changes or some more complex criterion such as the extra air change rate induced by the behavior. The latter is too complex to be handled and the total opening time was taken as criteria, since it is more related to air flow rates than the number of opening.

One can choose an "average" inhabitant, a "closer", or an "opener". Note that the definition of the "average" dwelling is not obvious. First of all, none of the 80 dwellings has opening times close to the general average for each window. Therefore, it makes no sense to generate an artificial average user by averaging the data over the 80 dwellings. It is proposed here to choose one user which is close to the general average.

This could be the one with the average opening time, μ, closest to the general average (the average being taken as well on time as on the windows), or the one which is the closest for each window and door, that is the one which has the smallest standard deviation, σ, to the average for each opening, summed over the 16 windows and doors.

Some figures are given in Table 2, which shows the dramatic differences between the dwellings. In this Table, μ is the average of the corresponding line and σ is the standard deviation between the corresponding line and the global average. Note that the database used to make that table and hence choose the interesting users is slightly smaller than the complete database used for the rest of the work.

Table 2: Relative windows (and doors) opening times, in ‰, for some selected dwellings.

Side	Gallery side							Balcony side										
Type of room	Bedroom				Kitch.		Door	Living			Bed		Large bedroom					
Opening No:	1	2	6	7	3	4	5	10	11	12	13	14	8	9	15	16	m	s
Global average	156	90	24	19	137	14	6	45	13	20	142	77	257	89	167	36	81	
Average users (see text above):																		
smallest s	135	0	2	0	107	1	1	7	0	1	143	12	303	0	15	0	45	58
closest m	18	4	6	0	145	2	2	0	0	6	320	18	607	99	134	0	85	113
"Closed" user	168	0	7	0	47	10	1	0	0	3	39	10	12	0	4	0	19	93
"Open" user	108	340	0	0	684	0	1	333	1	30	764	938	616	330	11	53	263	345

3.4 How take account of several windows?

The proper way allowing one to take account of the presence of 16 windows in a dwelling is not so obvious, since there are several possibilities. The model based on Markov chains reproduces **transitions** between **states**. The variable(s) representing the state should therefore be first defined.

Having 16 openings, a basic state of these could be represented by a 16-bit word, each bit representing one opening, and be 0 when the window is closed and 1 when open. There are theoretically 2^{16} (about 65 000) such states, hence $2^{16}\times2^{16}$ possible transitions whose probabilities could be represented in a square matrix with more than 4 billion numbers for each temperature class. Most of the elements of this matrix are zero and will not be stored but, nevertheless, this solution is neither practical nor possible. In particular, there are not enough available data (only about 17 000 transitions) to calculate the transition probabilities.

At the other end of the spectrum, each window could be considered as independent, with two states. In this case, the window and door openings of the dwelling would be modelled by 16 transition matrices, 2×2, that is 64 transition probabilities for each temperature class. This model can obviously not reproduce any intercorrelation between the opening sequence of different windows

Any intermediate model could be chosen between these extremes. As a first approximation, the simplest model is developed and tested below.

4. Independent windows model

The 16 windows and doors are assumed to be independent from each other and are treated separately. The state variables are the state of each window or door, e.g. 0 for closed and 1 for open. There are hence four transition probabilities (0 to 0, 0 to 1, 1 to 0 and 1 to 1) for each window and each temperature class.

4.1 Treatment of the data

To fill-up these 16 × 4 matrices (16 for each temperature class), the measured data were treated the following way:

1) A building is chosen and a file is generated from the big basic data file. This file contains, for the 17 000 time steps of 10 minutes, the meteorological data and the 16 window (or doors) openings of the chosen building.

Then, at each time step t_n and for each window or door:

2) the outdoor temperature is examined and the corresponding class noted,

3) the type of transition from the preceding state to the present one is determined and the corresponding element in the transition matrix for that window and that temperature class is incremented by 1. The elements are arranged as shown below:

Closed to Closed	Closed to Open
Open to Closed	Open to Open

4) When the complete file is treated that way, the elements of the transition matrices are divided by the sum of their lines or by 1, whichever is larger. This gives the 16×4 matrices of transition probabilities, for each window and each temperature class. Their elements are the transition probabilities to pass from the initial state to the next state. Since the windows are moved at time intervals which are generally much more than 10 minutes, these matrices are mainly diagonal.

   If a line does not contain any transition, the window is either always closed or always open. The corresponding transition matrices are then arificially modified as shown below:

   Always closed $\begin{pmatrix} 1 & 0 \\ 1 & 0 \end{pmatrix}$ Always open $\begin{pmatrix} 0 & 1 \\ 0 & 1 \end{pmatrix}$

   This slight change ensures first that the sums of the lines are equal to one, as should be the sum of transition probabilities, and secondly that the correponding window will be put in its permanent state at the first time step, even if the starting state does not correspond to the reality.

4.2 Results

The four dwellings presenting an interesting average opening time as shown in Table 2 were treated that way. The 16 976 valid measurements were distributed between the temperature classes the following way:

Temperature class	[- 273, 0[	[0, 8[	[8, 16[	[16, + ∞[
Number of measurements	2743	7495	4241	2497

The Markov transition matrices are given in appendix 1, and can be used in computer codes as described in Section 4.2 below.

Some interesting statistical data are shown in appendix 2. Note that, for all the four chosen dwellings, the window 7 is always closed and the entrance door (5) has a high probability of closing when open. Each dwelling has at least two windows which are always closed. The generous opener (dwelling 41) has three windows which are open more than 95% of the time and his windows 2 and 14 are always open.

4.3 Generation of opening sequences

The technique used to reproduce synthetic data of window opening angle refers to the inverse function method[10]. This method is commonly used with stochastic processes and therefore will just be presented roughly here.

The inverse function method allows the generation of time series of a stochastic process given its distribution function. The only requirement is to dispose of a random number generator with a uniform probability density function between 0 and 1. The generated numbers, going from 0 to 1, are compared to the distribution function as shown on figure 2: for every number given by the generator, there corresponds only one state. In our case, the distribution functions have only two steps and are deduced from the lines of the Markov matrices.

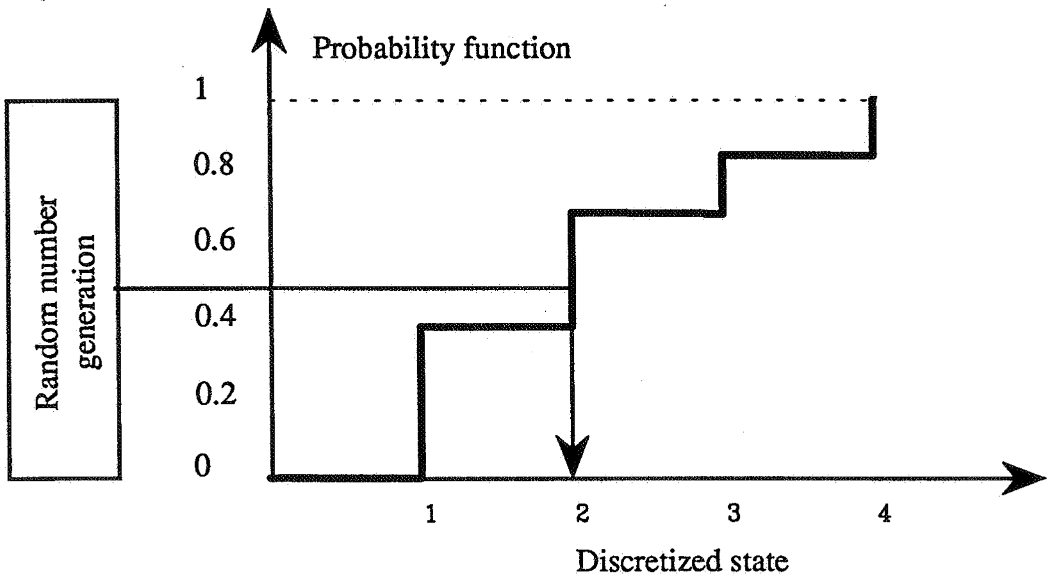

Figure 2: Generating a new state according a distribution function.

The following reconstruction procedure should be used for that model[3]:

1) At time t_0, a starting pattern of open windows is chosen arbitrarily.

2) The value of the outdoor temperature is examined, and the corresponding temperature class T ([- 273, 0[, [0, 8[, [8, 16[, [16, + ∞[ ) is noted. Choose the 16 transition matrices, $\underline{\underline{P}}_{j,T}$ (j = 1-16), corresponding to that class.

3) The line of the transition matrix corresponding to the state of the window j, contains the transition probabilities $P(S_0, S_1)$ to have the window in state S_1, at time t_1, knowing its preceding state S_0. Build the from that line of the matrix: the probability to become (or stay) closed is given in the first column and the probability to become either closed or open is 1..

4) The new state is generated at random according the distribution function, using the inverse function method.

5) Repeat the procedure from step 2 for the next time steps.

To take account of the very low night activity, the openings could be left unchanged from midnight to 7 AM. This was however not done in this work.

5. Evaluation of the Model

5.1 Comments on the evaluation procedure

It should first be stated here that a good evaluation procedure is to compare the air flow rates measured in a dwelling with the corresponding air flow rates obtained by a computer code using the presented model with its Markov matrices based on measurements in the same dwelling. Another, simpler possibility could be to compare computer code results for the same dwelling, obtained on one hand with measured opening schedules and on the other hand with opening schedules generated by the present model. These methods could however not be used within the present work, by lack of time to adapt an existing multizone infiltration code. This adaptation would require not only the present model but also a routine calculating air flow rates through large openings. This could be performed within the Annex 23 of the IEA-ECB research program.

A first estimate of the performances of this model can however be obtained by comparison of major characteristics of the generated data with reality. The compared characteristic are opening duration, frequency of changes, relation with the outdoor temperature and inter correlations between openings.

For that purpose, 6 opening schedules were reconstructed using the procedure described in Section 4.3 and the Markov matrices corresponding to the dwelling 43, whose total opening time was the closest to the global average. A different seed for the random generator was used for each schedule, but the real first state (i.e. the real status of the 16 openings at the first measurement) was always used as starting state. The reason is, that, when starting from a non realistic state (e.g. all windows closed), the Markov process takes some time to reach a realistic behavior. That way, even the first simulated days could be compared to the real data.

From these six rebuilt schedules, some statistics were calculated and compared with the same statistics extracted from the measured schedule. These comparisons are presented below.

5.2 Average duration of the openings

Table A 3.1 in Appendix 3 presents the number of 10 minutes time intervals during which the windows and doors are open, as well for the 6 calculated behaviors as for the measured one. It can immediately be seen that the average synthetic behavior is close to the measured behavior, except maybe for the window 13, in which a relative difference of more than 30 % is observed. χ^2 test, however, is not passed, even with a low probability.

The dispersion between the various rebuilt schedules varies with the opening. Large variations are seen in openings 1, 2, 4, 10, and 13 again. These openings are characterized by being seldom changed but changed anyway. In other words, they have many transitions from closed to closed and open to open, but very few (less than 5) transitions from open to closed or closed to open. In particular, window 13 started open and was closed once during the measurements.

In this case, the accuracy of the off-diagonal transition probabilities is poor (since based on a few transitions) and the re-calculated behavior is therefore not very accurate. This limit does not come from the model itself, but from the relatively small number of measurements on which the model is based. A good reproducibility of the total open time is obtained when the number of off-diagonal transitions is either 0 (always closed or open windows) or larger than 10.

This leads us to a first limitation: **The complexity of the model should be adapted to the available data.** In particular, it has no meaning to prepare detailed Markov matrices with many possibilities of transitions, if some of the transitions are poorly represented in the available data.

5.3 Number of transitions

Table A 3.2 in Appendix 3 presents the number of transitions from one state to the other. Here again, there is a good agreement between calculated and experimental data, the largest dispersions being for windows having few changes of state. This small discrepancy also comes from the reason evoked above. In this case, χ^2 test is passed, with a probability of 97.5 %.

Markov transition matrices were also rebuilt from the calculated data. They were found very similar, when not identical, to the Markov matrices built from the measured data. However, for particular windows like window 13, one rebuilt matrix (for temperature class 3) was purely diagonal, which looks strange, like if the window was closed and open, but without transition. In fact, the only transition was done in another temperature class and such a matrix tells that, for that temperature class, this window remains in the state it was when entering the temperature class.

5.4 Histogram of opening times

Figure 3 shows, always for dwelling 43, histograms of opening times, that is the number of windows open during less than 1 hour, between 1 and 2 hours, etc.... up to open more than 16 hours. The front histogram represents the experimental data, the next 6 ones are the 6 re-calculated data and the last one, in the back, is the average of these. This picture shows a good agreement between these data, except for the large opening times, where the algorithm overestimates the number of windows remaining open during more than 16 hours. Therefore, the χ^2 test is passed only with a probability of 10%.

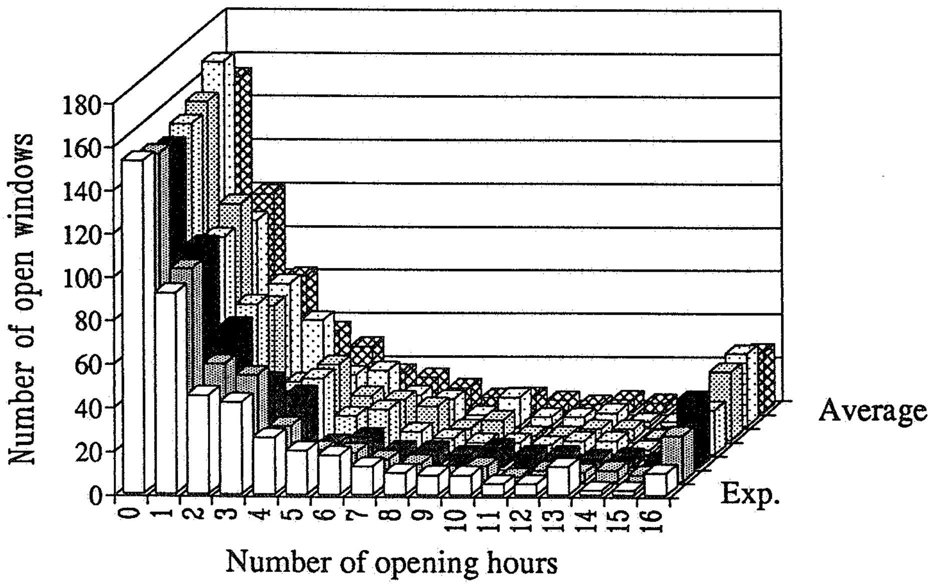

Figure 3: Histograms of opening times for dwelling 43. The experimented data are in front and re-calculated data are in back. The last histogram in the back is the average of re-calculated data.

5.5 Temperature dependance

Probability density function for the number of open windows in dwelling 43 and as a function of the outdoor temperature are presented on Figures 4 and 5, respectively for the experimental data and for one rebuilt set of data. Both figures show that the number of open windows increases with the outdoor temperature, and that general tendency is hence reproduced by the model.

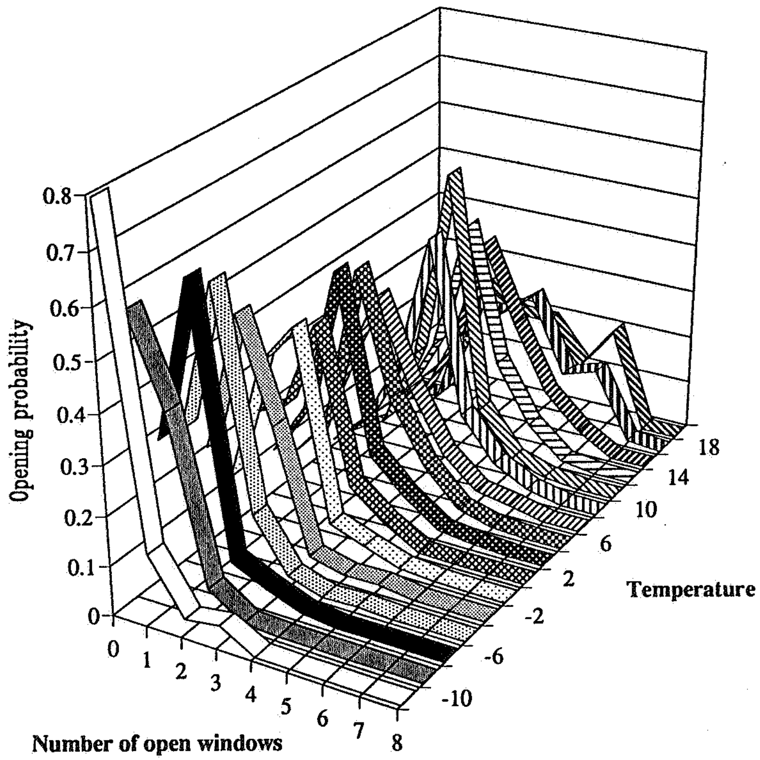

Figure 4: Probability density function for the number of open windows in dwelling 43 and as a function of the outdoor temperature.

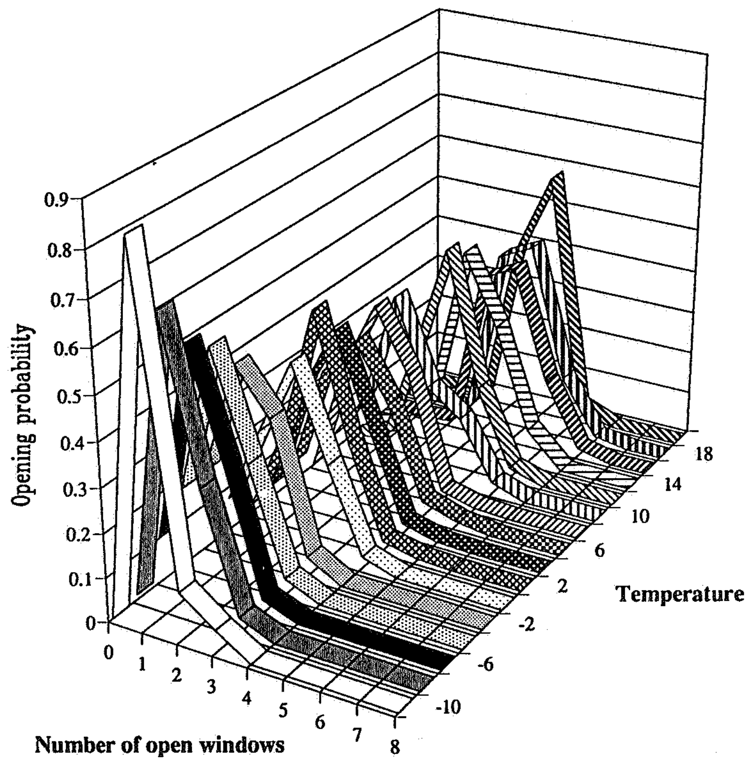

Figure 5: Probability density function for the number of open windows and as a function of the outdoor temperature for the data rebuilt using the model, based on measurements on dwelling 43.

However, large differences can be seen at very low and at high temperatures. At low temperatures (less than -6 °C), the algorithms underpredicts the probability to have all the windows closed and, therefore, overpredicts the probability to have one (or more) window open. At high temperatures (more than 12 °C), the model results in a probability density function which is narrower than the measured one. This summer phenomenon was already mentionned by Fritsch et Al.[3] who have restricted therefore the validity of their model to the heating season.

The small number of samples could also be a cause of that discrepancy. In the 2 degree wide classes which were used for these Figures, the 17000 measurements were inhomogeneously distributed: more than 500 measurements per degree class from -4 up to 8 °C, and 300 or less above 16 and below -6 °C.

5.6 Correlations and variances

The next stage was the comparison of the inter-correlations calculated from the synthetic and real time series of window openings. These cross correlation between the 16 windows and doors themselves and between these and the outdoor temperature and the number of open windows are shown on Tables A3.3 and A3.4 in Appendix 3, for the measured and re-calculated data respectively. These tables are symmetric, and on their diagonals are the variances of each opening.

The variances are very similar and, linking that result with the conclusions from Sections 5.2 to 5.4, one can say that the model reproduces the window openings with the same average opening time, the same average frequency of changes and the same variance. The slight exception is window 13, which moves only once during the measurement period used.

The cross correlations do not give, as one could expect, good results. First of all, there are correlations or anti-correlations between some windows which cannot be neglected, as is shown in Table A2.3. For example, there are some correlation (about 0.3 or more) between the following windows:

- 1 and 2: fanlights of the gallery-side bedroom,
- 8 and 9: fanlights of a balcony-side bedroom,
- 12,14 and 15: the balcony-side door and two bedroom windows located on the same facade.

The reason for the first four is quite obvious: these windows are open at the same time, either when going to bed or when waking up. Note that windows 1 and 2 are seldom open when windows 8 and 9 are open 60 to 80% of the time.

Windows 12, 14 and 15 are the most manipulated but the average opening time is relatively low: from 5% for the door 12 up to 34 % for window 14. It seems that they are open every day during a few hours to ventilate the dwelling.

There are also some anti-correlations, for example between the fanlight 8 and the window 15 located just under it. Window 13 also presents anti-correlations with several other windows, but, as already seen, one cannot have much confidence on the results implying the window 13.

The general conclusion of that is that **there are some correlations (positive and negative), which may not be the same for every user, but which cannot be neglected.** Therefore, the model presented here cannot be perfect, since it is based on independent windows.

This model, however, reproduces some correlations, as it is shown on Table A2.4. For example, openings 12, 14 and 15 as well as fanlights 8 and 9 are also slightly correlated in the reconstructed schedule, but with a lower correlation coefficient. On the other hand, the correlation between windows 1 and 2 disappears completely. These correlations remain because of the deterministic temperature dependance, and does not result from the model itself.

5.7 Time schedule

The daily time schedule can be reproduced only approximatively by this model, since it can only be introduced in a very rough way: by blocking the opening in their actual state during sleeping hours. In fact, no attempt was made in this direction for the present work, and the comparisons were made between the real time series and a series recalculated without any time-related constraint. Taking account of the real time schedule may give a more realistic result without making the model too complicated.

6. Conclusions

A stochastic model, allowing one to re-calculate the window opening for dwellings was developed from an existing model[3] and based on measurements taken in a large multi-family building located in the Netherlands[6,7,8]. This simple model requires only 16 numbers per opening, that is one 2 by 2 matrix for each temperature class and each opening. Since the sum of the lines of these matrices is one, even only half of these numbers should be really stored, that is a total of 515 numbers for 16 windows and 4 temperature classes

This model is simple. It assumes that the different windows of a dwelling are independent and refers to a basic stochastic process: Markov chains. The outside temperature acts as a driving variable for windows opening or closing. The required data are given for four different types of inhabitants, and allow therefore to simulate the effect of various behaviors on the ventilation in dwellings.

A simplified evaluation procedure was conducted on the generated series. The major statistic characteristics were compared and found to be similar, except for the openings with very few changes.

Two opposite limitations were found: on one hand, the model should be simple enough in order to be elaborated from a limited number of experiments. On the other hand, it could be improved to take account of the interactions between openings. An improvement which will not require more measured data is under study.

Nevertheless, this model could be implemented in the multizone air infiltration simulation programs. Together with a model calculating the air flow rates through large openings, it will allow to take account of different inhabitant behaviors and to predict their effects on ventilation.

Acknowledgements

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This work will be described in more details in an IEA-ECB Annex 20 report, which will be available by the authors and by the end of 1991.

Appendix 1
Markov matrices of transition probabilities

Table A1.1: Dwelling No 1: Least square deviation to the global average.

Window Number	Temperature class [°C] [-273-0]	]0-8]	]8-16]	]16-∞[
1	0.9921 0.0079 0.0275 0.9725	0.9911 0.0089 0.032 0.968	0.9885 0.0115 0.0183 0.9817	0.984 0.016 0.0018 0.9982
2	1 0 1 0	1 0 1 0	1 0 1 0	1 0 1 0
3	0.989 0.011 0.0865 0.9135	0.9861 0.0139 0.1123 0.8877	0.9842 0.0158 0.0424 0.9576	0.9713 0.0287 0.0129 0.9871
4	1 0 1 0	0.9999 0.0001 1 0	0.9998 0.0002 0.2308 0.7692	0.9933 0.0067 0.1538 0.8462
5	1 0 1 0	0.9997 0.0003 1 0	0.9986 0.0014 0.4 0.6	0.9909 0.0091 0.2637 0.7363
6	0.9996 0.0004 1 0	0.9991 0.0009 0.0968 0.9032	0.9993 0.0007 0.25 0.75	0.997 0.003 0.0376 0.9624
7	1 0 1 0	1 0 1 0	1 0 1 0	1 0 1 0
8	0.9926 0.0074 0.0818 0.9182	0.9904 0.0096 0.0102 0.9898	0.9855 0.0145 0.0043 0.9957	0.9773 0.0227 0.0004 0.9996
9	1 0 1 0	1 0 1 0	1 0 1 0	1 0 1 0
10	0.9993 0.0007 0.3333 0.6667	0.9985 0.0015 0.1831 0.8169	0.9966 0.0034 0.0079 0.9921	0.9934 0.0066 0.008 0.992
11	1 0 1 0	1 0 1 0	0.9973 0.0027 0.0578 0.9422	0.9953 0.0047 0.0896 0.9104
12	1 0 1 0	0.9973 0.0027 0.3333 0.6667	0.9926 0.0074 0.1965 0.8035	0.9634 0.0366 0.071 0.929
13	0.9989 0.0011 0.125 0.875	0.9963 0.0037 0.0368 0.9632	0.9944 0.0056 0.01 0.99	0.9981 0.0019 0.0086 0.9914
14	0.9996 0.0004 1 0	0.9995 0.0005 0.0781 0.9219	0.9953 0.0047 0.0305 0.9695	0.9901 0.0099 0.0148 0.9852
15	0.9996 0.0004 0.1429 0.8571	0.9982 0.0018 0.0522 0.9478	0.9935 0.0065 0.0439 0.9561	0.9756 0.0244 0.0147 0.9853
16	1 0 1 0	1 0 1 0	1 0 1 0	1 0 1 0

Table A1.2: Markov matrices of transition probabilities. Dwelling No 2 (Closed User)

Window Number	Temperature class [°C] [-273-0]	]0-8]	]8-16]	]16-∞[
1	0.9984 0.0016 0.0139 0.9861	0.9974 0.0026 0.0087 0.9913	0.9942 0.0058 0.0041 0.9959	0.9941 0.0059 0.0054 0.9946
2	1 0 1 0	1 0 0.0036 0.9964	0.998 0.002 0.0004 0.9996	1 0 0.0004 0.9996
3	0.9989 0.0011 0.0254 0.9746	0.9974 0.0026 0.0191 0.9809	0.995 0.005 0.0196 0.9804	0.9877 0.0123 0.0354 0.9646
4	0.9996 0.0004 1 0	0.9988 0.0012 0.2326 0.7674	0.9956 0.0044 0.1667 0.8333	0.9947 0.0053 0.2245 0.7755
5	0.9989 0.0011 1 0	0.9991 0.0009 0.2 0.8	0.9986 0.0014 0.5 0.5	0.9968 0.0032 0.36 0.64
6	0.9972 0.0028 0.0272 0.9728	0.9986 0.0014 0.0179 0.9821	0.9988 0.0012 0.0281 0.9719	0.9987 0.0013 0.013 0.987
7	1 0 1 0	1 0 1 0	1 0 1 0	1 0 1 0
8	0.9992 0.0008 0.0254 0.9746	0.9988 0.0012 0.0125 0.9875	0.9997 0.0003 0.0022 0.9978	0.9983 0.0017 0.0008 0.9992
9	1 0 1 0	1 0 0.004 0.996	0.9998 0.0002 0 1	1 0 1 0
10	0.9996 0.0004 1 0	1 0 1 0	1 0 1 0	1 0 1 0
11	1 0 1 0	1 0 1 0	1 0 1 0	1 0 1 0
12	1 0 1 0	0.9973 0.0027 0.2564 0.7436	0.9921 0.0079 0.0779 0.9221	0.9762 0.0238 0.0139 0.9861
13	0.9996 0.0004 0.1429 0.8571	0.9997 0.0003 0.0161 0.9839	1 0 0 1	0.9985 0.0015 0.0006 0.9994
14	0.9993 0.0007 0.1429 0.8571	0.9979 0.0021 0.0442 0.9558	0.9947 0.0053 0.0232 0.9768	0.9937 0.0063 0.0105 0.9895
15	1 0 0.3333 0.6667	0.9984 0.0016 0.0254 0.9746	0.9959 0.0041 0.0405 0.9595	0.9944 0.0056 0.0293 0.9707
16	1 0 1 0	0.9999 0.0001 0.0023 0.9977	1 0 0.0426 0.9574	0.9982 0.0018 0.0004 0.9996

**Table A1.3: Markov matrices of transition probabilities.
Dwelling No 41 (Open User).**

Window Number	[-273-0]		]0-8]		]8-16]		]16-∞[	
	1	0	1	0	0.997	0.003	1	0
1	0.0278	0.9722	0	1	0.0004	0.9996	0.0043	0.9957
	0	1	0.6667	0.3333	0	1	0	1
2	0	1	0.0001	0.9999	0	1	0	1
	0.9736	0.0264	0.9789	0.0211	0.9768	0.0232	0.9629	0.0371
3	0.0016	0.9984	0.0153	0.9847	0.0144	0.9856	0.0042	0.9958
	0.9996	0.0004	0.9999	0.0001	1	0	0.9971	0.0029
4	1	0	1	0	1	0	0.1321	0.8679
	1	0	0.9993	0.0007	0.9993	0.0007	0.9976	0.0024
5	1	0	0.3846	0.6154	0.6667	0.3333	0.875	0.125
	1	0	1	0	0.9998	0.0002	1	0
6	1	0	1	0	0.1111	0.8889	1	0
	1	0	1	0	1	0	1	0
7	1	0	1	0	1	0	1	0
	0	1	0	1	0	1	0	1
8	0	1	0	1	0	1	0	1
	0.998	0.002	0.9995	0.0005	0.9997	0.0003	1	0
9	0.0072	0.9928	0.0006	0.9994	0.0014	0.9986	1	0
	0.9855	0.0145	0.9961	0.0039	0.9995	0.0005	0.9977	0.0023
10	0.0004	0.9996	0.0014	0.9986	0.0022	0.9978	0.0006	0.9994
	1	0	1	0	1	0	1	0
11	1	0	1	0	1	0	1	0
	0.9985	0.0015	0.9921	0.0079	0.9887	0.0113	0.9655	0.0345
12	0.0519	0.9481	0.033	0.967	0.0099	0.9901	0.0085	0.9915
	0.997	0.003	0.9842	0.0158	0	1	0	1
13	0.0008	0.9992	0.0007	0.9993	0	1	0	1
	0	1	0	1	0	1	0	1
14	0	1	0	1	0	1	0	1
	0.9981	0.0019	0.9964	0.0036	0.9927	0.0073	0.9994	0.0006
15	0.0005	0.9995	0.0031	0.9969	0.0028	0.9972	0.0023	0.9977
	0.9992	0.0008	0.9987	0.0013	0.9995	0.0005	1	0
16	0.0348	0.9652	0.0073	0.9927	0.0202	0.9798	1	0

**Table A1.4: Markov matrices of transition probabilities
Dwelling No 43: Total average close to the global average.**

Window Number	[-273-0]		]0-8]		]8-16]		]16-∞[	
Window	0.9993	0.0007	0.9996	0.0004	0.9995	0.0005	1	0
1	0.0435	0.9565	0.0702	0.9298	0.0202	0.9798	1	0
	0.9996	0.0004	0.9999	0.0001	1	0	1	0
2	0.037	0.963	1	0	1	0	1	0
	0.9924	0.0076	0.9898	0.0102	0.9905	0.0095	0.9859	0.0141
3	0.058	0.942	0.0624	0.9376	0.0645	0.9355	0.041	0.959
	0.9996	0.0004	0.9995	0.0005	0.9998	0.0002	0.9992	0.0008
4	0.25	0.75	0.1739	0.8261	1	0	0.25	0.75
	0.9996	0.0004	0.9988	0.0012	0.9991	0.0009	0.9984	0.0016
5	1	0	0.5	0.5	1	0	0.5	0.5
	1	0	0.9996	0.0004	0.9991	0.0009	1	0
6	1	0	0.1667	0.8333	0.1071	0.8929	0.0714	0.9286
	1	0	1	0	1	0	1	0
7	1	0	1	0	1	0	1	0
	0.9969	0.0031	0.9939	0.0061	1	0	0.9987	0.0013
8	0.0035	0.9965	0.0013	0.9987	0.0003	0.9997	0	1
	0.9956	0.0044	0.9977	0.0023	0.9988	0.0012	0.9987	0.0013
9	0.014	0.986	0.0016	0.9984	0.0008	0.9992	0	1
	1	0	0.9999	0.0001	1	0	1	0
10	1	0	0.0167	0.9833	1	0	1	0
	1	0	1	0	1	0	1	0
11	1	0	1	0	1	0	1	0
	0.9996	0.0004	0.997	0.003	0.9934	0.0066	0.9862	0.0138
12	0.3333	0.6667	0.225	0.775	0.1714	0.8286	0.0537	0.9463
	1	0	1	0	1	0	1	0
13	1	0	0.0013	0.9987	0.002	0.998	1	0
	0.9963	0.0037	0.9926	0.0074	0.995	0.005	0	1
14	0.1842	0.8158	0.0679	0.9321	0.0083	0.9917	0	1
	0.99	0.01	0.9924	0.0076	0.993	0.007	0.9888	0.0112
15	0.0772	0.9228	0.0475	0.9525	0.0277	0.9723	0.01	0.99
	1	0	1	0	1	0	1	0
16	1	0	1	0	1	0	1	0

Appendix 2: Statistics.

16976 valid measurement periods of ten minutes, distributed as follows between the classes

Temperature class [°C]			
[-273-0[	[0-8[	[8-16[	[16-Ñ[
2743	7495	4241	2497

Table A2.1: Number of time intervals during which the window, (i = 1 to 16) is open.

Dwelling	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	sum
1 (small σ)	5850	0	3922	105	103	220	0	9302	0	2211	307	1036	2736	1565	2278	0	29635
2 (closed)	5768	5727	2552	201	73	1226	0	2982	325	1	0	1807	3348	1985	1225	764	27984
41 (open)	5148	16973	11766	55	24	8	0	16976	3034	11570	0	5688	16196	16976	9827	859	115100
43 (same μ)	179	28	2532	36	32	60	0	12692	8599	60	0	837	1260	5781	3839	0	35935

Table A2.2: Number of changes from open to closed or vice-versa, for each window or door (i = 1 to 16).

Dwelling	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	sum
1 (small σ)	218	0	388	36	60	36	0	149	0	65	44	223	99	76	136	0	1530
2 (closed)	74	5	120	81	48	50	0	26	2	2	0	162	8	93	78	10	759
41 (open)	11	1	239	18	28	1	0	0	13	25	0	192	15	0	45	25	613
43 (same μ)	14	4	291	16	36	14	0	27	39	2	0	152	1	139	215	0	950

Appendix 3: Comparisons, made on dwelling 43.

Table A3.1: Number of time intervals during which the window, (i = 1 to 16) is open.

Dwelling	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	sum
43 Rebuilt 1	154	1	2516	45	33	35	0	14458	10269	54	0	945	1325	5473	2797	0	38105
43 Rebuilt 2	293	33	2462	37	17	49	0	11766	7095	134	0	624	362	5589	3931	0	32392
43 Rebuilt 3	210	15	2323	16	38	50	0	12381	8029	48	0	689	1519	5240	3507	0	34065
43 Rebuilt 4	103	42	2860	5	21	55	0	9400	8805	1	0	826	1519	5120	3423	0	32180
43 Rebuilt 5	84	17	2785	34	32	22	0	12429	10976	17	0	641	383	5702	2951	0	36073
43 Rebuilt 6	238	80	3013	64	40	31	0	11217	10539	151	0	975	67	5207	3314	0	34936
Average	180	31	2660	35	30	40	0	11941	9286	68	0	783	863	5388	3316	0	34625
43 measured	179	28	2532	36	32	60	0	12692	8599	60	0	837	1260	5781	3839	0	35935

Table A3.2: Number of changes from open to closed or vice-versa, for each window or door (i = 1 to 16).

Dwelling	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	sum
43 Rebuilt 1	12	2	287	12	40	10	0	26	38	4	0	160	1	152	200	0	943
43 Rebuilt 2	18	4	277	14	22	12	0	37	29	4	0	148	1	191	240	0	997
43 Rebuilt 3	25	2	256	10	40	14	0	34	38	2	0	152	1	162	228	0	964
43 Rebuilt 4	16	6	334	8	26	8	0	25	33	2	0	152	1	143	219	0	973
43 Rebuilt 5	9	4	340	16	42	12	0	28	45	2	0	138	1	138	223	0	998
43 Rebuilt 6	20	10	301	28	36	12	0	30	47	4	0	170	1	169	228	0	1056
Average	17	5	299	15	34	11	0	30	38	3	0	153	1	159	223	0	989
43 (same μ)	14	4	291	16	36	14	0	27	39	2	0	152	1	139	215	0	950

Table A3.3: Cross-correlations between windows, dwelling 43, Experimental Data
On the diagonal (bold characters) are the variances of each window opening.

No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	T_{ext}	Sum
1	**0.01**	0.34	0.12	0.00	0.02	-0.01	0.00	0.03	0.00	-0.01	0.00	0.03	0.05	-0.01	0.07	0.00	-0.01	0.16
2	0.34	**0.00**	0.06	0.00	0.00	0.00	0.00	-0.07	0.00	0.00	0.00	-0.01	-0.01	-0.03	0.02	0.00	-0.06	0.04
3	0.12	0.06	**0.13**	0.03	0.07	0.04	0.00	0.09	0.05	-0.02	0.00	0.16	0.02	0.04	0.11	0.00	0.06	0.41
4	0.00	0.00	0.03	**0.00**	0.00	0.00	0.00	0.01	0.02	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.05
5	0.02	0.00	0.07	0.00	**0.00**	0.00	0.00	0.02	0.01	0.00	0.00	0.04	0.01	0.01	0.04	0.00	0.02	0.09
6	-0.01	0.00	0.04	0.00	0.00	**0.00**	0.00	0.03	0.03	0.00	0.00	0.01	0.04	0.05	0.06	0.00	0.03	0.12
7	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	0.03	-0.07	0.09	0.01	0.02	0.03	0.00	**0.19**	0.36	0.03	0.00	0.00	0.16	0.05	-0.11	0.00	0.16	0.50
9	0.00	0.00	0.05	0.02	0.01	0.03	0.00	0.36	**0.25**	0.06	0.00	0.08	-0.29	0.30	-0.02	0.00	0.26	0.57
10	-0.01	0.00	-0.02	0.00	0.00	0.00	0.00	0.03	0.06	**0.00**	0.00	0.02	-0.02	0.01	0.00	0.00	-0.01	0.07
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	0.03	-0.01	0.16	-0.01	0.04	0.01	0.00	0.00	0.08	0.02	0.00	**0.05**	-0.04	0.28	0.37	0.00	0.34	0.45
13	0.05	-0.01	0.02	-0.01	0.01	0.04	0.00	0.16	-0.29	-0.02	0.00	-0.04	**0.07**	-0.18	0.03	0.00	-0.01	0.09
14	-0.01	-0.03	0.04	-0.01	0.01	0.05	0.00	0.05	0.30	0.01	0.00	0.28	-0.18	**0.22**	0.44	0.00	0.77	0.64
15	0.07	0.02	0.11	-0.01	0.04	0.06	0.00	-0.11	-0.02	0.00	0.00	0.37	0.03	0.44	**0.17**	0.00	0.41	0.53
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00
T_{ext}	-0.01	-0.06	0.06	0.00	0.02	0.03	0.00	0.16	0.26	-0.01	0.00	0.34	-0.01	0.77	0.41	0.00		0.62
Sum	0.16	0.04	0.41	0.05	0.09	0.12	0.00	0.50	0.57	0.07	0.00	0.45	0.09	0.64	0.53	0.00	0.62	**1.77**

Table A3.4: Cross-correlations, dwelling 43. Rebuilt data

No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	T_{ext}	Sum
1	**0.02**	-0.01	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.05	-0.01	0.00	-0.03	-0.02	-0.05	0.02	0.00	-0.06	0.00
2	-0.01	**0.00**	-0.02	0.00	0.00	0.00	0.00	-0.02	-0.04	0.00	0.00	-0.01	-0.01	-0.03	0.03	0.00	-0.08	-0.04
3	0.00	-0.02	**0.12**	0.01	0.01	0.02	0.00	0.02	0.02	0.00	0.00	0.00	-0.06	0.07	0.02	0.00	0.07	0.23
4	-0.01	0.00	0.01	**0.00**	0.00	0.00	0.00	0.00	0.02	0.00	0.00	-0.01	-0.01	-0.01	-0.02	0.00	-0.02	0.01
5	0.00	0.00	0.01	0.00	**0.00**	0.00	0.00	-0.01	-0.01	0.00	0.00	-0.01	0.00	0.01	0.01	0.00	0.01	0.02
6	-0.01	0.00	0.02	0.00	0.00	**0.00**	0.00	0.03	-0.03	0.00	0.00	-0.01	-0.01	-0.03	0.03	0.00	-0.01	0.04
7	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	-0.01	-0.02	0.02	0.00	-0.01	0.03	0.00	**0.21**	0.15	-0.12	0.00	-0.03	0.10	-0.12	-0.03	0.00	-0.08	0.25
9	0.05	-0.04	0.02	0.02	-0.01	-0.03	0.00	0.15	**0.24**	-0.08	0.00	-0.02	-0.13	0.01	0.04	0.00	0.12	0.30
10	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.12	-0.08	**0.01**	0.00	0.01	-0.01	-0.04	-0.05	0.00	-0.02	-0.02
11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	-0.03	-0.01	0.00	-0.01	-0.01	-0.01	0.00	-0.03	-0.02	0.01	0.00	**0.04**	-0.03	0.19	0.13	0.00	0.22	0.26
13	-0.02	-0.01	-0.06	-0.01	0.00	-0.01	0.00	0.10	-0.13	-0.01	0.00	-0.03	**0.02**	-0.09	-0.08	0.00	-0.02	0.05
14	-0.05	-0.03	0.07	-0.01	0.01	-0.03	0.00	-0.12	0.01	-0.04	0.00	0.19	-0.09	**0.22**	0.27	0.00	0.69	0.56
15	0.02	0.03	0.02	-0.02	0.01	0.03	0.00	-0.03	0.04	-0.05	0.00	0.13	-0.08	0.27	**0.18**	0.00	0.33	0.45
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	0.00	0.00
T_{ext}	-0.06	-0.08	0.07	-0.02	0.01	-0.01	0.00	-0.08	0.12	-0.02	0.00	0.22	-0.02	0.69	0.33	0.00		0.68
Sum	0.00	-0.04	0.23	0.01	0.02	0.04	0.00	0.25	0.30	-0.02	0.00	0.26	0.05	0.56	0.45	0.00	0.68	**3.95**