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Comparison between monitored and simulated data using evolutionary algorithms: Reducing the performance gap in dynamic building simulation

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ABSTRACT

A correct thermal building design is a key issue on the viewpoint of energy-efficiency targets established by the United Nations Framework Convention on Climate Change. Dynamic energy simulation tools are often used to predict the thermal performance of new buildings or to recommend energy retrofit packages for refurbishment. To reduce uncertainties in model input definition, the dynamic calibration models assumes a crucial role in the accuracy of energy modelling. Thus, the research goal consists in the development of a calibration approach to reduce the differences between building simulation and real monitored data (performance gap) using a hybrid evolutionary algorithm in dynamic building simulation. A University building has been monitored over one year and the registered data was used to calibrate the numerical model and to validate the calibration methodology proposed. The results attained reveal agreement between predicted and real data with a CV RMSE index attained between 4.5 and 5.4.

1. Introduction and recent research

Thermal dynamic building simulation software are important tools to detail and to effectively evaluate the thermal behaviour in buildings [1]. Steady state methods do not provide detailed information required for making decisions on the best and optimal design options, neglecting thermal inertia and other sensible assumptions. Energy simulation software allows the estimation with high accuracy variables that can help designers to take decisions on the best measures to reduce the energy demand running costs and to improve indoor thermal comfort for users. However, the assignment to attain accurate simulation models is a difficult task as it depends on many variables and parameters. Adapted from Yu [2] there are four main key factors which directly influence on the energy consumption of buildings, illustrated in Fig. 1.

Climatic data represents known design boundary conditions for a given location. It is important to stress that the typical meteorological year weather file for most of the cities does not have extensive climate data for the best accuracy of the results. Building envelope and services data are directly important for thermal behaviour in buildings with important internal thermal loads affecting the energy performance of the building. Finally, human behaviour constitutes the most variable element related to known design data. However, this feature is uncertain, since the profile and the number of building occupants, as well human occupancy schedules are not precisely known. Thus, the accuracy of these considerations, are the main keys factors to achieve a reliable energy efficient building with respect to the indoor thermal comfort and final energy demand. In this sense, model calibration is a fundamental process to ensure that the building thermal behaviour is accurate, allowing to optimize these refereed factors.

Calibration process is defined across the input parameters variation and calculation to reduce the difference between the real building behaviour and the simulated results (performance gap). The uncertainty in the parameters is related to a number of factors in the design and construction phase of building envelope and systems, as indicated by Yu [2]. In general, the uncertainty of design parameters in the design phase is associated to the methodologies, tools or the inputs [3]. In the construction phase, the lack of workmanship and builders training, budget constraints or the unstudied changes of external envelope geometry, window/wall ratio, building components and materials, such as: thermal insulation, window openings and frame systems, heating and cooling systems, etc., have significant consequences. Thus, the foreseen consequences result in thermal bridges, high infiltrations rates and poor indoor thermal comfort leading to high energy losses and inefficient energy building performance [4,5]. Such phenomena is crucial in the calibration process. This process is usually obtained by trial error

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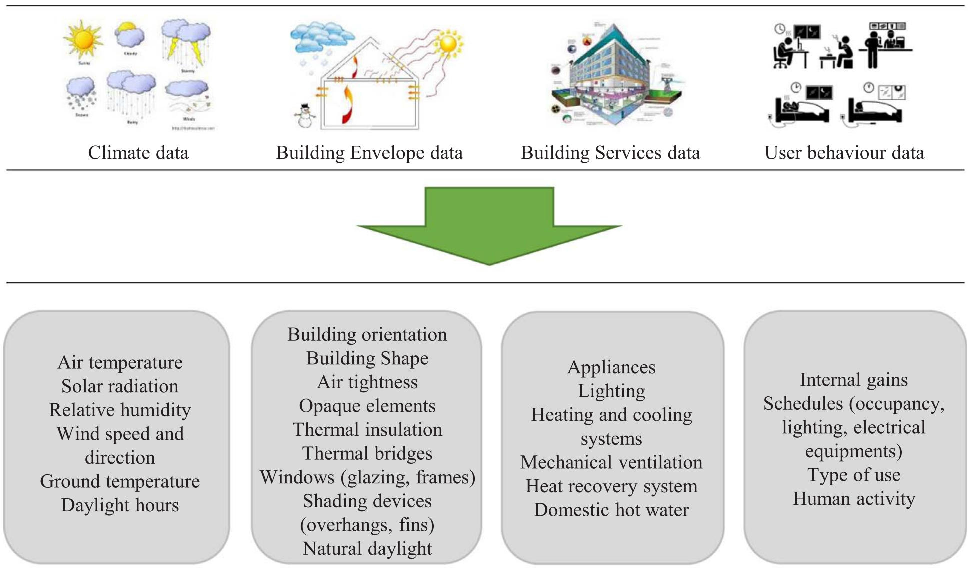

Fig. 1. Four main key factors with influence on the thermal dynamic simulation.

practice and is associated to an extensive and time consuming task to achieve a representative model of the real building thermal behaviour.

A review of current research on this field has revealed that it is impossible to identify the exact solution for the calibration process for Dynamic Building Energy Simulation models (DBES) and there is no generally implemented method for DBES calibration. Until 2008 three standards [6–8] documents with methodologies based on manual refinement of the DBES models were created as guidelines for DBES calibration. ASHRAE guideline 14 [6] is proposed to be a guideline that provides a minimum acceptable gap in the measurement of energy demand savings from energy management projects applied to residential and service buildings. The International Performance Measurement and Verification Protocol [7] purpose is to “provide an overview of current best practice techniques available for verifying results of energy efficiency, water efficiency, and renewable energy projects”. One objective of this document is to be intended as a quick measurement and verification guideline including procedural outlines content checklists and option summary tables. The latter [8] provides a wide range of guidelines and approaches for measuring and verifying energy, water, and cost savings associated with federal energy savings performance contracts.

Recently, new frameworks and methodologies for calibration of DBES models have arisen [9,10]. Daniel Coakley and other researchers [10] in 2014 presented a detailed review on methods to match building energy simulation models with measured data. This work focuses on the existent (in 2014) approaches for calibrations of DBES models, highlighting various combinations of analytical and/or mathematical and statistical techniques. From this brief review, the main conclusions on this field are:

(1) The calibration approach will be always an indeterminate problem with a non-unique solution;
(2) The limited measure data outputs, the sheer number of inputs and their uncertainties leads always the first problem in a calibration process;
(3) No consensus in a standard calibration definition to apply on a wide variety of buildings;
(4) Many of the approaches proposed for model calibration rely heavily on users and designers’ knowledge;
(5) Most of existing approaches are based on trial and error practices.

Monetti and other researchers [11] in 2015 used a methodology for the calibration of building energy simulation models based on optimization. A real case study was used coupling the EnergyPlus (EP) and GenOpt optimization tools. The strategy used consists in the definition of a set of parameters, referred as the most influencing the building energy consumption, to minimize the difference between simulated and monitored energy consumption. Regarding results, the model accuracy was considered consistent with the ASHRAE [6] guideline 14 limits, proving the viability of the calibration approach.

In another study Kim and other researchers [12] developed a novel method to calibrate building energy models based on the occupancy and plug-load schedules. The proposed method is novel because it considers interactions of the validated modelled occupancy patterns, processed electricity use patterns, and the calibrated building energy model results at the hourly level. The results show significant improvements on the CV RMSE index (coefficient of variation of the root mean square error) when the electricity was evaluated.

In the review published by Nguyen et al. [13], the optimization methods for building performance analysis are approached, presenting the progress in the nearly three decades of development of computer science in relation to the design of green buildings and the use of optimization methods in this field. To solve the numerous types of optimization problems several methods were developed and classified as local/global methods, heuristic methods, stochastic methods, single or multi-objective algorithms and others identified by Nguyen et al. [13]. In accordance with Nguyen et al. [13] the stochastic population-based algorithms, such as, Genetic Algorithms, Particle Swarm Optimization, Hybrid algorithms and evolutionary algorithms are the most frequently used methods in building performance optimization. In general, it is infeasible to establish a generic rule for the algorithm selection due to the complexity and the diversity of real building conditions. The choice of optimization method is not trivial and usually the following list ordered by Nguyen et al. [13]:

(1) Natures of design variables: continuous variables, discrete variables or both;
(2) The presence of constraints on the objective function;
(3) Nature of objective functions (linear or nonlinear, convex or non-convex, continuous or discontinuous, number of local minima, etc.);
(4) The availability of analytic first and second order derivatives of the objective functions;
(5) Characteristics of the problem (static or dynamic, etc.);
(6) Performance of potential algorithms which have similar features.