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Energy Procedia 111 (2017) 1060 – 1069

Energy Procedia

8th International Conference on Sustainability in Energy and Buildings, SEB-16, 11-13 September 2016, Turin, ITALY

Optimization Tools for Building Energy Model Calibration

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Abstract

Different optimization tools have been developed to find the best trade-off between competitive goals. The optimization problem is typical of the design process, where different design solutions have to be compared to achieve one or more objectives, often in contrast with each other. A quite novel application of optimization is building energy model calibration. The use of well-calibrated energy simulation models is key for successful buildings' retrofit or operation management and the optimization techniques can improve the reliability of the results. The typical optimization method consists in the analysis of all the alternatives' performances, developing a full factorial plan and simulating all the possible options (brute-force approach). However, this process could take unsustainable long time. That is why some optimization tools, based on evolutionary algorithms have been developed to speed up the process.

This study compares results obtained through the brute-force approach and the evolutionary optimization methods applied on the calibration of a large educational building model located in the province of Treviso, north of Italy. The total design space consists of about 72 000 EnergyPlus building models. Two optimization-based calibrations have been repeated using a genetic algorithm by means of jEPlus+EA on a local computer and through parametric simulations implemented by jEPlus on a cloud service. The quality of results from the evolutionary optimization tools as compared to a full parametric study applied on calibration have been discussed. Scenarios of applicability are drafted. On a practical level, the research is a contribution for the selection of methods and tools for the preparation of models that can lead to optimized retrofit interventions and rationalization of building management and operation.

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doi:10.1016/j.egypro.2017.03.269

Keywords: Parametric analysis; Genetic Algorithm; Optimization; Retrofit

1. Introduction

Building energy performance simulation tools have been developed to represent the physical behavior of buildings and to perform detailed calculations of the energy needed to maintain specific indoor conditions. If adopted during the design process, they can ensure the achievement of a certain energy performance and assist the designer in the decision-phase. As stated by Coakley [1], a large number of studies have demonstrated that significant differences are often found when comparing actual metered energy uses with those calculated by means of energy simulation models. Especially when the existing building stock is the energy design target, simulation models can fully express their potential only if able to predict closely the actual building energy performance. For this reason, model calibration can be exploited to reduce the discrepancies between energy use and other indoor quality indicators and actual measured energy performance and conditions. However, calibration is a complex issue, involving the analysis of numerous parameters.

Parametric analysis tools allow exploring all possible alternatives compatible with predefined constraints, such as admissible ranges of values for input data, both variables and parameters. This approach is not actually a solution technique since all the configurations attainable from any combinations of options are considered and evaluated, and it is known as "brute-force" or "exhaustive search" [2]. However, even if finding the best solution is ensured, it may be very time-consuming and require high computational costs [3,4].

Many optimization methods have been developed to overcome this drawback: enumerative, deterministic and stochastic algorithms are applied in the identification of the optimum solution [5]. Some of these cannot be taken for granted but these algorithms are much more efficient in the search process. Among them, optimization evolutionary algorithms [6], and in particular genetic algorithms, *GA*, are increasingly being used in building energy performance research. These meta-heuristic algorithms are inspired by the Darwinian evolution theory [7] and implement the process described in Figure 1. The *GA* start with an initial population of randomly chosen individuals (i.e., the first generation). Each configuration is treated as a "chromosome" containing a certain number of variables, or "genes". Best "chromosomes" are selected to create new generations by changing "genes" from the different solutions (i.e., cross-over) or introducing random changes (i.e., mutation). The process is repeated until either enough suitable solutions are found, or the pre-established maximum number of generations is reached.

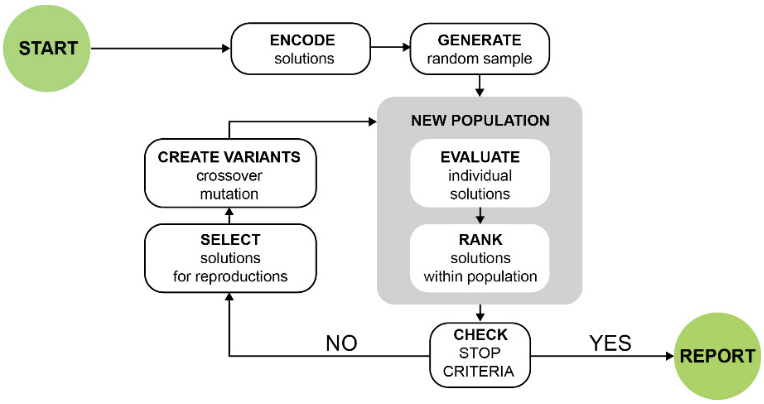

Fig. 1. Flowchart of Evolutionary Algorithm process.

While *GA* advantages are well known in building design and refurbishment optimizations [8,9], the possible applications in building model calibration are not investigated in detail. In this paper, a large school building located in the province of Treviso, north of Italy, has been modelled with EnergyPlus and calibrated against its energy consumption data of the 2012-2013 heating season. The results of the calibration process obtained by means of the

NGSA-II *GA* implemented in jEPlus+EA have been compared to those from "brute force" approach on cloud computing, in order to underline the potential of *GA* in calibration context.

2. Method

2.1. School building model

The High School State Institute Francesco da Collo in Conegliano Veneto (lat. 45° 53' N, long. 12° 17' E), province of Treviso, has been modelled. This school has been selected because identified in previous researches [10] as one of the reference buildings of a large stock owned and managed by the Province of Treviso. The school was built during the late 1980s and has a total floor area of 10 185 m², developed on three levels above ground. It has a reinforced concrete frame construction, with concrete slabs and roofs in the classroom areas and metal structure and roofing covering the spaces with larger spans, such as the gymnasium and the auditorium. External walls were built almost entirely using exposed clay brick, without plastering, exception made for the few areas for which glass blocks were used. According to the available documentation for the school year 2012-2013, the building had an energy consumption for space heating of 891 511 kWh.

The thermal model of the building has been developed using SketchUp [11] and OpenStudio [12], an EnergyPlus [13] user-interface developed by the National Renewable Energy Laboratory (NREL) of the U.S. Department of Energy.

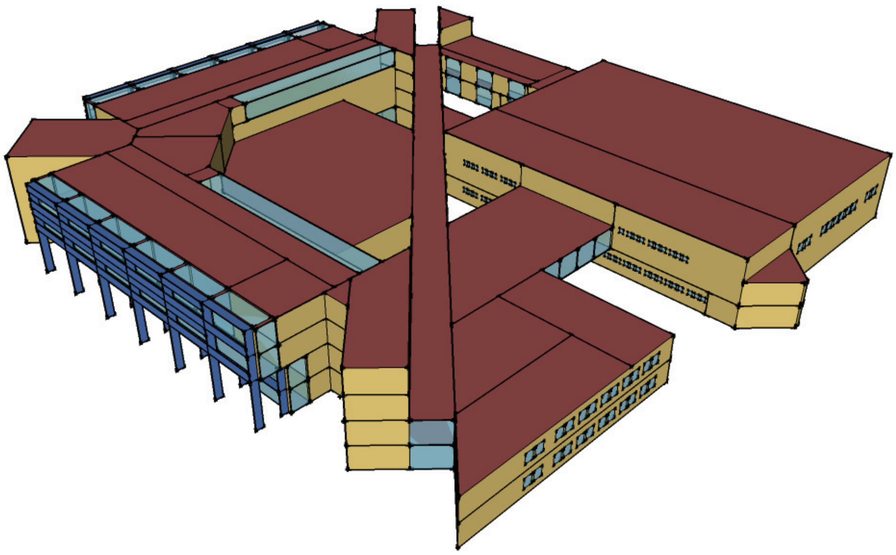

Fig. 2. Building energy simulation model of the school.

For the simulated period, the Veneto Region Environmental Protection Agency (ARPAV) provided local hourly profiles of air temperature, relative humidity, and horizontal global solar irradiation. With these data, an EnergyPlus EPW weather file has been prepared. The building envelope characteristics have been defined according to the data included in the energy audit report provided by the Local Authorities; as average, the calculated thermal transmittance of the whole building envelope is 0.82 W m^{-2} K^{-1}. Occupancy profiles, communicated by the school administration, have been used to estimate the heat gains due to people, lighting, and equipment for the different thermal zones. For each type of space, such as classrooms, offices, auditorium and gymnasium, separate occupancy schedules have been defined. The number of people and lighting devices inside each zone have been determined combining pieces of information by the school administration and suggestions by technical standards, such as UNI 10339:1995 [14] – about the density of people per square meter, and ASHRAE 90.1:2007[15] – regarding the installed lighting power per square meter.

An initial set of values for infiltration and ventilation rates has been used in the model. Considering that the whole building was constructed in the same period and with a single construction technique, the same constant air flow rate by infiltration of 0.15 ACH, calculated assuming high permeability according to [16], has been imposed for all thermal zones. Ventilation rates, instead, have been considered differently for each space category during their occupancy time, in accordance with UNI 10339:1995 [14]: 0.0070 $m^3\ s^{-1}\ person^{-1}$ have been set in the classrooms, 0.0110 $m^3\ s^{-1}\ person^{-1}$ in the offices, 0.0055 $m^3\ s^{-1}\ person^{-1}$ in the auditorium and 0.0165 $m^3\ s^{-1}\ person^{-1}$ in the gymnasium. The only exception is the restrooms, for which a constant ventilation air flow rate of 8 ACH has been imposed.

Due to the lack of reliable information describing short-term performance of the heating system, we have modelled an ideal air load system keeping the indoor air temperature at 20 °C during the occupancy time. Then, the monthly heating energy needs simulated in this way have been converted into final uses for space heating by means of the monthly global efficiencies evaluated in the Province audit report.

2.2 Calibration process

2.2.1 Selection of calibration variables

A preliminary sensitivity analysis has addressed the identification of the variables characterized by the highest uncertainty and the largest impact on the discrepancies between simulated and measured daily final uses for space heating of this case study. Those variables regard setback temperature of the heating system and air infiltration and ventilation rates, which, as expected, are often very far from the normative prescriptions [17–20].

The set of calibration variables has been defined as follows: parameter *P1* is the infiltration flow rate for all spaces, *P2*, *P3*, *P4* and *P5* the ventilation air flow rates in classrooms and laboratories, auditorium, sports hall and offices, respectively, and parameter *P6* is the setback temperature of the heating system during unoccupied time. Regarding parameters from *P1* to *P5* (Table 2), proper ranges of values have been selected taking standard UNI 10339 prescriptions as maximum values and the 40 % of them as minimum; the ranges have been subdivided by adding five intermediate values. For *P6*, instead, possible values range from 12 to 15 °C, with a step of 1 °C.

Table 1. Ranges of air infiltration and ventilation air flow rates used in calibration.

	Ventilation Air Flow $m^3\ s^{-1}\ person^{-1}$			
Space Type	UNI 10339	MIN	STEP	MAX
Classroom	0.0070	0.0028	0.00070	0.0070
Laboratory	0.0070	0.0028	0.00070	0.0070
Auditorium	0.0055	0.0022	0.00055	0.0055
Gymnasium	0.0165	0.0066	0.00165	0.0165
Office	0.0110	0.0044	0.0011	0.0110
Infiltration Air Change Rate (all spaces) [h^{-1}]	0.15	0.1	0.05	0.3

2.2.2 Optimization methods applied on calibration

Simulated final uses have been contrasted to measured daily energy consumption of the 2012 - 2013 heating season (from October 15th 2012 until April 15th 2013). For this work, we have used jEPlus (v1.6.3) [21], which, coupled with

EnergyPlus, can perform parametric analyses, take into account multiple design variables, create and manage simulation jobs and results. Considering the combinations of all alternatives reported in Table 1, 72 030 possible configurations have been simulated. Each EnergyPlus simulation job has been named systematically with a unique identification code describing the specific set of parameters being considered. In order to run such a high number of simulations of the whole building model, large computational resources are needed. To overcome this issue, simulations have been executed on the jEPlus Simulation Server (JESS) [22] with assistance from Green Prefab Italia as part of a collaboration for the ASCETiC European project [23].

Defining, as target, the minimization of the discrepancies between simulated and measured energy uses, a heuristic search problem can identify the configuration bringing simulation outputs closer to the reference data. To implement this *GA*-based calibration approach – specifically the NGSA-II algorithm, another software, jEPlus+EA v1.7 [24], has been used together with jEPlus. In our case, two objective functions have been set for minimization - the normalized Mean Bias Error, *NMBE*, and the Coefficient of Variation of the Root Mean Square Error, *CV(RMSE)*, calculated between simulated and measured daily heating energy uses for each day of the heating season. *NMBE* and *CV(RMSE)* have been selected in agreement with the ASHRAE Guideline 14 [25] and IPMVP [26] prescriptions which fix the acceptable percentages for the monthly and the hourly calibration method (Table 2). A Phyton [27] script has been written to evaluate simulation deviation, calculate both indices and give feedback to the NGSA-II algorithm. The population size has been set to 10 individuals in order to ensure enough variability in creating new solutions and the maximum number of generations (i.e., the total number of iterations that the algorithm may run) has been fixed at 200. With this setting, the maximum number of simulations has been limited to 2000, in order to be able to run the optimization using a local computer with a lower computational capacity. The cross-over rate, which determines how often new solutions are created based on existing solutions, has been maximized to 1. Mutation rate, which defines how often random changes occur to new solutions, has been imposed to 0.2, with the aim to prevent the algorithm to follow a random "trial and error" process.

Table 2. Acceptable Calibration Tolerances (source: [25, 26]).

Calibration type	Index	Acceptable values	
		ASHRAE	IPMVP
Monthly	$NMBE_{month}$	5 %	20 %
	$CV(RMSE_{month})$	15 %	-
Hourly	$NMBE_{month}$	10 %	5 %
	$CV(RMSE_{month})$	30 %	20 %

3. Results

3.1 Parametric calibration results

The complete parametric project took 4746 calculation hours to run, with an average duration for the single configuration of nearly 4 minutes. Figure 3 reports the results of daily *NMBE* and *CV(RMSE)* for all the simulated configurations. Values are between 0 % and 50 % for the former and from 43 % to more than 80 % for the latter. Both indices have been re-calculated on monthly basis to check compliance with ASHRAE tolerances, which provide references for either monthly and hourly calibrations. The final ranking of the best ten configurations is detailed in Table 3. For each configuration, the simulation job ID assigned by jEPlus is reported, together with the corresponding parameter values and the results of the indices calculation.

Error indices show that configuration *Best 1* has daily *NMBE* equal to 3.19 % and a daily *CV(RMSE)* of 45.13 %. When calculated on monthly basis, the *CV(RMSE)* is reduced to 15.2 %. The first index complies with the prescribed 5 % tolerance, whereas the second one is slightly over the accepted range of 15 %. As displayed in Table 3, index results for the rest of the best ten configurations vary from 45.08 % to 45.15 % for daily *CV(RMSE)* and from 3.15 % to 5.3 % with regards to daily *NMBE*. Among the configurations with *NMBE* lower than 5 %, *Best 1* has the lowest

CV(RMSE) value and, therefore, it represents the configuration with the best trade-off between the two calibration indices.

Table 3. Ranking of the best ten solutions from Parametric Analysis.

		P1	P2	P3	P4	P5	P6	CV(RMSE) [%]	NMBE [%]
CONFIGURATION		AIR INF	CLSRM VENT	AUDIT VENT	GYM VENT	OFFICE VENT	SETBACK TEMP		
B-0_0_0_3_0_4	BEST 1	0.1	0.0028	0.0022	0.01155	0.0044	14	45.1313	3.1960
B-0_0_0_3_1_4	BEST 2	0.1	0.0028	0.0022	0.01155	0.0055	14	45.1355	3.1860
B-0_0_0_3_2_4	BEST 3	0.1	0.0028	0.0022	0.01155	0.0066	14	45.1400	3.1752
B-0_0_0_3_3_4	BEST 4	0.1	0.0028	0.0022	0.01155	0.0077	14	45.1448	3.1637
B-0_0_0_3_4_4	BEST 5	0.1	0.0028	0.0022	0.01155	0.0088	14	45.1498	3.1517
B-0_0_1_2_6_5	BEST 6	0.1	0.0028	0.00275	0.0099	0.011	15	45.1038	5.2598
B-0_0_1_2_5_5	BEST 7	0.1	0.0028	0.00275	0.0099	0.0099	15	45.1005	5.2726
B-0_0_1_2_4_5	BEST 8	0.1	0.0028	0.00275	0.0099	0.0088	15	45.0969	5.2850
B-0_0_1_2_3_5	BEST 9	0.1	0.0028	0.00275	0.0099	0.0077	15	45.0934	5.2970
B-0_0_1_2_2_5	BEST 10	0.1	0.0028	0.00275	0.0099	0.0066	15	45.0899	5.3085

Among these results, a value of 0.1 ACH for air infiltration flow rate is found in all the configurations, whereas the classrooms' ventilation flow rate is always 0.0028 $m^3 s^{-1} person^{-1}$. Parameters *P3*, *P4* and *P6* -ventilation flow rate for auditorium and gymnasium and setback temperature, have two different values, whereas for the office ventilation flow rate seven different values, between 0.0044 $m^3 s^{-1} person^{-1}$ and 0.011 $m^3 s^{-1} person^{-1}$, were found.

3.2 GA-based calibration results

Results from the *GA*-based optimization are plotted in Figure 3, reporting the *NMBE* and *CV(RMSE)* values for all configurations considered during the optimization process. Equivalent results of the Pareto front have been achieved after 137 generations, with a total of 1368 simulations run in 90 computation hours (i.e., 52 times less than the calculation time of the parametric calibration).

Best solutions from those located in the Pareto front, which contains 88 solutions, have been analyzed to select the ones complying with the ASHRAE acceptable tolerances (Table 4). All the combinations in the top-10 ranking have the same values for the first two parameters – i.e., air infiltration flow rate of 0.1 ACH and ventilation flow rate in the classrooms of 0.0028 $m^3 s^{-1} person^{-1}$. Regarding the ventilation flow rate for the sports hall, only two different values have been found: 0.0099 $m^3 s^{-1} person^{-1}$ and 0.01155 $m^3 s^{-1} person^{-1}$. This is the case also of the setback temperature, whose values are 14 °C for half of the top-10 and 15 °C for the remaining five best configurations.

Two different configurations - B-0_0_1_2_5_5 and B-0_0_0_3_0_4, have been selected because in close match with the abovementioned requisites and included also in the top-10 ranking found in the parametric calibration. Combination B-0_0_1_2_5_5 has values of 0.00275, 0.0099 and 0.0099 $m^3 s^{-1} person^{-1}$ for parameters *P3*, *P4* and *P5*, respectively, and 15 °C for *P6*. In configuration B-0_0_0_3_0_4, instead, *P6* is equal to 14 °C, whereas 0.0022, 0.01155 and 0.0044 $m^3 s^{-1} person^{-1}$ are the values chosen for parameters *P3*, *P4* and *P5*.

Regarding the indices, configuration B-0_0_1_2_5_5 has 5.27 % for the daily *NMBE,* 45.1 % for the daily *CV(RMSE)* and 14.9 % for the monthly *CV(RMSE)*. The first index is only slightly beyond in the 5 % limit, whereas the second one is in the acceptable range. Values calculated for configuration B-0_0_0_3_0_4 are better, having a lower daily *NMBE* of 3.2 %, a daily *CV(RMSE)* of 45.13 % and a monthly *CV(RMSE)* of 15.2 %, only slightly exceeding the ASHRAE tolerance [25]. To be noted, however, that for both configurations indices comply with IPMVP recommended values [26].

Table 4. Ranking of the best ten solutions from *GA*-based calibration.

		P1	P2	P3	P4	P5	P6	CV(RMSE) [%]	NMBE [%]
CONFIGURATION		AIR INF	CLSRM VENT	AUDIT VENT	GYM VENT	OFFICE VENT	SETBACK TEMP		
B-0_0_0_2_5_5	BEST 1	0.1	0.0028	0.0022	0.0099	0.0099	15	45.0273	5.5940
B-0_0_1_2_0_5	BEST 2	0.1	0.0028	0.00275	0.0099	0.0044	15	45.0836	5.3293
B-0_0_1_2_1_5	BEST 3	0.1	0.0028	0.00275	0.0099	0.0055	15	45.0866	5.3193
B-0_0_1_2_2_5	BEST 4	0.1	0.0028	0.00275	0.0099	0.0066	15	45.0899	5.3085
B-0_0_1_2_5_5	BEST 5	0.1	0.0028	0.00275	0.0099	0.0099	15	45.1005	5.2726
B-0_0_0_3_0_4	BEST 6	0.1	0.0028	0.0022	0.01155	0.0044	14	45.1313	3.1960
B-0_0_0_3_1_4	BEST 7	0.1	0.0028	0.0022	0.01155	0.0055	14	45.1355	3.1860
B-0_0_0_3_2_4	BEST 8	0.1	0.0028	0.0022	0.01155	0.0066	14	45.1400	3.1752
B-0_0_0_3_3_4	BEST 9	0.1	0.0028	0.0022	0.01155	0.0077	14	45.1448	3.1637
B-0_0_0_3_4_4	BEST 10	0.1	0.0028	0.0022	0.01155	0.0088	14	45.1498	3.1517

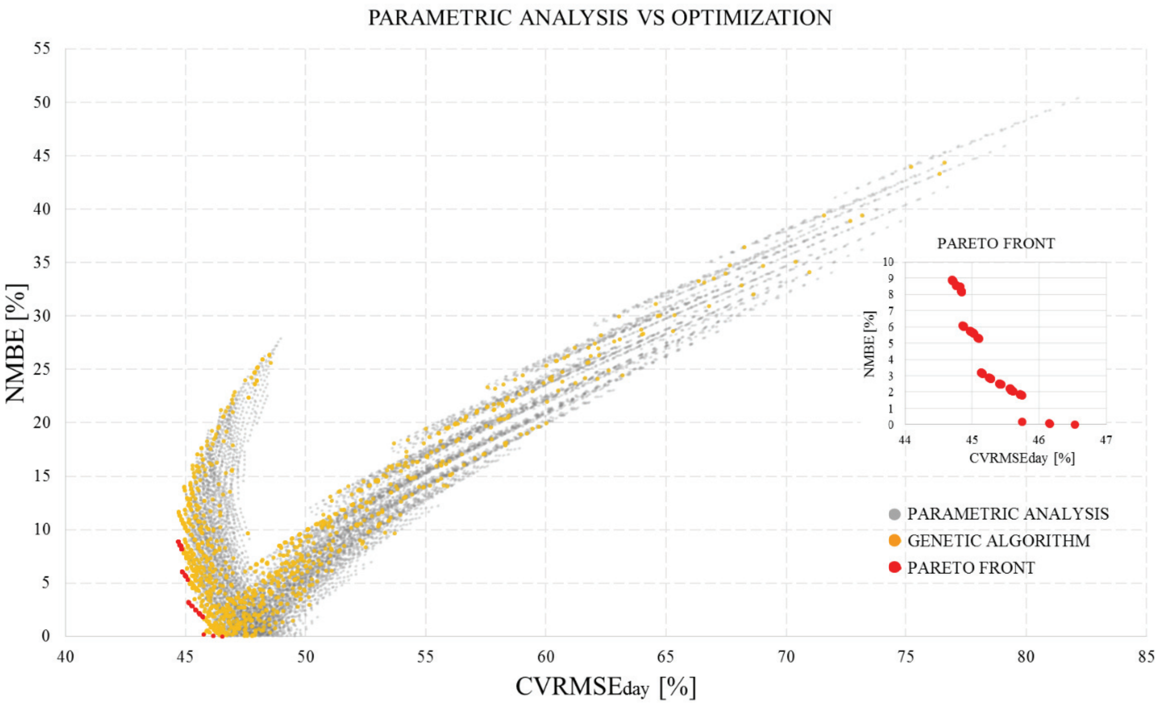

Fig. 3. Parametric Analysis and *GA*-based simulation error indexes.

3.3 Approaches comparison

Data processing time and required computational resources have been compared to evaluate the efficiency of the *GA*-based calibration with respect to the parametric one (Table 5). The comparison highlights differences of the two approaches in term of required number of cores, computation time, number of simulations and estimated cost. Considering that *GA*-optimization can be implemented on a common computer without adding extra-costs, it is evident the great advantage due to time and economic convenience while achieving the same results.

Table 5. Computation values comparison between Parametric Analysis and Genetic Optimization (*in average, as cores are dynamically allocated).

	NUMBER OF CORES	COMPUTATION TIME [hours]	TOTAL SIMULATIONS	COST [euro]	Best monthly NMBE [%]	Best monthly CV(RMSE) [%]
PARAMETRIC ANALYSIS	60*	4746	72030	1566	15.20	3.196
GENETIC OPTIMIZATION	8	90	1368	-	15.20	3.196

3.4 Validation of the calibrated model

In order to validate the calibrated model, a yearly simulation has been run for the 2013 - 2014 heating season. This period has been selected because of monthly measured consumption data availability. The monthly simulated consumptions in the two heating seasons have been plotted in Figure 4. As it can be seen, the calibrated model predicts quite well the trend during the 2012 - 2013 calibration period and even better during the 2013 - 2014 validation one.

Moreover, by comparing the actual annual energy consumption with the simulated annual energy demand it is possible to observe that during 2012 - 2013 the difference is of 3 % (583 939 kWh against 565 277 kWh) while during 2013 - 2014 is about 14 %, thus demonstrating a good reliability of the calibrated model.

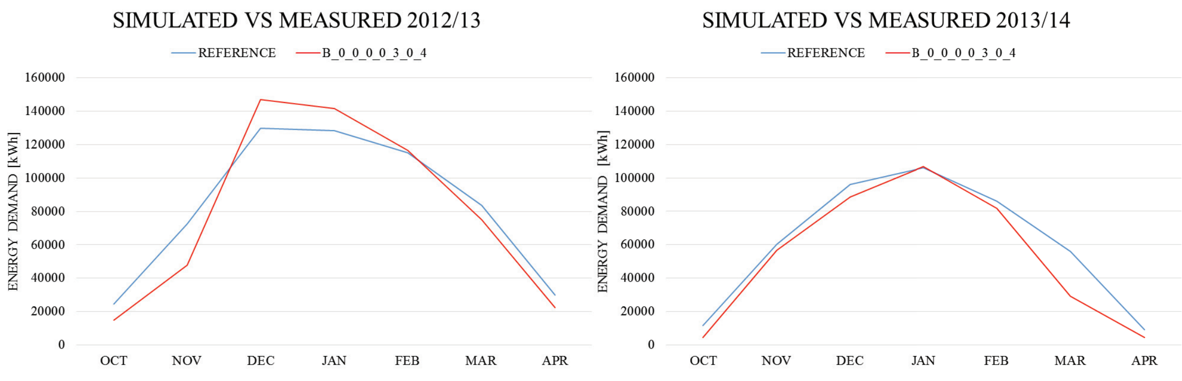

Fig. 4. Comparison between reference and simulation values regarding monthly energy demand for 2012 – 2013 (left) and 2013 – 2014 (right) heating seasons.

Regarding the acceptable tolerances reported in Table 2, the model is not complying with ASHRAE recommendations, because results for *CV(RMSE)* and *NMBE* calculated on a monthly basis are of 17.2 % for the former and 12.5 % for the latter. However, these values are still within the values recommended by the IPVMP, which are slightly higher.

Therefore, the school calibrated model obtained may be considered as a reliable instrument to assist in the building energy refurbishment process, able to predict the expected energy savings related to different intervention scenarios and, if properly updated, becoming a useful post-retrofit verification and evaluation tool.

4. Conclusions

In this paper two different calibration approaches have been compared in order to discuss the advantages and drawbacks of each. On the one hand, parametric analysis results are exhaustive and show the entire spectrum of results for a given problem, providing a complete picture of the possibilities to consider. On the other, this straightforward ´brute force´ approach proved to be quite resource-demanding both regarding calculation time and computational capacity, preventing its implementation when a complex building simulation model is analyzed. In this work, the use of software tools specifically developed for the management of parametric studies in building a simulation, coupled with the availability of adequate computational resources, permitted to follow such an analysis in a seamless way. Indeed, for the reference building model calibration presented in this research work, 72 030 simulations of the whole building multi-zone model have been carried out, one for each single configuration of the parameters to be tuned, for a total 4746 calculation hours expenditure.

The second approach tested is the multi-objective optimization-based calibration by means of Genetic Algorithm. In this case optimization is achieved faster with a lower need of computing resources. In fact, best results from this approach, which needed 137 generations for a total of 1368 simulations to be run, are equivalent to those obtained running the full parametric analysis.

Acknowledgements

We would like to thank the Province of Treviso for making available the data used for this research and Green Prefab Italia that allowed the use of the toolbox developed within the European Project ASCETiC, project funded by the Seventh Framework Programme for research, grant agreement number 610874.

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