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Energy and Buildings 30 (1999) 61-71

**ENERGY
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Confidence of simulation results: put a sensitivity analysis module in your MODEL

The IEA-ECBCS Annex 23 experience of model evaluation

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Abstract

The goal of performing sensitivity analysis of a simulation model is to determine the effect of input variation and the effect of input uncertainty on the output data. Sensitivity analysis is an unavoidable step in model validation, and it is also generally useful in performing simulations. The user must know the influence of the accuracy of the data that is input to the program. This paper presents a methodology for performing sensitivity analysis as well as the tools that implement this methodology, MiSA and LiSA, that were developed within the IEA-ECBCS Annex 23 'Multizone air flow modeling'. The basic concepts of sensitivity analysis as well as the main characteristics of the developed tool are presented. More detailed information are available in the final report of the sub-task 3 'Evaluation of COMIS' of the Annex 23 [J.-M. Fürbringer, C.-A. Roulet, R. Borchiellini, Evaluation of COMIS, final report IEA.ECB & CS Annex 23 Multizone Air flow Modelling, LESO-PB, EPFL, 1015 Lausanne, Switzerland, 1996.]. © 1999 Elsevier Science S.A. All rights reserved.

Keywords: Sensitivity analysis; Model validation; Network air flow model; Monte-Carlo simulation; Factorial design

1. Introduction

Validation is a word which is somewhat abused in discussions of simulation models since a model can never be validated, but rather not invalidated. The use of simulation in practice requires a warranty that the results conform to reality, and this is only possible by a comprehensive evaluation and a generalized sensitivity analysis. In order to assess simulation results, several tools have been developed, tested and improved within the IEA-ECBCS Annex 23 'Multizone Airflow Modeling'. The whole methodology of 'validation' has been reviewed, re-analyzed and adapted to the field of multizone air flow simulation [1,5].

An up-to-date methodology with a robust background and efficient tools is taking form. The main conclusion of all the validation work within the IEA-ECBCS Annex 23 is « Put a SAM in your model », SAM being the acronym for Sensitivity Analysis Module. This study highlighted that a good model must feedback to the user the influence of the accuracy of the input parameters to the model. This can be done by calculating confidence inter-

vals for the results. This paper shows how this can be done and what types of tools are needed. Another paper on this issue illustrates this with examples from the annex work [8].

The necessity of integrating a tool for sensitivity analysis into the modeling environment has appeared since it became evident that sensitivity to input uncertainty depends not only on the structure of the building (number of floors and zones as well as their geometrical distribution) but also on the input values themselves, for example, the wind direction or the temperature difference between two zones. Large sensitivity to input uncertainty appears often near equilibrium situations which occur for specific values of structural parameters or weather conditions. When large sensitivity is detected, it is critical to evaluate if it is due to an intrinsic instability of the numerical solution or if it depends on a particular ratio between some input parameters, a ratio which may have only a small probability to be reproduced in reality.

The performance of a sensitivity analysis allows trends to emerge. In the future, the use of interval arithmetic to model physical behavior of a building would make the formulation of output in terms of trends. This will have a more significant physical meaning than the one point simulations commonly being made today, which are rarely

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secured by error analysis. The SAM is an intermediate step towards this improvement.

Another important advantage of integrating a SAM in your model is that it gives the possibility of performing parametric study and optimization 'on line'. Those who did such work with a one-run model and a closed user interface, and who remember the boring work of creating successive input files for this back and forth process, will certainly appreciate the possibility of managing this in an easier way.

A SAM will allow the user more time for conceptual and creative phases of a project. A SAM enables the comparison of different solutions to determine whether or not they correspond to significantly different results, and through the parameter effect determination, it makes it possible to understand why they differ.

One of the original goals of the SAM development within the Annex 23 was to facilitate the use of factorial design for the sensitivity analysis of simulation models. The use of factorial design provides the possibility of a feedback on the input as well as satisfactory concepts to handle the multivariable aspect of the problem. The technique of factorial design comes from the experimental field. Fisher set it up as an improvement of the Latin square design in 1926 when he was working in the agricultural research establishment of Rothamsted [3]. The technique was used in simulation by Naylor [15] in 1969. After one gains an understanding of the main concepts of this technique, it can be applied to any field to improve the way simulations or measurements are performed. New techniques arise today with quasi Monte-Carlo methods that are more efficient in the presence of strong non-linearity but factorial designs are a reference because of their simplicity [7,10,12,19].

2. Knowledge structure

The verification of the output data of a model with corresponding experimental data is equivalent to the scientific process of iteratively changing from model to reality and back. A maximal redundancy is required between information contained in the program results and the experimental data used for comparisons. But it is not correct to consider experimental data as the reality, the absolute reference. Because of their uncertainty, experiments give only an image of reality and the fidelity of this image is determined by the confidence intervals.

These epistemological concepts are important to defining a correct validation procedure. Fig. 1 presents the knowledge model used in the project. This model is based on the epistemology of Kant [11]. This theory affirms that we never directly access the pure reality called *noumenon*. Through the measurement, we access the *phenomenon* that is the sensible reality.

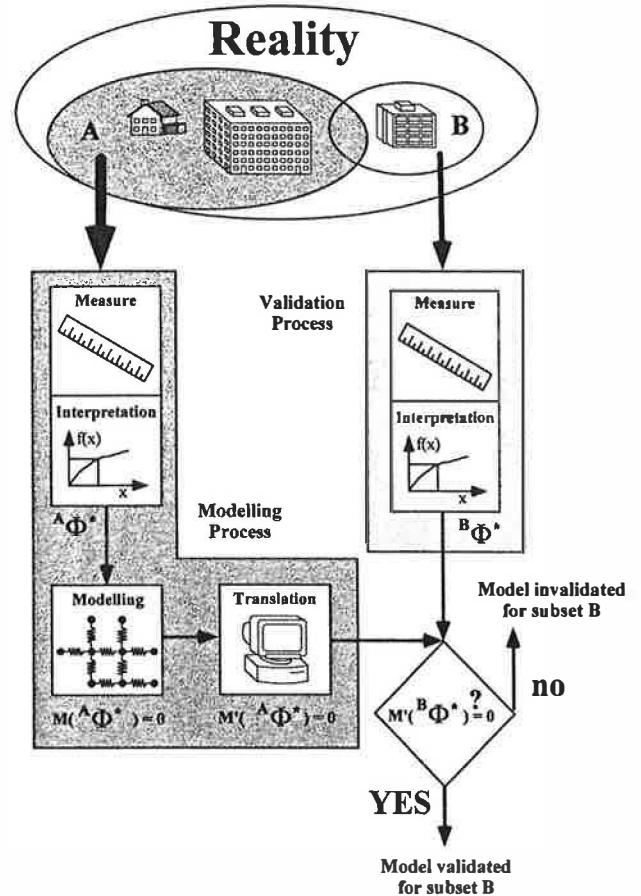


Fig. 1. Knowledge model used to elaborate the validation process. Squares represent operators acting on the reality or on the output of other operators. The reality is first questioned to obtain data used to model the phenomenon. Interpretation, modeling and translation (in computer algorithm) are the main operations for obtaining a simulation model. When validating this model, new measurement on a distinct subset is necessary.

The measurement of some observables on object A, which is a subset of reality, provides a set ${}^A\Phi$ of data that gives an image of the reality. The rough results depend on the type of probes. These results are interpreted to obtain a set of observables in the usual units of temperature, pressure, flow rates, etc. This interpretation is based on a model of the measuring device. The interpretation of a temperature measurement, for example, implies the modeling of the thermometer. In building physics, the measuring device model is sometimes extremely complex.

The modeling of object A consists in determining the link between some elements of ${}^A\Phi$ to reproduce its behavior and predicting the values of some observables as a function of the values of some other ones, typically energy flows and comfort variables as a function of weather conditions and building characteristics. If M is the function linking interpreted observables, this can be represented by Eq. (1)

$$M({}^A\Phi) = 0 \quad (1)$$

The building of a program on the basis of this model M consists of translating it to M' following the constraints of

numerical and computer science. By definition the model is compatible with the data upon which it is based.

But the interest of a model lies in the possibility of a generalization, which means the possibility of modeling with the function M , another object B similar for some points to A . Typically, for the case of building physics, researchers are elaborating models reproducing thermal and aerualic behavior of the largest possible number of buildings in various weather conditions. The validation consists of verifying that whatever the object B satisfying the validity criteria of the model, Eq. (2) is verified:

$$M({}^B\Phi *) = 0 \quad (2)$$

When the relation is not verified it is necessary to understand the cause, to know whether it is a limit of the model or an error. Each operator constituting the measurement, the interpretation, the modeling and the translation are susceptible to errors (Fig. 1). The validation procedure must take that into account and allow the screening between modeling, measurement and programming errors. The numerical methods available for that task are the Monte-Carlo and the factorial techniques.

3. Global sensitivity by Monte-Carlo design

The Monte-Carlo technique (Fig. 2) allows the estimation of the conjugate influence of the varying input parameters, which are chosen at random in accordance with their probability distribution. With a relatively small number of runs ($N_{\text{run}} < 100$ independent of the number of variables), it is possible to determine the means and standard deviations of the output parameters with 10% accuracy (See Refs. [6,17] for technical details). The Monte-Carlo method is currently used in many research fields. Examples of its application in the field of building physics can be found in Ref. [13].

Random selection of values for input parameters limits the number of runs necessary to test the model, and makes the number of simulations independent of the number of input parameters. However, the resulting confidence inter-

val is global, i.e., the effects of all the varied parameters as well as the conjugate effects merge.

The range of the input probability distribution gives the opportunity to handle the validity domain of the resulting sensitivity:

- For a local sensitivity analysis focused on a precise point of the input parameter domain, small ranges of only a few percent or even less are used.
- For realistic analysis aimed at the determination of the confidence intervals, the actual input parameter confidence intervals are used.

4. Effect determination by factorial and similar designs

For determining separately the effect of input parameters, a more sophisticated technique must be used: the factorial method or a similar one. The factorial design consists of choosing the simulation points at the edge of the multi-dimensional domain defined by the input parameter ranges. For learning about this design of experiments and its theoretical background please refer to Refs. [2,9]. The use of factorial matrices in simulation is detailed in Refs. [4,6]. The method consists of fitting the simulation results to an appropriate polynomial function corresponding to a Taylor series of the analyzed model.

Full factorial design allows the determination of all the coefficients of a linear model with all possible interactions (cf. Eq. (3)) with 2^{N_p} runs. This design has the disadvantage of requiring a lot of runs and is practicable only for small numbers of input parameters.

$$Y = \alpha_0 + \sum_{i=1, N} \alpha_i X_i + \sum_{i \neq j} \alpha_{ij} X_i X_j + \sum_{i \neq j \neq k} \alpha_{ijk} X_i X_j X_k + \dots + \alpha_{ijk \dots N} X_i X_j X_k \dots X_N \quad (3)$$

The fractional factorial design takes advantage of the small probability that all the effects are significant. The effects are distributed in subsets by mean of linear relations. Those relationships are based on the group properties of the set of columns of a factorial matrix associated with the multiplication operation. One handles these groups through the concept of aliases. The latter are the relationships between elements of a subgroup, and generators. Generators define at the same time the relation between the column of the fractional factorial matrix as well as the distribution of the coefficients into the subgroups. The number of runs to obtain the desired effects is now divided by 2^{N_s} . The literature provides a list of generators to build convenient matrices for a given situation [2,14]. Additional runs can be performed afterwards to complete the initial set and increase the 'resolution power' of the design.

The Plackett and Burman [16] design can be efficiently used when the interactions between input parameters are assumed to be negligible. In $N_p + 1$ runs, the main effects of input parameters are estimated with a higher accuracy than a star design treating each parameter separately in

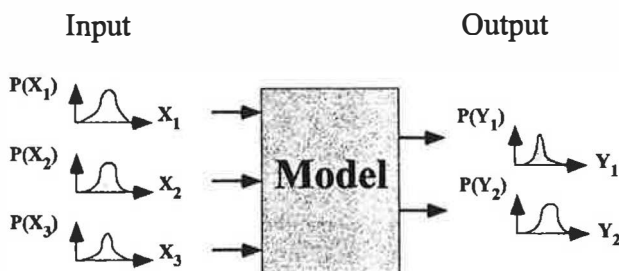


Fig. 2. Scheme of Monte-Carlo technique for sensitivity. The output parameter uncertainty characterized by the probability distribution $P(Y_i)$ is obtained by multirun simulation with input data chosen at random following the distributions $P(x_i)$.

$2N_p$ runs. Plackett and Burman designs exist for up to 200 parameters. Efficient algorithms exist for N_p equal to a power of 2.

5. The steps of the sensitivity analysis

It is practical to separate the different tasks to be done by this procedure: (1) *Aim selection*: The user must choose the technique to be used. The choice depends on the analyzed model. It can be a sensitivity analysis, a surface response or a parametric study. It could be also a sophisticated optimization procedure. (2) *Factor selection*: The choice of the factors whose influence on the model have to be determined is a critical point of sensitivity analysis. In the Monte-Carlo method, as the number of varied parameters is not related to the number of simulations, the best strategy consists of including the maximum number of input parameters in the study. In factorial design, the number of simulations is strongly related to the number of factors. The choice must be a balance between the resolution of the design and the magnitude of the investigated field. To compensate for these types of limitations, groups of factors can be constituted. For example, all the volumes of a building can be grouped and then varied at the same time and in the same proportion. A distinction can then be made between an actual input parameter that would be in this case the volume of a zone of the building and the volume as a generic parameter. The factor selection ends by the transmission of this information to the simulation process (see below). This is done, in a simulation environment based on input files, by the edition of a so-called REFERENCE file(s) which is (are) similar to the input file(s), but the parameters to be varied are preceded by numbered flags whose order corresponds to the column order in the experiment and range matrices. In models receiving their parameters directly from the keyboard, additional procedures must be written. (3) *Design selection*: Depending on the number of parameters and the initial knowledge, different strategies are available depending on the desired goal. For sensitivity study, the choice resides, among others, between Monte-Carlo, factorial, fractional factorial, or Plackett–Burman designs. These designs are provided through algorithms that produce normalized matrices by care of generality and efficiency (cf. post-processing). The simulation environment must accept a matrix of simulation as input and provide output in the form of a matrix. Such a matrix is arranged with parameters by column and simulations by row. (4) *Range selection*: By only changing the variation range of the input it is possible to perform different types of analyses. One possibility is a ‘general’ study, in which all the parameters are treated the same way. Another possibility is to study specifically the influence of a given pattern of inaccuracy. The usual shift of the range is from a proportional range of a few percent for all the parameters to a range pattern corresponding to the actual confidence interval of each

input parameter. The uniform increase of the input parameter ranges is also used to observe the evolution of the interactions around a given point of the experimental domain. The effects will be closer to the local derivatives for smaller ranges, but the domain of validity of this information is also reduced in the same proportion. A special treatment is reserved for parameters which can have discreet values only. (5) *Input file edition and multi-run interface*: The automation of the input file edition avoids the very boring task of entering repetitive answers by the keyboard. This multirun facility is the key to popularizing the use of sensitivity analysis and optimization techniques. If the model requires an unformatted input file, a simple routine of text editing is used to replace flagged numbers by the correct values calculated from the design and range matrices. If the program requires a formatted input file, special care must be taken when editing it so that the format will be respected, and the process of scanning a flagged input file will remain useable. After the input file editing process, the model is run several times, and the results are sent to an output file. If the program does not read input from files, data coming directly from a user interface, the technique must be adapted, requiring the modification of the code. (6) *Post-processing*: This step of the analysis varies from one strategy to another. With the Monte-Carlo technique, this step consists of calculating means and standard deviations of selected output data. Confidence intervals can then be calculated from statistical distributions as Student and Chi-square. For factorial design, the effects are determined by resolving a linear system by least square fit. For optimization, the analysis process emerges on a new set of simulations. The most practical situation is to have the output in a matrix of the same structure as that of the input parameters, ordered horizontally by output parameters and vertically by runs. (7) *Analyses and graphing*: For the Monte-Carlo method the interesting results consist of the mean and the standard deviation of each output data. If the output data is a time series, a band can be drawn which shows clearly the zone of probable response (Fig. 3b). The limit of the band can be roughly estimated as a function of the standard deviation. More precisely, it is the integration limits of the output histogram corresponding to a given ratio of the total area of the histogram (Fig. 3c). To control the convergence of the simulation it is also informative to plot the evolution of the mean value and the standard deviation (Fig. 3a). For the factorial design, the analysis is based on the fitting of an empirical model by the least square method. From the model of Eq. (3), model matrix \mathbf{M} is built and the coefficients $a_i, a_{ij}, a_{ijk}, \dots$, corresponding to the main and conjugate effects of the input parameters, are calculated following Eq. (4) (The second part of the equation being valid only when the matrix of experiment is orthogonal) [3]:

$$\alpha = (\mathbf{M}^T \mathbf{M})^{-1} \mathbf{M}^T \mathbf{Y} = 1/N_{\text{run}} \mathbf{M}^T \mathbf{Y} \quad (4)$$

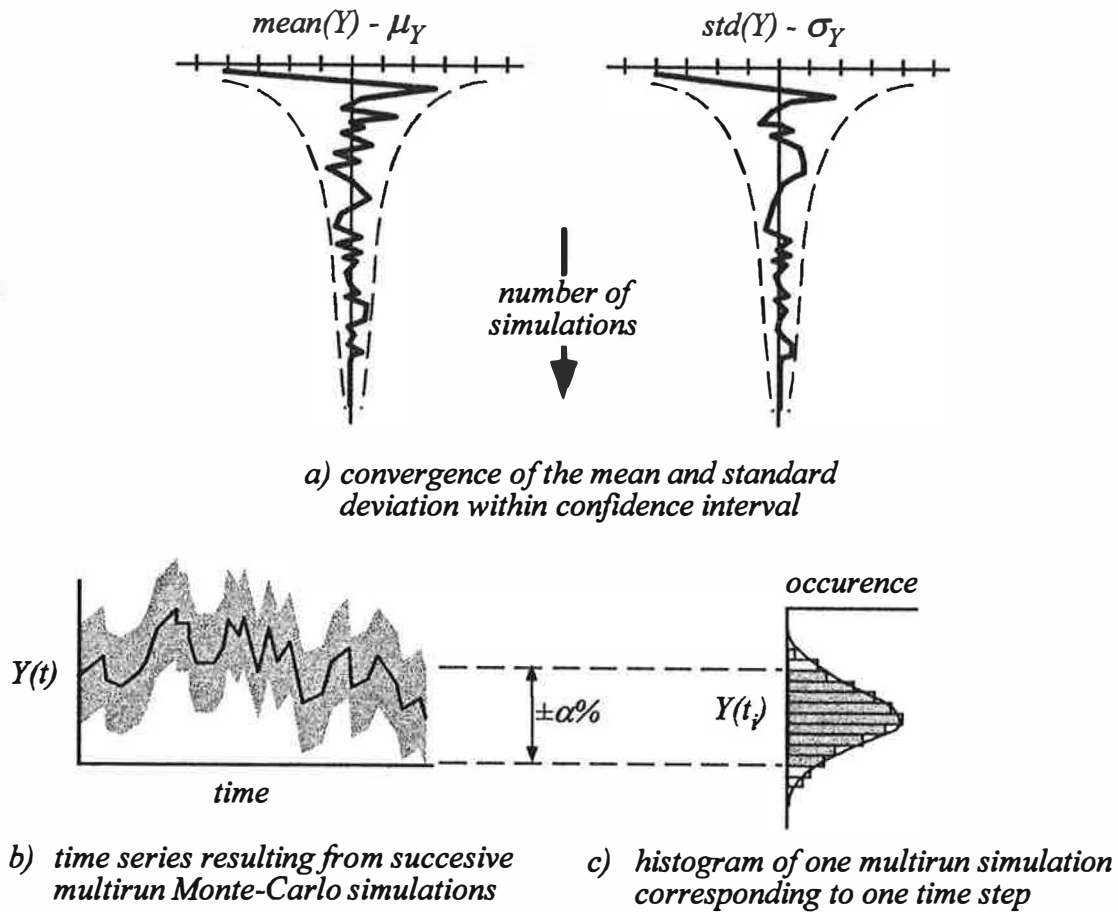


Fig. 3. Graphical analysis of a Monte-Carlo simulation. In (a) the convergence of the mean and standard deviation is checked by plotting the statistics obtain after each run. In (b) the confidence interval around the time series of an output $Y(t)$ is estimated using the MC technique, to each time step corresponds a set of results which can be analyzed with a histogram (c).

An informative way of presenting these results consists of plotting the relative effects in a bar chart as presented in Fig. 4. The relative effects are obtained by dividing main

and conjugate effects by the mean effect α_0 . The effect of the factorial design can be used to estimate the standard deviation and then the confidence interval of an output.

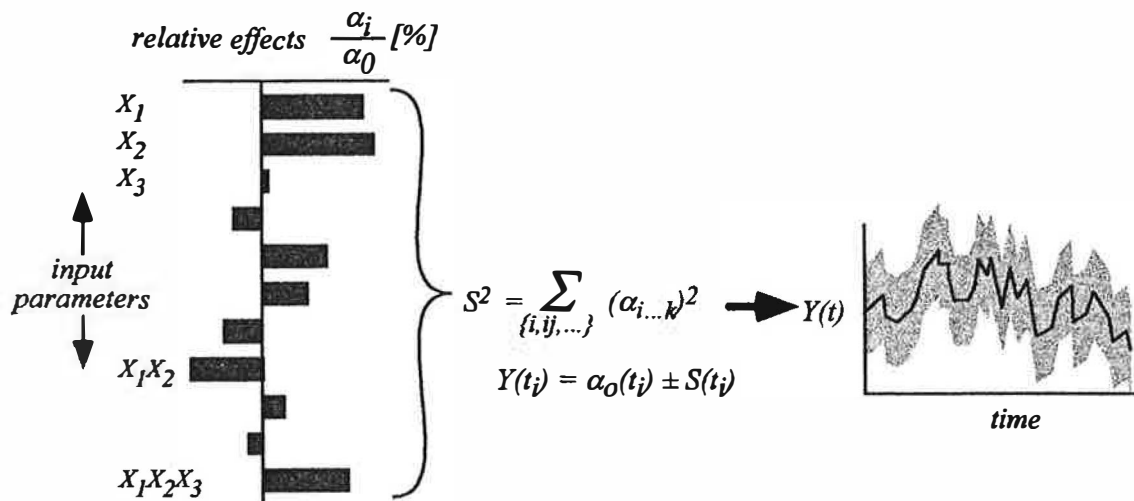


Fig. 4. Graphical output from factorial or similar design simulation. The input parameters are varied simultaneously in an orthogonal way which allow the estimation of the main and interaction effects (left). The effects are interesting for themselves. However, it is also possible to calculate from them a confidence interval (right).

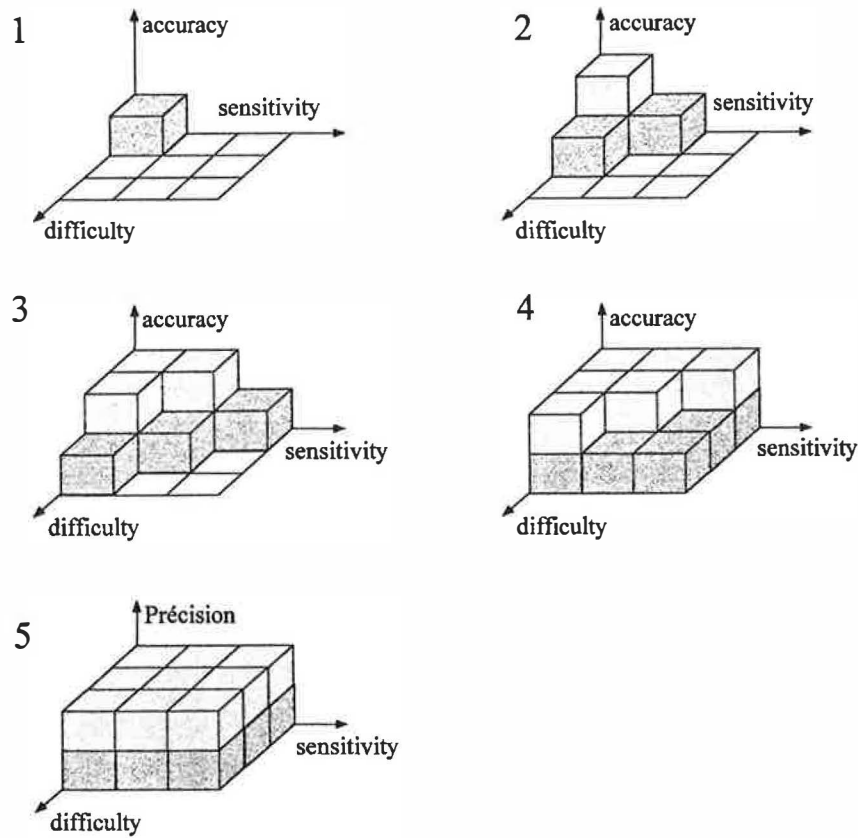


Fig. 5. Main levels of accuracy constraint on the input factors. The levels are defined using a qualitative cost function. In (1) the first factors whose accuracy has to be improved are the ones corresponding to the highest sensitivity of the model and whose more accurate measurement or estimation is the cheapest in comparison of the other. In (2), the accuracy of the 'cheapest' resonant factors is again improved, the accuracy of the active factors whose improvement corresponds to an average cost are also improved, and finally the accuracy of the only active factors but whose accuracy improvement is cheaper than the other are improved. This progression continues in the same way until (5) where all the factors have to be measured to their maximum accuracy level.

There might be some differences between the confidence obtained by this technique and the Monte-Carlo technique. These have been discussed in Ref. [6]. (8) *Optimization and reliability*: Simulation can be used to optimize a process. When using simulation during the design process, a given confidence interval might be required. These two different tasks can be simplified by using the results of a factorial sensitivity analysis. From the input variation effects only, the input accuracy requirement, for obtaining a

given accuracy on an output, can be determined as follows: (a) A list of the input parameters is created along with an indication of their respective accuracy, (b) this list of input parameters is sorted into nine subsets according to two criteria. One criteria is the difficulty for an accuracy improvement; the second criteria is the effect of the parameter on the given output. The first partition is done by estimating for each parameter a rough cost coefficient indicating whether the accuracy improvement is easy, nor-

Table 1
Discrimination of parameters as a function of their influences on the model and the relative difficulty of improving their accuracy

	Precision improvement			
	Easy	Normal	Difficult	Impossible
	1	2	3	4
The inaccuracy of inert parameters is dumped by the system	I	I1	I2	I3
The inaccuracy of active parameters is transmitted by the system	A	A1	A2	A3
The inaccuracy of resonant determined parameters is amplified by the system	R	R1	R2	R3

mal or difficult (cf. Fig. 5). A fourth subset is possible for parameters having an accuracy that cannot be improved and are therefore removed from the studied set. The second criteria for sorting the parameters has also three levels which discriminate the parameters according to whether they are inert, (grouping parameters having only small effects on the output), active (the effect is proportionally of the same magnitude as the parameter variation) or resonant (a small change of the parameters ends in large change of the output) Table 1. (c) The error function of a given output parameter can be estimated by Eq. (5) by using the sensitivity coefficients:

$$E^2(l_i) = \sum_{i=1}^N \left(a_i \frac{\Delta X_i(\text{ref})}{\Delta X_i(l_i)} \right)^2 + \sum_{i=j}^N \left(a_{ij} \frac{\Delta X_i(\text{ref})}{\Delta X_i(l_i)} \frac{\Delta X_j(\text{ref})}{\Delta X_j(l_j)} \right)^2 \quad (5)$$

The idea of the optimization is to first improve the accuracy of the most active parameters corresponding to the lowest cost for improvement and last, if really necessary, to improve the most expensive ones with smallest effect. This idea is represented in Fig. 5 where intermediate levels have also been represented. Table 2 presents the different levels of this system. Each level corresponds to an increasing output accuracy and a monotone increasing of the cost function (as long as the hypothesis for dividing the parameter into the nine subsets is valid).

Table 2
List of main and secondary levels used to minimize the cost of input accuracy improvement when trying to satisfy a given output accuracy

Main levels	R1	A1	R2	I1	A2	R3	I2	A3	I3
0	0	0	0	0	0	0	0	0	0
1	0.5	0	0	0	0	0	0	0	0
	0.5	0.5	0	0	0	0	0	0	0
	0.5	0	0.5	0	0	0	0	0	0
	0.5	0.5	0.5	0	0	0	0	0	0
2	1	0.5	0.5	0	0	0	0	0	0
	1	0.5	0.5	0.5	0.5	0	0	0	0
	1	0.5	0.5	0.5	0.5	0	0	0	0
	1	1	0.5	0	0.5	0	0	0	0
	1	1	0.5	0.5	0.5	0	0	0	0
3	1	1	1	0.5	0.5	0.5	0	0	0
	1	1	1	0.5	0.5	0.5	0.5	0	0
	1	1	1	1	0.5	0.5	0.5	0.5	0
	1	1	1	1	1	0.5	0.5	0.5	0
	1	1	1	1	1	0.5	0.5	0.5	0.5
4	1	1	1	1	1	1	0.5	0.5	0.5
	1	1	1	1	1	1	1	0.5	0.5
	1	1	1	1	1	1	1	1	0.5
5	1	1	1	1	1	1	1	1	1

Number 1 corresponds to the maximum possible improvement and 0.5 corresponds proportionally to half of it.

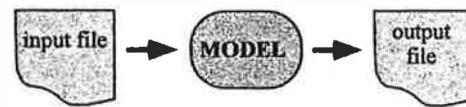


Fig. 6. Scheme for usual simulation. An input file is processed by the model and the result are provided in an output file.

The accuracy of each level can be quickly evaluated as it is necessary only to calculate the error function corresponding to each level. Nevertheless a good strategy consists of: (a) Estimate accuracy of level '0' to verify if the required output accuracy is not yet obtained. (b) Estimate accuracy of level '5' to verify if the required output accuracy is effectively obtainable within the allocated range. If not, it is not necessary to continue. The maximum accuracy limits must be evaluated again. But there is perhaps no solution with the present technology. This gives us the opportunity to highlight that sensitivity analysis is a key method for discovering where technical improvement are required. (c) Estimate successively, down the list, accuracy of the main levels until the required output accuracy is passed, (d) estimate successively up the list, to find the level corresponding to the cheapest operation which provides the required output accuracy.

This strategy can be made more precise by sorting the parameters into a continuous series according to their increasing sensitivity coefficients instead of sorting them into three subsets, and the cost/effort evaluation can also be made more precise.

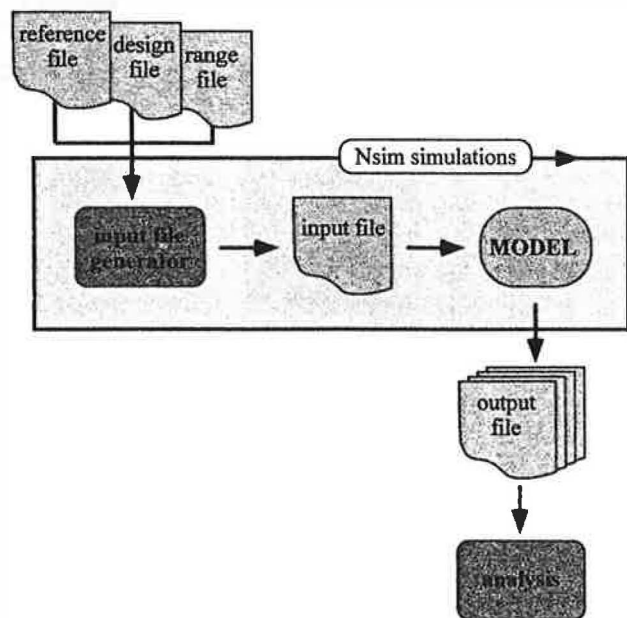


Fig. 7. Scheme for multirun procedure. According to the chosen design and range, the reference file is processed by a text processor and an input file is produced. This input file is then processed by the model and results are written into an output file which is collected for post-processing.

6. Tools

Whatever the design used to do sensitivity analysis, it will require several runs. It could be, as presented above, a sensitivity analysis aimed towards determining the consequences of input inaccuracies. It could also be a parametric study. In this perspective it is important to provide practi-

cal tools within the simulation environment to perform multi-run procedures.

6.1. MISA (Multirun Interface for Sensitivity Analysis)

Developments made within Annex 23 address simulation programs working in a batch sequence as shown in

Table 3
The steps of a typical session of sensitivity analysis




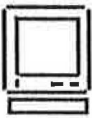

Action	Example
 <ul style="list-style-type: none"> The user chooses a COMIS input file (or an internal model at the user interface level) corresponding to the building to be analyzed. 	<ul style="list-style-type: none"> The file LESO.CIF is chosen
 <ul style="list-style-type: none"> SAM provides the list of the parameters that can be chosen as variables. 	<ul style="list-style-type: none"> The list contains air tightness coefficients C_i, related exponents n_i, crack height h_i and length l_i, pressure coefficients C_{p_j}, zone temperature T_k, volumes V_k, wind velocity, direction etc....
 <ul style="list-style-type: none"> The user chooses the number of groups and the parameters whose effects should be analyzed. 	<ul style="list-style-type: none"> The user chooses four parameters: <ul style="list-style-type: none"> X_1 = front door leakage X_2 = front door flow exponent X_3 = front door pressure coef. X_4 = Temperature of one zone.
<ul style="list-style-type: none"> The user chooses the level of interactions to consider and the metrics in which the selected parameters have to be varied. The user chooses the type of design: Plackett and Burman, fractional factorial or Monte Carlo. 	<ul style="list-style-type: none"> The user chooses to consider mean effect a_0, main effects (a_1, a_2, a_3, a_4) and first order interactions ($a_{12}, a_{13}, a_{14}, a_{23}, a_{24}, a_{34}$). The user chooses a factorial fractional design.
 <ul style="list-style-type: none"> SAM can provide a preferred number of groups and level of interaction. 	<ul style="list-style-type: none"> SAM advises the user that with one more parameter, a better design for the same number of simulations can be obtained.
<ul style="list-style-type: none"> SAM provides the number of simulations, the alias set and the list of estimable coefficients. 	<ul style="list-style-type: none"> The design proposed has 8 simulations and has the following alias list: $a_{12} = a_{34}, a_{13} = a_{24}, a_{14} = a_{23}$. Then the estimable coefficients are $a_0, a_1, a_2, a_3, a_4, a_{12}, a_{13}, a_{14}$.
 <ul style="list-style-type: none"> The user can adapt his requirements to the SAM advises. 	<ul style="list-style-type: none"> The user decides that this design is satisfactory. Sufficient information on wind effect has been obtained.

Table 3 (continued)




- | | | |
|--|---|--|
|  | <ul style="list-style-type: none"> • The user chooses the variation ranges of the selected parameters either group by group or uniformly, either relatively or absolutely • SAM provides a list of output parameters and offers the possibility of building combinations with them. | <ul style="list-style-type: none"> • The user chooses to fix the variation range to $\pm 10\%$. • The list of output parameters is : the pressures P_i in all the zone of the building and the volume and mass transfer between the zones, the global incoming air flow, the thermal loss, etc. |
|  | <ul style="list-style-type: none"> • The user chooses the output parameters to be analyzed and gives the definition of the possible synthetic output parameters. • SAM manages the runs, collects the output data and provides selected effects on tables and charts with some basic interactive possibilities. | <ul style="list-style-type: none"> • The user chooses the global incoming air flow and the sum of the air entering zone 1 from outside and from zone 2. • SAM provides tables and bar charts with some interactive tools, of the effects a_i and a_{ij} of the variation of the selected input parameters on the global incoming air flow. |
|  | | |

Fig. 6. The multirun facility developed consists of varying the input file(s) according to the simulation plan. Using an input file generator written in FORTRAN, a REFERENCE file is processed for producing a new input file according to information about the range of variation and the simulation plan (see Chap. 6). The new input file(s) is (are) submitted to the program and the results are collected Fig. 7.

6.2. LiSA (Library for Sensitivity Analysis)

LiSA means Library for Sensitivity Analysis. The idea is that resources for sensitivity must be available for the largest possible number of models within the building physics field and outside. The idea is to make available up-to-date simulation and statistical techniques. In that perspective, the concept of a simulation environment with an open architecture is preferable to a collection of models with a closed architecture. This is because a good simulation tool should include up-to-date treatment of the physics and also up-to-date methods on the statistical and simulation aspect.

LiSA is also intended to be a library available for software developers who would like to insert a sensitivity analysis into their simulation program. The library is still under development and only a prototype is available today.

This prototype is being developed using MATLAB which is a commercially available mathematical software package having a user-friendly open environment.

LiSA has routines dedicated to:

- building matrices of experiments for Monte-Carlo, factorial, fractional factorial and other types of designs,
- the analysis of the properties of matrices of experiments including alias extraction, variance matrix, inflation factors,
- the post processing of simulation data such as the calculation of averages, standard deviations, main and interaction effects, confidence intervals, histograms, exchange coefficients, least square fit and some typical graphics,
- the optimization of input accuracy,
- dimensionless number calculation.

6.3. Steps in a sensitivity analysis session

At the beginning of the project a month or more was necessary to make a sensitivity analysis. With MISA, a building can be investigated in one week, but with SAM, this work will take no more than one day. This progress is possible by integrating the sensitivity analysis in the environment of simulation and taking advantage of the graphical interface provided with COMIS 3 [18]. The steps of a

typical session of sensitivity analysis are presented in Table 3.

7. Conclusion

A sophisticated method for sensitivity analysis has been described. This method can be used for all types of simulation models which work in a batch mode with unformatted input and output files. For models starting simulation from a user interface, additional modules must be developed.

The process of analysis presented here is applicable to any type of static simulation. In dynamic recursive simulations, because the output of the previous time step is used as input for the next one, the Monte-Carlo and factorial techniques can be used, but the procedure must be adapted. Currently, the integration of suitable sensitivity analysis modules is a key point for improving the confidence of simulation.

This work is the basis of an exacting treatment of uncertainty in simulation that is an absolute requirement for a confident use of simulation in practice. It is a challenge for modelers to distribute products that can not be easily misused: put a SAM in your model.

Important progress has been made in sensitivity analysis within the Annex 23. At the beginning of the project, four years ago, performing a sensitivity analysis of a modeled building was a long job, depending on the complexity of the building; for a small administrative building it was about one month in addition to the modeling step! Now, within a week or probably less, it can be made, providing a real tool to answer questions about important parameters and testing different strategies. With an integrated SAM, this work will require only a few hours, making the mandatory requirement for sensitivity analysis a possible goal.

However, the important difficulty of determining the input uncertainty still remains. This is the real handle governing the accuracy of the simulation. It is up to the user of the model to know the accuracy of the data to be used and to adapt it to the goal of simulation. It is also up to any data provider to assess the accuracy of their data and indicate it in the publications. A data without an uncertainty range has no scientific value. Nevertheless, a list of input data along with their typical uncertainty can be found in Ref. [4]. Those levels of uncertainty depend on the type of technology used to perform the measurement and diminish regularly when new technologies are made available. The exceptions are parameters, like wind profile exponent, which are not measured but selected from literature on a case by case basis. Their uncertainty then depends on many factors, among them the ease of discrimination between the cases. Regrettably, those parameters are often presented in the form of typical values as opposed to a range of values which would clearly indicate

the uncertainty associated with those factors due to the process of case selection.

The future work will include the development of the MISA software as a user-friendly tool on a PC platform making available the powerful technique of the factorial and associated designs.

8. Nomenclature

A	subset of reality
a_i	sensitivity coefficients of factor i
a_{ij}	interaction coefficient of factors i and j
C_{ij}	air tightness coefficient between node i and j of the air flow network, [$\text{m}^3\text{h}^{-1}\text{Pa}^{-n}$]
ΔP_{ij}	pressure difference between node i and j of the network [Pa]
$E^2(I_k)$	estimated error of an output for the input accuracy pattern k
I_k	level of accuracy of the input parameter set
n_{ij}	air tightness exponent between node i and j of the air flow network, [–]
N_{run}	number of runs of the model when performing a SA
N_p	number of input parameters
N_g	number of generators for a fractional factorial design
M	function (model) linking observables between themselves
q_{ij}	air flow rate from node j to i of the network, [m^3h^{-1}]
Q_{ij}	element of the air flow matrix, [m^3h^{-1}]
Q	flow matrix, [m^3h^{-1}]
A_Φ	observable set from subset A
A_Φ	interpreted observable set from subset A
X_i	input parameter
Y_j	output parameter

Acknowledgements

Funding for that work was provided by the OFEN, the Swiss Energy Federal Office.

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