AN APPROACH TO THE CALIBRATION OF BUILDING ENERGY SIMULATION MODELS

J A Clarke, PhD, P A Strachan, PhD and C Pernot

ABSTRACT

As part of the model validation and development activities of a European research initiative in the area of passive solar architecture, a validation/calibration methodology has been developed which emphasises the use of empirical data in the model proving process and, if necessary, model calibration before use. This procedure has been applied to the ESP-r system in order that it might be used to investigate the replication potential of several passive solar components - most notably conservatories and advanced glazing systems. It is believed that the technique can equally be applied to the performance of building components other than passive solar.

This paper describes the validation/calibration methodology. A major feature of the approach is the depth of detail: high quality, high resolution data is used throughout. This is in contrast to the more general approaches which use data from a large number of sparsely monitored buildings. The paper also describes the application of the methodology to the ESP-r system and the program's subsequent use to investigate the benefits to accrue from the use of conservatories in a domestic context.

BACKGROUND

In 1986 the European Community's energy R&D directorate established a major collaborative venture in the field of Passive Solar Architecture known as PASSYS (Wouters and Vandaele 1990). The aim was to increase confidence in passive solar systems through 1) the development of a component testing procedure, 2) the validation and refinement of a reference simulation program to permit performance scaling and replication assessment and 3) the development of better design tools. The work of PASSYS was undertaken within three specialist sub-groups addressing test methodology, model validation and simplified design tools. To enable the collaborative dimension of the project, each national consortium (representing ten European countries) had access to identical test cells, with integral heating/cooling plant and data acquisition. In support of the model validation work, each team utilised Unix workstations on which were resident the simulation program ESP-r – for Environmental Systems Performance, research version (Clarke 1985).

The work summarised in this paper is the outcome of work undertaken within the model validation sub-group of PASSYS as reported in full elsewhere (Jensen 1993).

THE PASSYS METHODOLOGY

The methodology has validation, calibration and scaling/replication elements as follows.

Program Validation

The methodology extends the work of earlier researchers, most notably those at the National Renewable Energy Laboratory (formerly Solar Energy Research Institute) in the US (Judkoff 1983) and those at the Building Research Establishment and academic institutions in the UK (Bloomfield et al 1988). The methodology comprises 4 components, not all of which need be applied in a given context:

- Initial examination of a program's theory and a thorough inspection of the corresponding source code.
- Analytical verification involving a comparison of predictions with analytical solutions which apply to some well defined, usually simplified case.

- Inter-program comparison involving an assessment of the level of agreement between a target program and other programs which are usually better known to the validators or may have been subjected to a greater degree of previous testing.
- Empirical validation involving a comparison of predictions with measured data for the same problem.

Of these components perhaps the most important is empirical validation since it has the potential to both quantify prediction accuracy and indicate possible causes if poor. This component received most attention within the PASSYS project and has the following elements:

- Prior to an experiment, an estimate of the likely principal factors are obtained to ensure that the resolution of the captured data set is well matched to the model to be tested. This might be carried out by the target simulation program so that its inherent sensitivities become the focus of the experiment. The use of a simulation program will require:
  - An accurate description of the experimental configuration - a test cell in the case of PASSYS - with measured parameters used where possible.
  - A sensitivity analysis to assess the influence of the program's input parameters on predictions in order to determine sensor and accuracy requirements.
- Experimental implementation adhering to the requirements and constraints as identified in the preceding step.
- As the experiment proceeds, the recorded data will require careful logging, pre-processing, checking and documenting if the data set is to approach high quality. This aspect received significant attention within the PASSYS project (Jensen 1993).
- Program/data comparisons can now proceed and will involve the following steps:
  - An initial `blind' run of the program is made using the carefully formed system model and the measured climatic data.
  - Goodness-of-fit is then assessed by means of parametric sensitivity analysis which is used to estimate the uncertainty bands associated with the predicted time series.
  - For cases in which dynamic aspects dominate and/or where more information is required on the cause of poor agreement, a statistically-based approach (Palomo et al 1991) is employed, which is based on an analysis of residuals (the difference between measurements and predictions). This entails estimating the autocorrelation function and power spectrum of the residuals and determining the cross-correlation functions between program inputs and residuals in the time and frequency domains. Tests applied to these data can yield information on which program inputs are responsible for the residuals and so give an indication of which physical processes are not being adequately represented by the program.

As simulation techniques become more widely used as the basis of future design tools so the need for program accreditation will grow (Van de Perre et al 1991). Validation methodologies will be an essential part of accreditation, acting to ensure that, for a limited number of cases at least, the predictions from candidate programs are acceptable.

It should be noted that a distinction is made between the program (the simulator) and the model (simulator plus the representation of the problem being studied).

Model Calibration

The foregoing empirical validation methodology is powerful in that it can be used to identify the cause of poor program performance. Ideally such knowledge can be used to explore possible solutions - in the form of theoretical extensions or refinements to the input model. Unfortunately this process is complicated by several issues:

- Algorithms may have been developed from limited experimental evidence so that their range of validity is constrained.
- All software implementations will have internal assumptions which may not be explicitly stated.
- Energy models tend to be complex with many interactions.

- There may be some uncertainty associated with the basic properties of the building to be simulated.

While it is often possible to vary input parameters to minimise residuals, the difficulty lies with ensuring judicious intervention. Clearly, if a program is to be used to undertake design studies, it is essential that any `tweaking' be fully justified. In some cases, where residuals are not great and where removing the cause of the problem is difficult, an alternative approach is to use the experimental data to calibrate the model and so align its predictions with the measurements. By this means a model can be tuned to represent a system over a realistic range of operating conditions. The calibrated model can then be used, with caution, to extrapolate performance to other contexts by means of the scaling and replication procedures as outlined in the following section.

As has been noted by many workers (e.g. Bronson et al 1991), actually calibrating a model can be problematic in that the user has to decide which of the inputs must be changed in order to reconcile measurements and predictions. There are two aspects to this problem. Firstly, the input parameter(s) that may be in error must be selected, or a deficiency in the simulation program must be isolated. Secondly, the modification(s) required to achieve a good fit must be calculated. The expertise of the user is a large factor in both cases.

This problem has been tackled in a number of ways: from manual, iterative, pragmatic intervention (Carabott 1989, Kaplan et al 1990); through the production of a suite of informative graphical comparative displays (Bronson et al 1992) and the use of special tests and analysis procedures to isolate and compare individual energy flows (Subbarao 1989, Balcomb et al 1993); to a technique for automatically adjusting user selected input parameters to reduce the discrepancy between measured and predicted data (Carroll et al 1989, Carroll and Hitchcock 1993).

Within the PASSYS methodology, calibration entails the selection and justification of the interventions to be made, either to the model of the system under study or to the program. The process comprises some or all of the following steps.

- The use of other sensor information - for example surface temperature and flux measurements - to isolate potential reasons for large residuals.
- Establishing, by sensitivity studies, the inputs or algorithmic adjustments that are significant in terms of the predicted performance characteristics.
- Establishing, by residuals analysis, the correlation between program inputs and the residuals.
- The application of identification techniques to determine appropriate values of `lumped' model parameters to minimise residuals (Van Dijk 1991). For example, identification using measured data can extract the effective construction UA value for comparison with the predicted value. If necessary, the program or its input model can then be adjusted (assuming that the experiment has been suitably designed to minimise the standard errors associated with the identified value). Attempts have also been made within PASSYS to directly identify values of the input parameters which would minimise the residuals, but this technique is not yet proven.

To give an example of the calibration process, assume that a program has been shown by the validation methodology to be deficient in its modelling of the convective processes at internal surfaces. After study of measured and predicted air and surface temperatures, it is suspected that the problem lies within the algorithms for the estimation of the buoyancy driven convection coefficients. It is confirmed by sensitivity study and residuals analysis that increased convective coefficients lead to better agreement between the measured and predicted surface and air temperatures. As an alternative to theoretical intervention, it is a relatively simple task to impose measured convection coefficients on a simulation so that the program can be applied to study other aspects of performance, which have been demonstrated by the validation methodology to be adequately represented.

With the PASSYS methodology, the process of model calibration is especially enabled because of the potential to produce high quality data sets and the possibility of rapidly configuring passive solar components as required. The process differs in two respects from the techniques of the other researchers

as cited above:
- The subject is a particular building component whose performance is investigated in detail on a test cell, whereas the other approaches are largely concerned with generic studies based on data from full-scale buildings.
- Changes are only made when there is evidence to support the conclusion that incorrect values had been used in the original model or that the program is deficient in some way.

The approach is possible because all experiments are test cell based, with high levels of instrumentation, close control and deliberate design to isolate the cause of any prediction shortcoming.

Scaling and Replication

Application of the PASSYS validation methodology to a particular test component and operating regime will have one of two outcomes: either a program will be shown to give acceptable predictions or it will not. In the latter case it may be possible to improve predictions by theoretical means or calibration. After confidence in a program's ability to model the performance of a given passive solar component is achieved, it can be used to scale the component's behaviour to real buildings and to undertake replicability studies by assuming alternative design/climate configurations. In this way modelling can be used to bridge the gap between the controlled environment of the test cell and the complex issues encountered in practice. This was a principal mode of use of the ESP-r system within the PASSYS project: to determine the extent to which the performance benefits of conservatories and advanced glazing systems, as indicated by test cell experiment, translated to real designs when subjected to realistic patterns of occupancy, climate and air flow (Strachan and Guy 1991).

As elaborated within the PASSYS project, scaling and replication - the complement of calibration – involves the following considerations.
- Selection of a reference design.
- Simulation of this design before and after application of the passive solar component and its associated control (where a calibrated program is used, the component is modelled in the same way as in the test cell experiment).
- Analysis of performance in terms of energy and comfort criteria.
- Incremental adjustments to the design parameters, with repeated simulations in order to determine the optimum configuration.

Replication entails studying the impact of alternative design options when placed in different climate contexts. Clearly, a passive solar component that works well for one design/climate combination may perform badly for another. Replication involves extrapolation which implies that the program may be used outside its proven confidence limits. This is thought to be an acceptable `risk' provided that 1) the initial proving experiments are designed in such a way as to ensure that the passive solar component is tested across a representative range and 2) that experimental uncertainties are minimised by ensuring that monitoring standards are high. The PASSYS facility is well equipped in these respects.

APPLICATION OF CALIBRATION

As an example of the application of the calibration methodology, consider the case of the PASSYS test cells as shown in Figure 1. The left-most cell has an attached conservatory, the right-most cell has a well insulated south wall used in experiments to determine the response of the test cell (this was termed a `calibration' wall - not to be confused with the subject of this paper). The aim of the research was to determine the performance of conservatories. This required the production of a model of the test cell and conservatory, an empirical validation study to confirm that the conservatory performance could be successfully predicted over a representative range of conditions, calibration if required, and finally a scaling of the observed performance to a real building context. Details of the test cells, the conservatory, the experiment and the ESP-r model are available elsewhere (Wouters and Vandaele 1993, Jensen 1993).

Figure 1: The PASSYS test cells in Glasgow.

Initial experiments were carried out on the cell fitted with the calibration wall to ensure that the ESP-r model of the test cell itself was adequate - the prerequisite to studying the test cell fitted with a passive solar component. In the event it was shown that edge effects and thermal bridges gave rise to significant modelling uncertainty which could not be easily overcome by input parameter modification or theoretical improvements. For this reason it was necessary to enter model calibration mode.

Calibration of the Test Cell Model

Given the test cell geometry and construction details, a model was developed to conform to the input requirements of the ESP-r system. The relatively thick walls (400mm) of the test cell introduced the problem of large differences between the internal and external surface areas, which rendered a uni-directional conduction modelling scheme unsuitable. On the basis of 2-D and 3-D steady-state calculations, changes were made in the test cell model to account for these effects by introducing additional `edge' constructions (Jensen 1993).

A comparison of the measured and predicted results for experiments of 9 weeks duration undertaken by several teams at different European sites showed that there were still significant discrepancies. Lumped parameter values from identification analysis and observations of other measured and predicted parameters (e.g. surface temperatures) led to the conclusion that the test cell model

- under-predicted heat losses (primarily due to effects of temperature-dependent conductivities),
- had too high an internal capacity, and
- under-predicted internal convective heat transfer coefficients.

<u>Estimation of Internal Capacity:</u> The results from identification, from ESP-r analysis and from a 2-D dynamic analysis indicated that the internal capacity in the test cell model should be reduced in the edge constructions. Here, internal capacity is defined as the heat stored when the internal temperature of the cell is increased, with external conditions being unchanged. The identified value of the internal capacity of one of the test cells at the Belgian Test Site was 2.25 MJ/K while that of one of the UK test cells was 2.33 MJ/K.

For the internal capacity, all the walls are taken into account except for the south wall and for the partition wall between service room and test room. In an iterative process of changing the density and heat capacity for the edge constructions in the original test cell model, three different schemes were used to estimate the internal capacity of the test cell:

1. Summing the volume weighted specific heat capacities of each homogeneous element. A first estimate of the internal capacity was then obtained by halving this value (for homogeneous constructions this is true).
2. Applying ESP-r against an internal air temperature step and then adding the capacities of each layer when multiplied by the temperature drop from the starting value (15°C) to its equilibrium temperature. The conditions for the simulations were:
   - external climate constant 15°C, no solar irradiation, no wind;
   - internal air temperature step from 15°C to 25°C;
   - internal and external surface convection coefficients 1000 W/m^2 K to ensure that the air temperature is equal to the surface temperature;
   - external emissivities set to zero to remove the longwave exchange;
   - no infiltration;
   - no casual gains.
3. Summing the difference between the external and internal convective flux for each time step during the simulation period (because this is the only mechanism through which energy is transferred to the mass). The conditions for the simulations are the same as in scheme 2.

The results from these three schemes are given in Table 1. For reasons of clarity, only three different runs of the iterative process are shown.

Table 1: Results of the analysis of the internal capacity of the test cell (in MJ/K).

nr	Test Cell Model	Scheme 1	Scheme 2	Scheme 3
1	Original model, exclusive north & south walls	4.40		3.56
2	As 1 but other combination of density and heat capacity[#]	2.49	2.35	2.25
3	As 1 but other combination of density and heat capacity[##]	2.37	2.25	2.27
[#] Density and heat capacity for the edge constructions, 83 kg/m^3 and 1800 kJ/kg respectively. [##] Density and heat capacity for the edge constructions, 67 kg/m^3 and 1800 $kJ/kg respectively.				

The combination 67/1800 for the density and heat capacity for the edge constructions seems to be satisfactory. The result of the first scheme of 2.37 MJ/K is in the identified range although it is a little large because the construction is not homogeneous. The second scheme yields 2.25 MJ/K and is equal to the identified value. The calculated internal capacity by ESP-r, 2.27 MJ/K, is also very close to the identified values.

From this analysis the conclusion was reached to use the construction model as generated for calculation number 3 in the above table.

<u>Internal Convective Heat Transfer Coefficients:</u> To ensure full mixing in the test cells, air is circulated using fabric hoses. Because of this it was thought likely that the internal convective heat transfer coefficients (htc) as calculated by ESP-r, based only on buoyancy-driven convection, would be too low. For this reason it was considered justifiable to use calculated values from the measured data. The identified internal htc for different data sets vary oin the order of 3 to 7 W/m^2 K. For the datasets:

Belgian calibration wall 1:	7.1 W/m^2 K
Belgian calibration wall 2:	7.3 W/m^2 K
Greek calibration wall:	3.3 W/m^2 K
German calibration wall :	4.5 W/m^2 K

The values were deduced from an analysis of the four datasets. Inputs of the calculations are mean internal air temperature ($\theta_{i,air}$), mean internal surface temperature ($\theta_{i,s}$) and mean external temperature ($\theta_{e,s}$) averaged over the experimental period. The estimated heat transfer coefficients were calculated from:

$$h_{i,c} = 1/R \text{ x } (\theta_{i,s} - \theta_{e,s}) / (\theta_{i,air} - \theta_{i,s})$$

Extra evidence was provided by measurements from the German team, who reported a value of 3.5 W/m^2 K. Therefore, it was decided to use fixed internal convective coefficients for all interior surfaces of the test cell: as a first estimate, a value of 5 W/m^2 K was selected.

UA-values: The overall UA value of the test cell model was also calculated from simulations and compared with identified values. This predicted value of 7.8 W/K compared with identified values from the Belgian and UK experiments of 7.95 W/K and 7.39 W/K respectively. The modified test cell model therefore yields an overall UA value that is within the identified range.

The predicted UA value of the partition wall between the service room and the test room was 1.7 W/K, compared with identified values from the Belgian and UK experiments of 1.84 W/K and 2.1 W/K respectively. This is thought to be due to the thermal bridging of pipes and wires through the wall, not taken into account in the simulation model. Accordingly, an adjustment was made to the modelled partition wall construction.

Temperature Dependent Conductivity: Ideally it is preferable to apply temperature dependent conductivities. An increase of conductivity of 5% per 10°C is typical for insulation materials, so over the operating range of temperatures in the cells errors introduced by applying temperature independent conductivities could be significant. However, in the timescale of the work programme, it was not considered feasible to incorporate the required code modifications.

Other Considerations: The cells were thoroughly sealed and checked with pressurisation and tracer gas measurements. A representative value of infiltration (on the order of 1% of overall cell losses) was included in the model. For testing of components where infiltration was not negligible, the test site facility included the capability of continuous tracer gas measurements which could be superimposed on the simulations.

Results: Figures 2 and 3 show the measured and predicted comparison before and after the calibration procedure. A sensitivity study was undertaken which showed that the majority of the remaining observed differences could be accounted for by considering temperature dependent conductivities. However, as mentioned previously, code modifications were not introduced at this stage. It was considered that the agreement between measured and predicted temperatures was satisfactory.

Given a calibrated model of the test cell, it was then possible to progress to the study of passive solar components. A number of components were studied in detail in the course of the PASSYS programme, including a lightweight reference wall, the same wall with the addition of thermal mass, a wall with transparent insulation, a Trombe wall, a curtain wall and a Timber-Frame wall with different glazing types (Jensen 1993).

Calibration of the Test Cell and Conservatory Model

The results presented here are for the case of a conservatory operated in buffer mode, that is with no air interchange between the conservatory and the test cell. (Other conservatory modes of operation, notably solar ventilation pre-heat, and other components were also studied.) After establishing an ESP-r model of the configuration, simulations were performed using measured climate data but with no knowledge of test cell performance. The uncertainty bands associated with the ESP-r predictions were then obtained from sensitivity analysis using two techniques:

- Differential Sensitivity Analysis (DSA) in which the total uncertainty band was obtained as the root mean squared summation of the individual uncertainties due to each input parameter.
- Monte Carlo Sensitivity Analysis (MCSA) in which the total uncertainty band was obtained by perturbing all the input parameters simultaneously.

The results from the two techniques were similar. The predicted internal air temperatures in the conservatory are shown in Figure 4 with uncertainty bands from the MCSA technique superimposed. Overall uncertainty bands are narrow, reflecting effective control of the experiment in terms of the ESP-r input parameters. The magnitude of the uncertainty band is however temperature-dependent, primarily because a major part of the uncertainty in conservatory air temperature prediction is caused by the solar radiation measurement (the instrument accuracy is about ±3%).

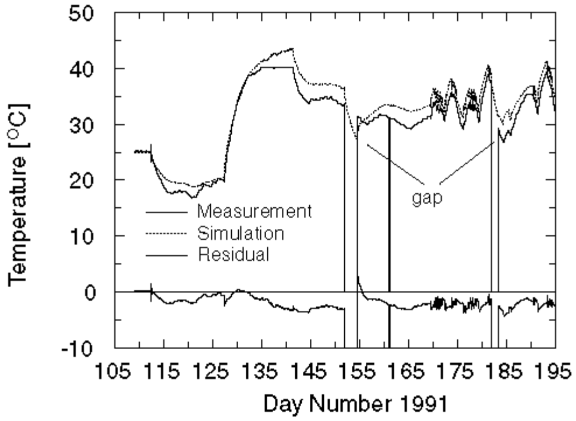

Figure 2: Comparison of measured and predicted cell air temperatures <u>before</u> calibration.

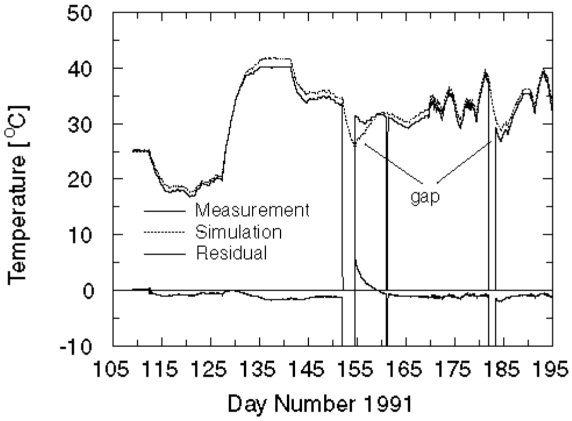

Figure 3: Comparison of measured and predicted cell air temperatures <u>after</u> calibration.

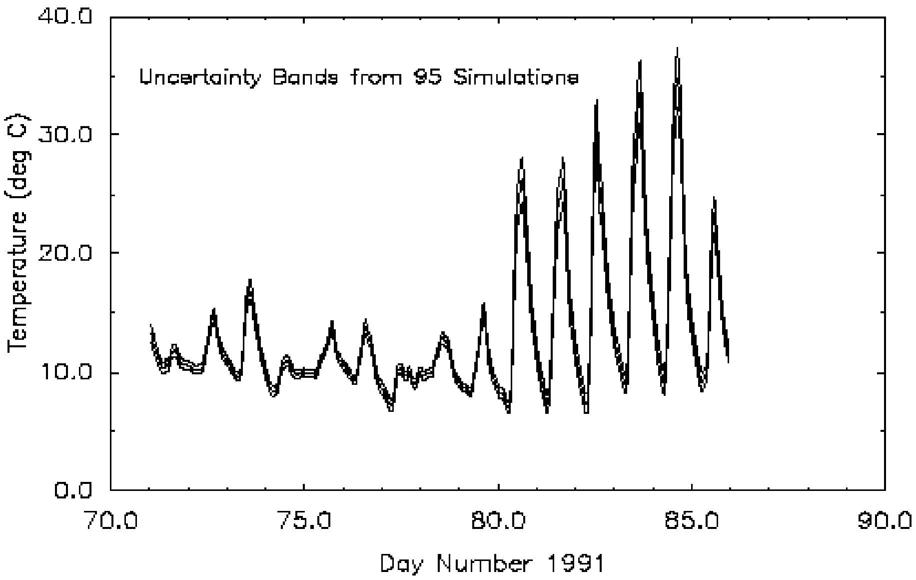

Figure 4: Predicted conservatory air temperature with Monte Carlo uncertainty bands.

With respect to the measured conservatory air temperature, the average of 7 sensors distributed through the conservatory are plotted. The uncertainty in individual measurements is ±0.2°C. However, the spread in temperature among the sensors varies from ±0.25°C at night up to ±1.5°C at mid-day. An overall uncertainty of ±0.5°C has therefore been assumed, although a more detailed analysis would produce uncertainty bands for the measured data that vary in line with the variation among the sensors. Figure 5 shows the comparison of measured and predicted conservatory air temperatures over the full period, plotted together with the external air temperature. (For clarity, only uncertainty bands on the predictions are shown on this graph.) The analysis presented here is for hourly-averaged data. More detailed analyses were also carried out with 1 minutely measured and simulated data.

It should be noted that the comparison presented is based on a `blind' validation. No changes were made to the input description of the conservatory as defined before the experiment. Overall, it is considered that the results show a good level of agreement between measurements and ESP-r predictions, given that the performance of a single-glazed conservatory is likely to be very sensitive to the algorithms for internal and external convection, longwave flux exchange and shortwave distribution. For most of the period the predicted and measured temperatures lie within the narrow uncertainty bands. At times when the uncertainty bands do not overlap, the implication is that there is a deficiency in the input model or the program (if not the data). The most obvious occasion is at night in the second half of the simulation period, when daytime solar radiation levels are high and when the sky is probably clear at night time. However, as shown in Figure 6, there are occasions in the first period of the simulation (notably at day numbers 77.7 and 79.0) when there is a sudden difference between measurements and predictions. These do not appear to be correlated to time of day.

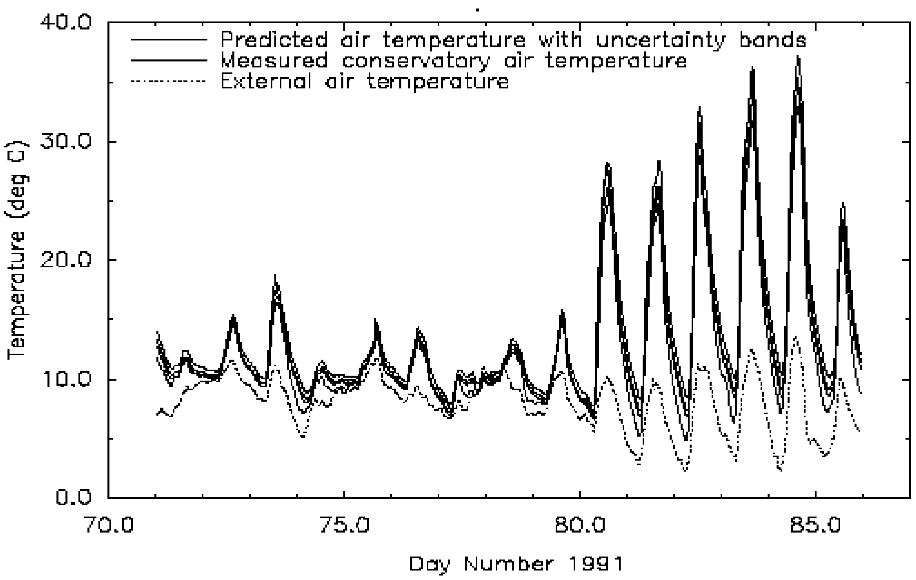

Figure 5: Comparison of measured and predicted conservatory temperatures for 15-day period: buffer mode.

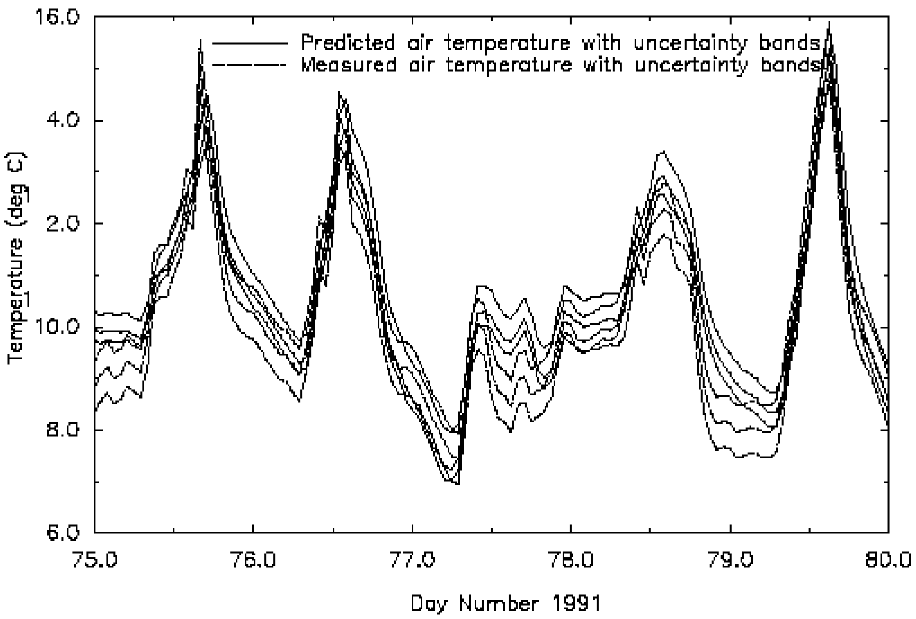

Figure 6: Magnification of part of the time series comparison of measured and predicted conservatory air temperatures.

In order to investigate the cause of these disagreements the PAMTIS statistical analysis package (Palomo et al 1991) was used to analyse the residuals. This package enables the analysis of stochastic multivariate processes in the time and frequency domain.

In the analysis, the variables included are those which the user considers may be important in explaining discrepancies between measured and predicted results, together with the residuals. In the case of the conservatory, which is primarily driven by external climate, the principal parameters were considered to be the solar radiation (direct and diffuse), the external temperature, wind speed, relative humidity and the temperature inside the test cell. This was confirmed by the results of a sensitivity analysis, which calculated the impact of uncertainty in all model input parameters.

Figures 7 and 8 show the residuals plotted alongside the chosen input parameters. The mean of the residuals, a measure of the capability of the model to reproduce the steady-state response, is -0.56°C. The variance, which indicates the fluctuation of the residuals about the mean value, is 0.92°C. Both these indicators confirm that the overall agreement between measured and predicted data is good. It is clear that there is a correlation between the residuals and solar radiation, external temperature, humidity and test cell temperature. However, these parameters are also strongly cross-correlated: for example the test cell temperature rises above its 20°C heating set-point during periods of high solar radiation.

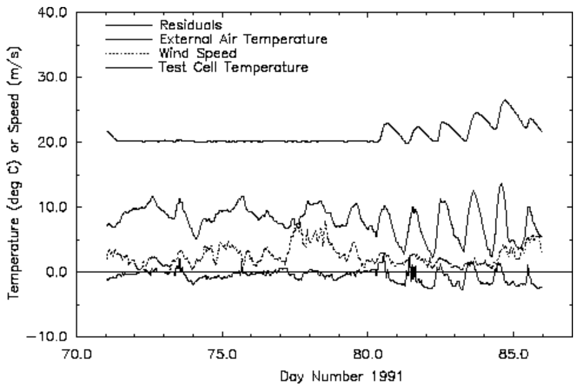

Figure 7: Residuals, temperature and wind speed.

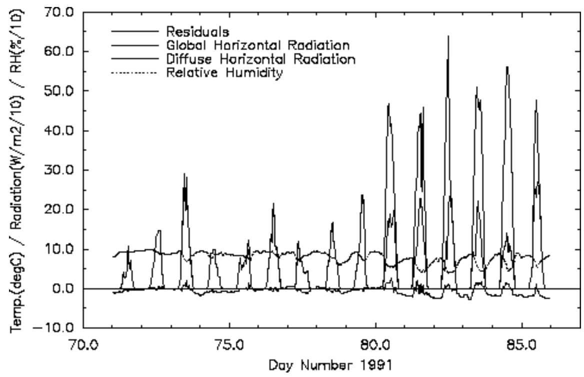

Figure 8: Residuals, solar radiation and relative humidity.

In the present case, the most informative outputs from the analysis were the plots of squared multiple coherency together with the partial coherencies (shown in Figures 9 and 10) for the selected input parameters. The squared multiple coherency gives an indication of the proportion of the residuals spectrum that can be predicted from the selected inputs. For example, in the Figures, at a frequency of 0.05 (approximately 1.25 hours), over 90% of the residuals can be explained from a combination of the 6 chosen input parameters. The partial coherencies show the portion attributable to the individual input parameters. These statistical measures are particularly important in this case because they take into account the (high) cross-correlations between the input parameters.

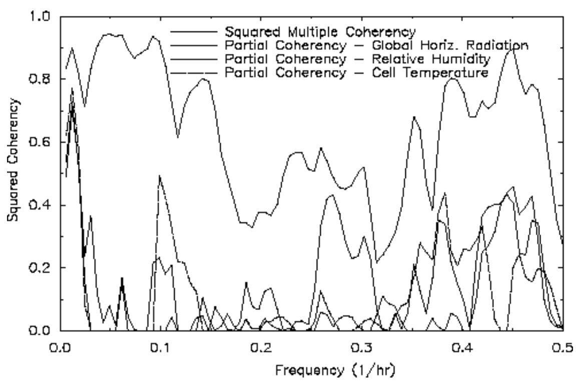

Figure 9: Results of residuals analysis – multiple and partial coherencies.

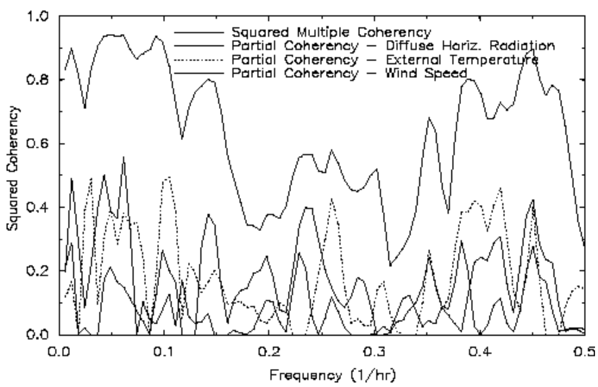

Figure 10: Results of residuals analysis – multiple and partial coherencies.

From the residuals analysis, it was concluded that:

- At high frequencies (equivalent to periods of 2-3 hours) and low frequencies (equivalent to periods greater than 6 hours) most of the residuals can be predicted from the selected inputs.
- At the frequencies where the inputs could explain most of the residuals (frequencies around 0.04 and 0.08-0.1) the important inputs are wind speed, external temperature and cell temperature. At lower

frequencies (approaching steady-state) global horizontal radiation, internal cell air temperature and relative humidity are indicated as being significant.
- At the higher frequencies, the important inputs are solar radiation (global and diffuse), external temperature and relative humidity.

One problem with the use of residuals analysis in the experiment presented here is the particularly strong correlation between the important factors determining conservatory response. Ideally the experiment should de-correlate these factors by, for example, applying random heating pulses or using blinds, which are operated independently of solar intensity levels. However, three tentative conclusions were drawn from the study.

- ESP-r's external longwave exchange algorithm should be investigated. Predicted temperatures are higher than measured on clear nights and relative humidity, as used by ESP-r to estimate night time sky temperature, has been shown to be important in the residuals analysis. Additionally, the sensitivity analysis indicated that conservatory response was particularly sensitive to the sky view factors. (As a result, external longwave flux and glass surface temperatures were measured in later experiments.)
- The thermophysical properties of the Timber-Frame Wall (between the conservatory and the test cell) should be checked. Laboratory measurements were used for all material densities and conductivities, but an assumed value was used for the solar absorptivity of the outside surface, which was shown by the sensitivity analyses to be important. The solar absorptivity should be measured, or inferred from the measured temperature profiles through the wall construction.
- Because any uncertainty in surface convection flux transfers could account for the observed importance of external temperature in explaining the residuals, the sensitivity of predictions to assumptions regarding internal convection coefficients should be checked (possibly by using alternative algorithms as available in ESP-r).

For the conservatory experiment, the level of agreement between measured and predicted data from the blind validation run was considered sufficient that no adjustments were necessary before the conservatory model was utilised in the scaling study. However, it is believed that the type of analysis discussed can be useful in identifying sources of discrepancy, and thus in enabling calibration should this be required. For example, the enhancement of ESP-r's calculated night time longwave fluxes would have led to slightly better agreement.

USE OF THE CALIBRATED ESP-r MODEL

Given the good level of agreement between the measured and predicted performance of the conservatory on the test cell, it was considered justifiable to extrapolate to a real building. The aim of the scaling exercise was to compare the performance of a reference design when operated with and without a conservatory. Only brief details are presented here to indicate the approach and the potential.

The reference design was selected on the basis of a community consultation aimed at ensuring typicality and acceptability. The final selection comprised a direct gain, passive solar, detached house with a U-value of 0.03 W/m^2 K. The house is of conventional block and brick, with an above average glazing area on the south facade.

A detailed 14-zone `base case' model of the house was developed, with occupancy schedules and air flow networks defined. In the results presented here, a light occupancy schedule typical of a working family was used. Instead of assuming fixed air change rates, a moderately tight leakage scheme was defined so that pressure and buoyancy-induced air flow was represented and modelled explicitly. This meant that zone infiltration rates and inter-zone air flows were calculated at each time-step as a function of the changing zone temperatures and wind-induced surface pressures. Simulations were then carried out with this base case model.

A single-glazed conservatory was then added to the building in accordance with best practice and simulations carried out for several operational modes including:

Buffer: The model of the house and leakage distribution was unchanged except for the leakage path from the living room. It was found that adding the conservatory reduced ventilation in the living room below acceptable levels. The size of the opening to the conservatory was thus increased to give comfortable levels of ventilation.

SVPH: Solar Ventilation Pre-Heat mode involved the ducting of air from the conservatory to the living room, with the rest of the house leakage unchanged. Results are presented for two cases: 0.5 changes per hour for the living room and 0.5 changes per hour for the whole house.

Simulations were conducted using climate data from the UK example year, Kew 1967 (52°N). Table 2 shows the predicted energy consumption for space heating for the whole house over an assumed heating season of October to April inclusive.

Table 2: Space heating requirements (kWh).

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	Total
Base	530.6	1151.2	1680.9	1789.1	1421.6	1040.4	914.9	8528.8
Buffer	494.7	1139.1	1680.8	1780.9	1392.9	984.9	869.2	8342.4
SVPH (0.5 ac/h living room)	482.1	1090.5	1614.4	1706.5	1335.1	925.3	814.9	7968.8
SVPH (0.5 ac/h whole house)	485.1	1151.2	1695.7	1786.8	1388.2	946.4	817.9	8271.2

Conclusions drawn from this scaling study included:

- Energy savings are small in the middle of winter but increase significantly towards the start and end of the heating season.
- Performance is governed by the impact of the conservatory on air flow rather than on solar gain. For example, 0.5 volume changes per hour SVPH for the whole house gives rise to higher air flow through the house and thus greater ventilation cooling.

It was found that the significant benefits of solar ventilation pre-heat, calculated during the test cell experiments, were much reduced when modelling a real building where occupancy and infiltration effects reduced the utilisation of the available energy. Once the base model has been developed, it is then possible to test various parametric variations of the model in order to optimise performance and establish the replication potential of the device or process.

CONCLUSIONS

The PASSYS project has elaborated a model validation/ calibration methodology, which places the emphasis on the empirical component. In essence, the methodology is simple: use simulation to obtain model predictions and parameter sensitivities; use developed guidelines to initiate an experiment and capture a high quality data set; use prescribed techniques to quantify residuals and determine their cause; then, as appropriate, implement algorithmic modifications, impose measurements or use identified parameters to produce the calibrated model. The program/model combination can then be used to undertake design studies, which extend the scope and depth of the initial experiments.

Although in essence simple, implementational difficulties will derive from such factors as data uncertainty, statistical interpretations, and uncertainties when extrapolating from the test cell to full scale. As the use of simulation grows, there will develop a need for procedures to accredit programs. The emerging validation and calibration techniques point to a future in which program proving and application can be placed on a rational basis.

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