

Energy performance of air conditioned buildings based on short-term weather forecast

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Abstract. One of the possible ways to improve balance between building energy consumption and occupant thermal comfort in existing buildings is to use simulation-assisted operation of HVAC systems. Simulation-assisted operation can be formulated as a type of operation that implements knowledge of future disturbance acting on the building and that enables operating the systems in such a way to fulfill given goals, which in nature can often be contradictory. The most important future conditions on building energy consumption are weather parameters and occupant behavior and expectations of thermal environment. In order to achieve this type of operation, optimization methods must be applied. Methodology to create HVAC system operation strategies on a daily basis is presented. Methodology is based on using building energy performance simulation software EnergyPlus, available weather data, global sensitivity analysis, and custom developed software with particle swarm optimization method applied over the moving horizon. Global sensitivity analysis is used in order to reduce number of independent variables for the optimization process. The methodology is applied to office part of real combined-type building located in Niš, Serbia. Use of sensitivity analysis shows that the reduced number of independent variables for the optimization would lead to similar thermal comfort and energy consumption, with significant computer runtime reduction.

1 Introduction

Building energy performance modeling and simulation represent very powerful and useful method in all stages of building lifecycle. Most of the tools which are used nowadays and are known as BEPS (building energy performance simulation) software, were developed for use in the design (pre-construction) phase, and allow, among other benefits: comparison of different architectural concepts [1-5], comparison between different construction materials [6-7], selection and comparison between various HVAC systems [8-11], selection of proper RES available [12-13] and also as a support for policy making [14-15].

Numerous researches have shown that there are huge discrepancies between simulated and measured energy performance [16-18], even for buildings where some of the BEPS tools were used in the design phase. This “performance gap” can decrease confidence in using BEPS and must be properly addressed, especially if the tools are going to be used for improving energy performance of the existing buildings. The only way to eliminate or to decrease the “performance gap” is to calibrate building energy model, i.e. to adjust inputs in the

model in such a way that simulation outputs and measured values are satisfyingly close [19-21]. Since energy models often have several hundreds and thousands of input variables, it is clear that obtaining calibrated model manually is very hard (if possible at all), so the use of statistical and analytical methods is the only way [22-23]. Once calibrated, energy model of the existing building can be used for further research.

Over the last years, possibility to improve building energy performance by improving operation of existing HVAC systems through implementation of optimal operation strategies is recognized [24-26]. When using BEPS for defining optimal strategies simulation-assisted operation is achieved. One of the techniques applied frequently for simulation-assisted operation improvement is model-predictive control [27-28] which allows integrating prediction of future disturbances that will act on the building (such as weather [27, 29-31] and occupancy [32]), possibility to use building thermal mass, possibility to put constraints on inputs and outputs of the optimization process etc. Optimal values are determined by applying moving horizon approach [29, 33] where optimal values are implemented only in first part of the

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prediction horizon, and the process repeats while shifting forward in time.

The main drawback of using BEPS for simulation assisted approach is in large number of independent variables for the optimization process, which leads to significant computer runtime due to the fact that BEPS have incorporated high-order white-box models of the underlying physical process that occurs in the building and its systems.

One of the possible ways to reduce computer runtime is to apply global sensitivity analysis (fig 1) in order to reduce number of independent variables for the optimization by selecting only variables which have biggest influence on one or several elements of the cost function [34].

In this paper, sensitivity-based simulation-assisted approach is shown and compared to the classical simulation-assisted approach for the HVAC systems serving building located in City of Niš, Serbia, by applying moving horizon optimization. Model of the building is created by using EnergyPlus [35] which is also used in all stages of this research.

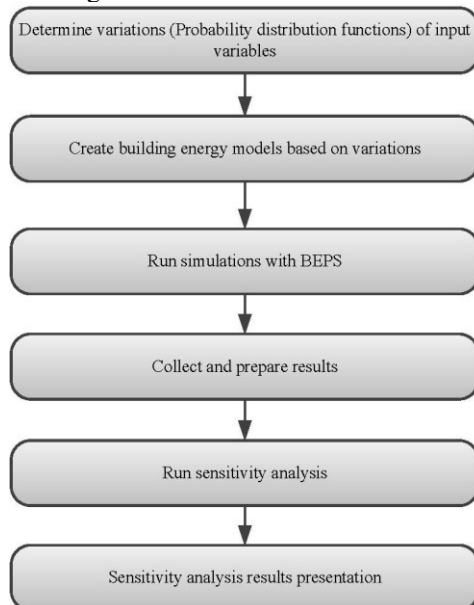


Fig. 1. Sensitivity analysis workflow.

2 Methodology

Creating energy model of the existing building besides describing building geometry, construction materials used, HVAC and other installed systems has to include the description of building usage through defining patterns (schedules) of occupancy and number of occupants, schedules of artificial lighting systems use, schedules of electrical appliances and equipment use and the most importantly, through proper description of existing control systems installed in the building. Most sophisticated BEPS, like EnergyPlus, allow real representation of common HVAC control systems by defining:

- Setpoints of the controlled variables (zone air temperature, relative humidity etc.)
- Availability of installed HVAC systems and components
- Order of HVAC systems and components running
- Control laws implemented in HVAC systems (outside temperature offset control – heating curve, fresh air intake through damper positions etc.)

Modelling sophisticated controls like optimal and supervisory is hard within the simulation tools itself so some form of external evaluation and co-simulation approach are being used. These controls require models of the controlled process and represent model based control. Typical goal of the optimal control is to reduce energy consumption without reducing occupant thermal comfort. This control can be realized either as offline (system operation is optimized externally) or as online (system operation is optimized in real time thus incorporating BEPS in the actual control loop of the building).

The purpose of using BEPS for simulation-assisted operation can be divided in two directions:

- For development and evaluation of new controls (model-based dominantly) created with other tools and techniques [27, 29],
- For development of general environments and methodologies around the tool for either online [36] or offline [31, 36] applications.

This concept is generally implemented as supervisory level of control, with the cost function representing single variable or combination of several variables:

- Energy consumption [36-37],
- Occupant thermal comfort [36-38],
- Operation costs [39-40],
- Time when thermal comfort is unsatisfied [41].

Considering occupant thermal comfort, usually operative temperature, zone air temperature, PMV index and PPD index are selected as output variables. Optimization methods used for simulation-assisted approach are numerous with PSO [36, 41-42] and genetic algorithms [43, 44] being the most frequent.

Optimal operation strategies are developed in order to minimize building energy consumption while preserving occupant thermal comfort in given boundaries, during occupied period. The same approach can be used for daily operation strategies with different cost functions. Particle swarm optimization (PSO) algorithm was selected and custom optimization environment around EnergyPlus was developed. The process of determining optimal operation strategies of existing HVAC systems was realized in the form of offline optimization and is illustrated in figures 2 and 3. It consists of optimization algorithm, simulation tool and the building itself in which the results are implemented. The building or the building model is used as feedback for the next planning horizon (thermal history of the model).

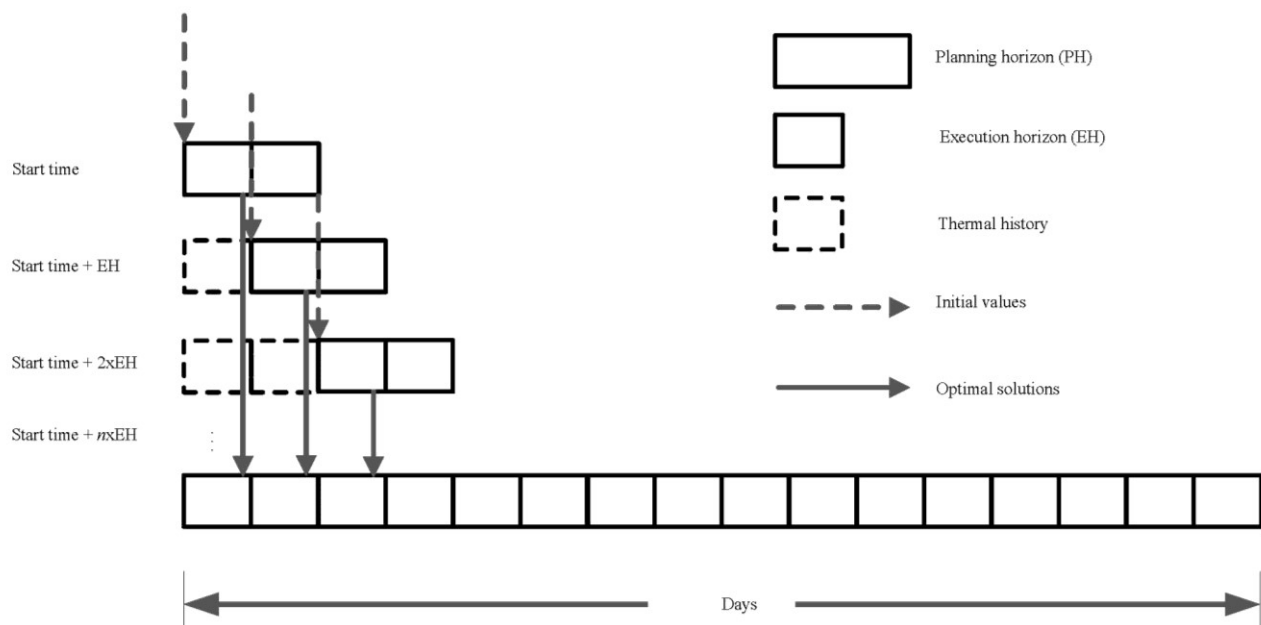


Fig. 2. Moving horizon for optimization.

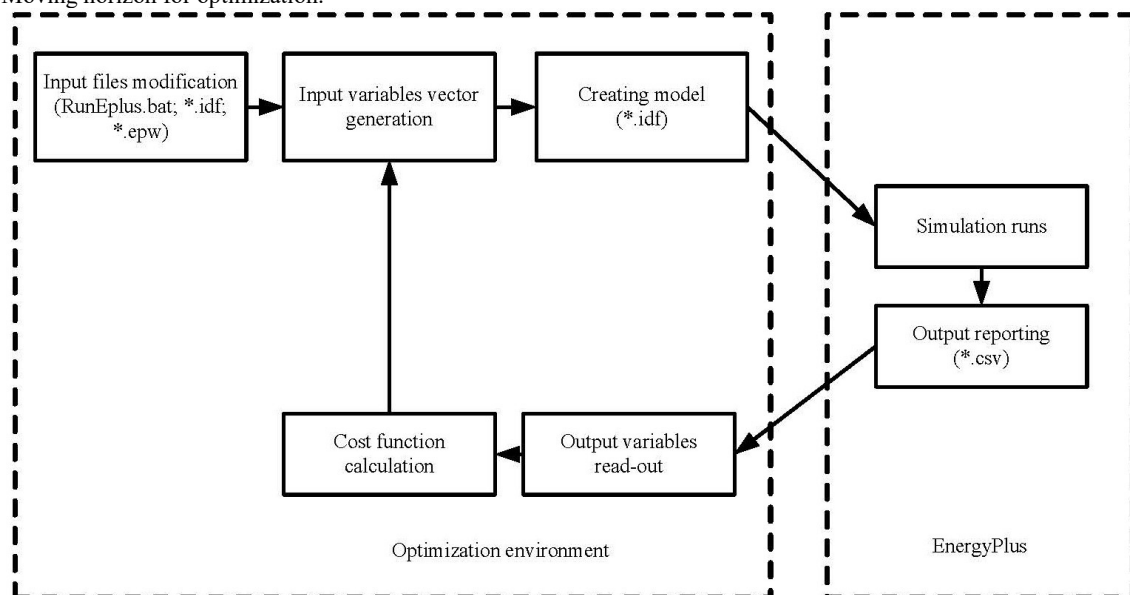


Fig. 3. Offline optimization process.

Independent variables for the optimization process are all physical parameters on which user can act in the building systems, whether these parameters being local (zone air temperature setpoint by thermostatic valves position or some indoor air thermostats) or central (outdoor temperature compensated supply water temperature, system availability within some periods of time, mass flow of available energy carriers etc.). Planning horizon is of adjustable length and can span from one hour up to three days (typical length of short-term weather forecasts). The control horizon is shorter than the planning horizon and can range from 1h up to 24h. Each day of the planning horizon is divided in several blocks (figure 4) during which independent variables remain constant. Typically, each day should be divided in at least two blocks representing occupied and unoccupied

period. Further division with shorter durations is allowed also in this environment.

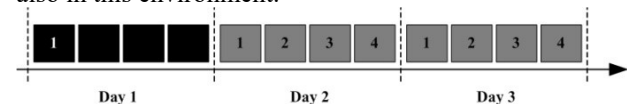


Fig. 4. Planning horizon spanning 72 hours.

In the optimization algorithm, vector of independent variables is generated with each variable placed in the exact place of energy model. With this vector, the simulation is started externally from the optimization environment with proper weather file (which can contain either actual climatic weather data or the forecasted data with data treated either as deterministic or stochastic). After simulation completes, from the output file necessary data for calculating cost function are extracted. Based on cost function, new vector of independent variables is generated and the process repeats until one of the exit criteria is being reached (either time for the runtime or

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change in cost function through consecutive generations of input vectors). After satisfying exit criteria, optimal values are implemented in building or become part of model thermal history, and the process starts for the new planning horizon, shifting forward in time for the length of control horizon. The optimization environment was realized to use multi-thread processing enabling use of all computer cores simultaneously.

If the planning and control horizons are divided in large number of blocks, huge number of independent variables (several hundred variables for the basic HVAC systems) for the optimization process are necessary to find and the computation runtime can extend significantly. One of the ways to prevent excessive computation time is to constrain computation time to reasonable measure, which can lead to unsatisfying results, especially for online optimization. On the other hand, for offline optimization, computation time is not of greatest importance, but using significant computational resources can increase costs for developing new controllers. This is

why researchers tend to use simpler white-box or black-box models and to use BEPS models only for controller evaluation. There is also a possibility to use sensitivity analysis in order to reduce number of independent variables for the optimization process. The main idea is to incorporate process shown in figure 1 in processes shown in figures 2 and 3, i.e. to systematically reduce number of independent variables by applying global sensitivity analysis. Inputs for the sensitivity analysis are all independent variables after defining planning and control horizons (subdivision in blocks of occupied and unoccupied periods), while the outputs are dependent variables which form the cost function. Inputs which are shown to have significant impact on the outputs (the most influential on cost function) become independent variables for the optimization process while all other inputs remain on initial values. The optimization process follows the procedure described above with sensitivity analysis run at the beginning of each new planning horizon. This process is illustrated in figures 5 and 6.

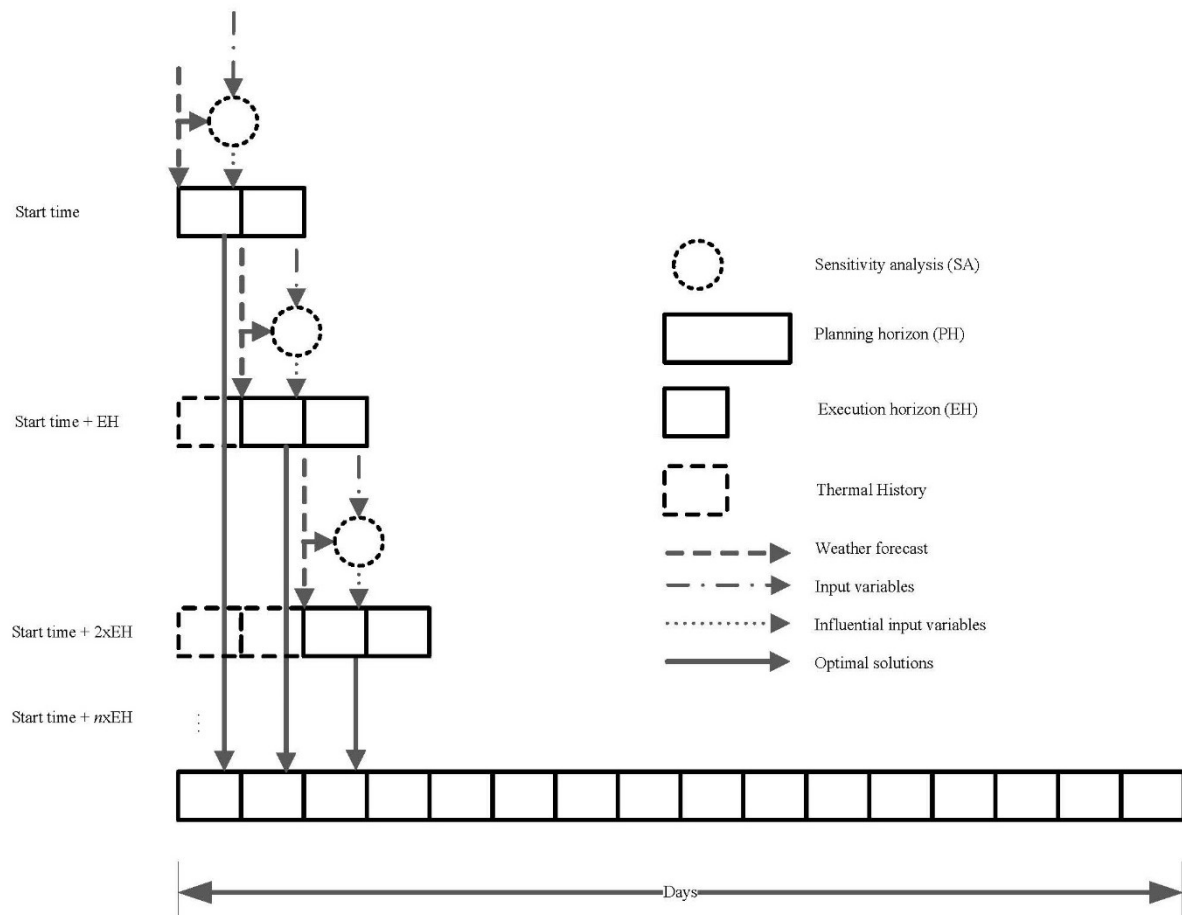


Fig. 5. Moving horizon with sensitivity analysis.

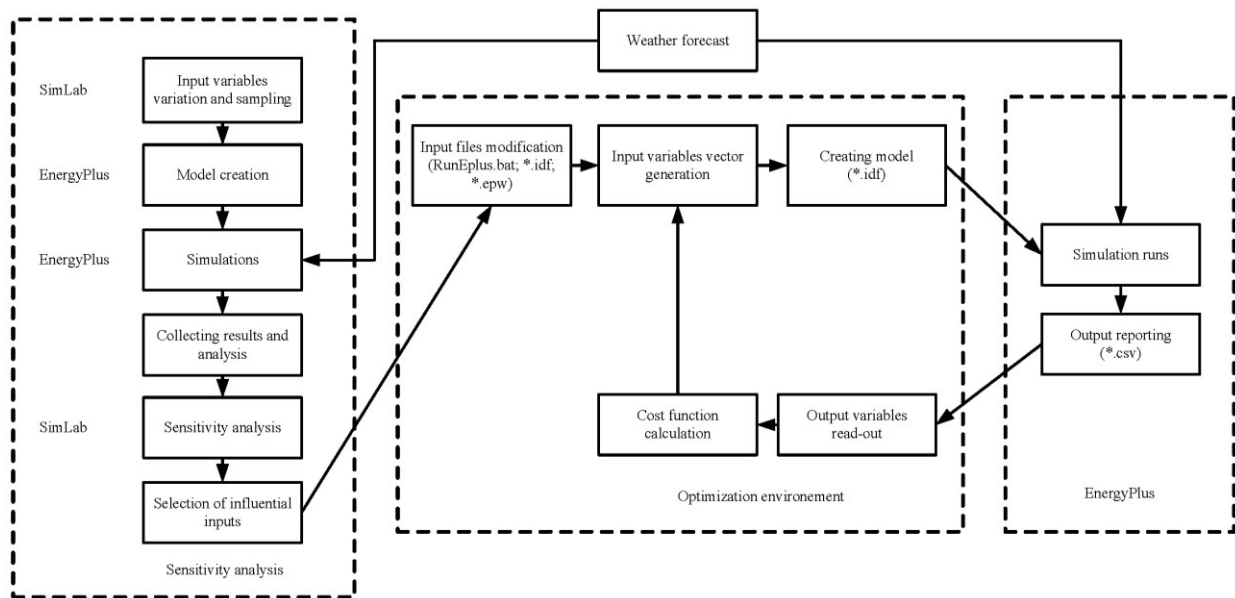


Fig. 6. Sensitivity analysis based offline optimization.

2.1. Reference building and application of the methodology

The described processes of determining daily optimal operation strategies with minimization of energy consumption while maintaining thermal comfort are applied to the office part of the Feniks BB company building shown in figure 7 (more details about the building geometry, constructions used and HVAC systems and controls can be found in [34]) The building is located on the outskirts of Niš, the largest city in Southeastern Serbia.

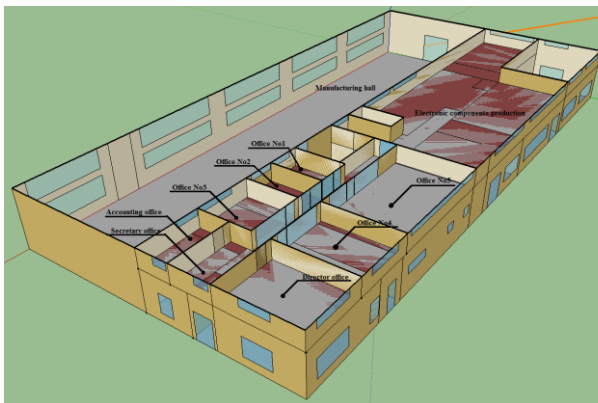


Fig. 7. Office part of the building.

Most of the office part of the building is equipped with radiator heating system (except offices No1, No2 and No3) which is the main heating system in whole building. In addition, office part (all offices) is equipped with constant air volume air conditioning system as the sole system for cooling, which can also be used for heating this part of the building. Radiators are equipped with thermostatic valves for local individual control. In addition, central control is implemented in both radiator and air conditioning system with some important control features: supply water temperature control is realized as a

function of outside air temperature (4-point heating curve); there is a possibility to correct supply water temperature within predefined periods of day; in air conditioning system supply air temperature control is implemented based on exhaust air temperature; air conditioning start and stop time can be defined on daily basis, as well as airflow within this system by using frequency drive.

Building energy model was calibrated with values from supervisory control and data acquisition system. The planning horizon is set to two days, while the control horizon is one day. Each day is divided in four blocks representing: unoccupied period before occupants arrive (00:00 – 06:00); occupied period 1 (06:00 – 11:00); occupied period 2 (11:00 – 16:00); unoccupied period after occupants leave (16:00 – 24:00). Based on installed control systems, 99 independent variables were identified for the described planning horizon: airflow in air conditioning system (1 independent variable); supply water temperature correction (8 variables); air conditioning system availability (8 variables); supply air temperature setpoint (8 variables); radiator availability in offices (32 variables for total of 5 offices); radiator setpoint (35 variables, unoccupied periods before occupant arrival have the same value); required heat capacity of the heating substation (7 variables). The cost function:

$$\min E = \sum_{\tau=1}^{\tau=\tau_{HP}} E_{DEL}(\tau) \quad (1)$$

Has an ε constraint implemented :

$$-\varepsilon < TCF < \varepsilon \quad (2)$$

where:

$E_{DEL}(\tau)$ - delivered energy to the building in every hour of the planning horizon, output from simulations

ε – constant related to prescribed values of PMV according to [45] and was kept at 0.5

TCF – number of people weighted thermal comfort function which is calculated as:

$$TCF = \sum_{j=1}^{j=6} (\min PMV_j) \times \frac{N_j}{N_{tot}} \quad (3)$$

with

j – index of the occupied office,
 $\min PMV_j$ – minimum value of PMV index in office j during occupied periods of the planning horizon, output from simulations,
 N_j – number of occupant in office j (1 in Director office, 2 in Accounting office, 2 in Secretary office, 2 in Office No3, 4 in Office No4, 3 in Office No5),
 N_{tot} – total number of occupants in the office part of building.

The procedure for obtaining optimal operation strategies was run for the period 06.02.2017 – 10.02.2017 assuming weather forecast to be perfect (deterministic approach using actual weather data from the location itself, rather than using forecasted data) with population size set to 1000, number of generations set to 50 without exit criteria defined.

On the other side, the procedure was expanded by adding global sensitivity analysis as the first step. In sensitivity analysis (Monte Carlo), each of the 99 identified variables was assigned probability distribution function and range (uniform for continual and discrete with equal probability for binary variables) and Latin

Hypercube Sampling with 1500 values was performed in software Simlab 2.2. This resulted in the fact that at the start of each planning horizon 1500 simulations were run in order to identify input variables which effect either energy consumption or TCF function during the planning horizon. Standardized regression rank coefficient was selected as sensitivity index with threshold value of 0.05. After the sensitivity analysis, only variables with SRRC greater than threshold value became independent variables in the optimization process, while all others held their initial values. In this case, population size was set to 500 with same number of generations and also without exit criteria.

The simulations were run on a 24-core Intel Xeon working station with 32GB of RAM memory.

3 Results and discussion

The PMV variations in case with full number of independent variables (99) for the selected periods is given in figure 8, while the PMV variation for the same period but with application of sensitivity analysis is given in figure 9. Difference between PMV variations in selected office is shown in figure 10. Figures 11 and 12 illustrate difference in energy consumption and optimized operation parameters.

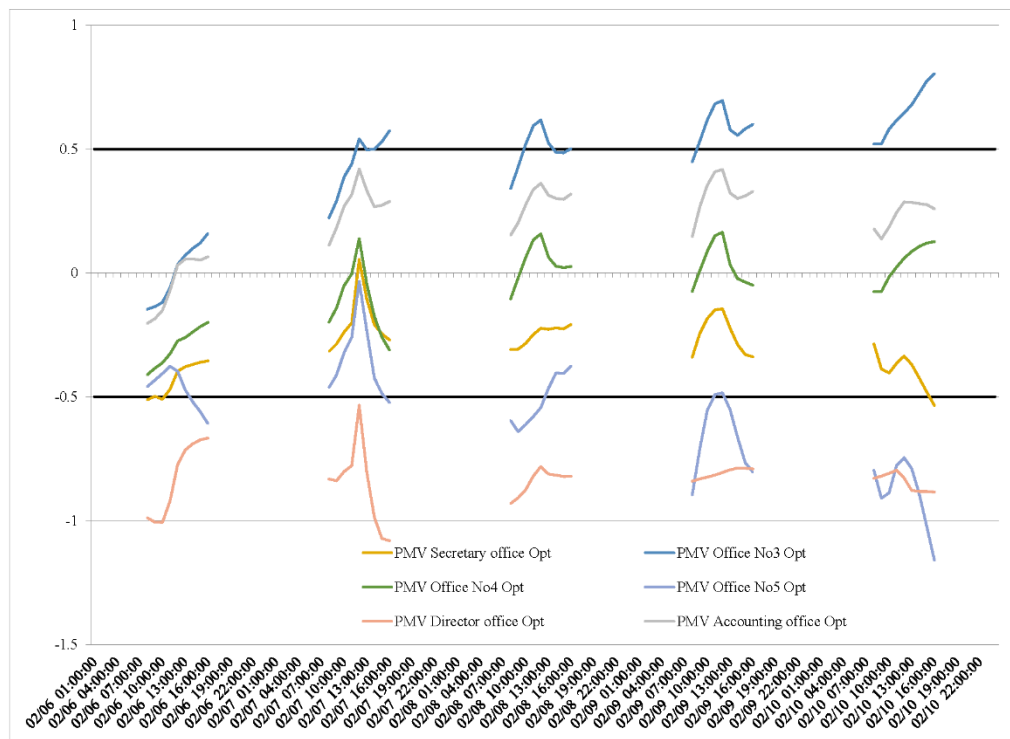


Fig. 8. PMV variations in all offices with full number of independent variables.

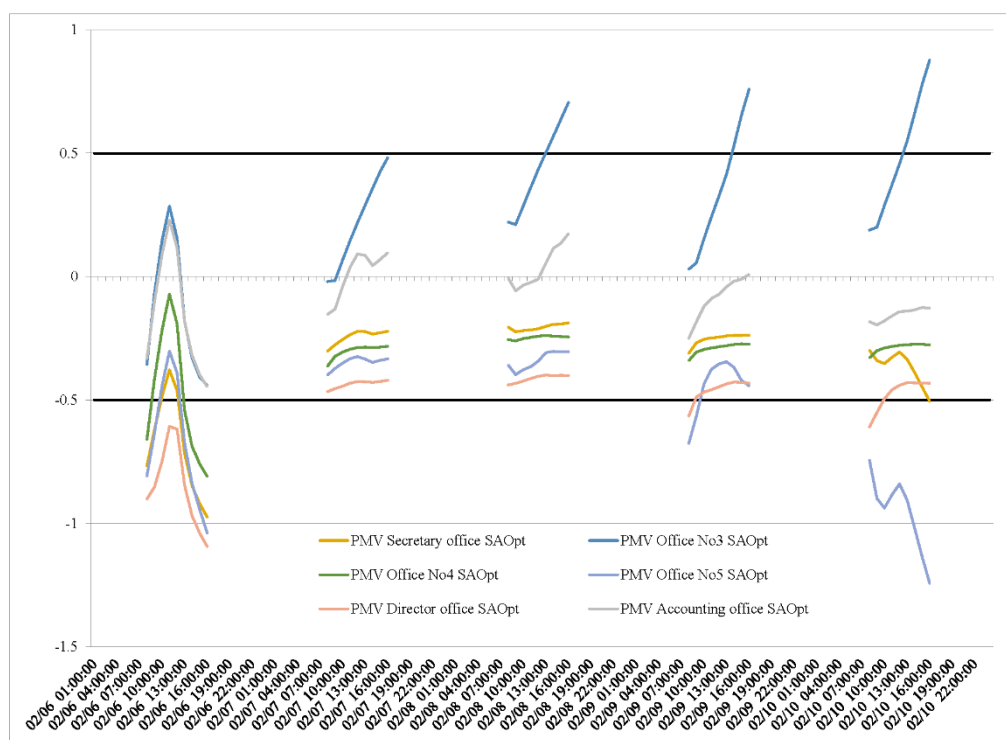


Fig. 9. PMV variations in all offices with reduced number of independent variables.

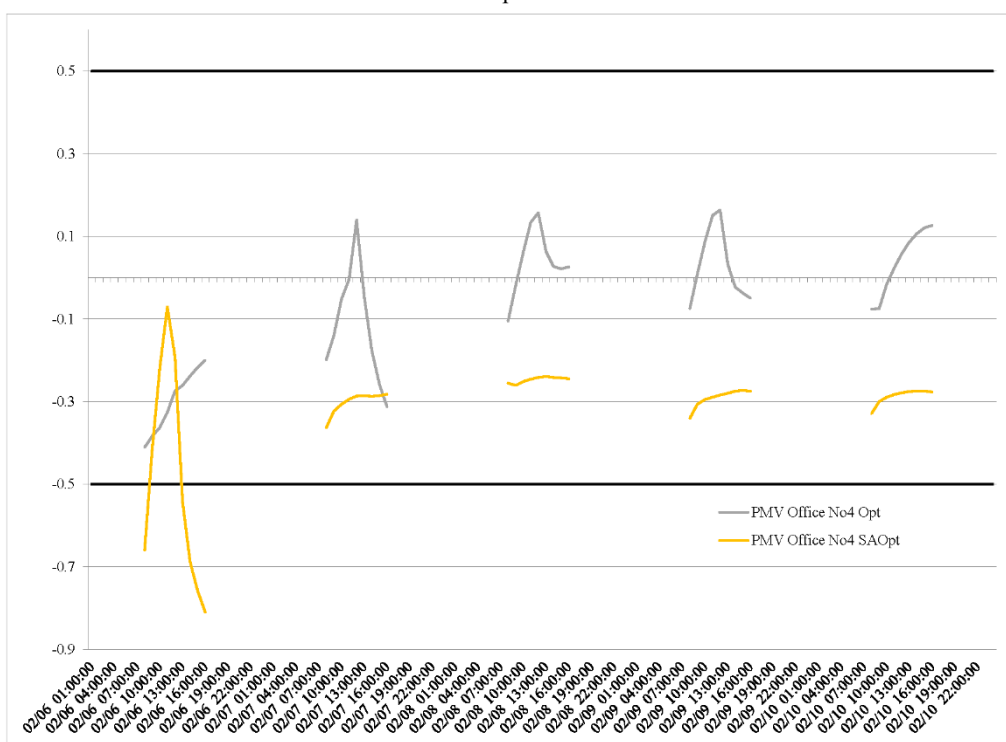


Fig. 10. PMV variations in office No4.

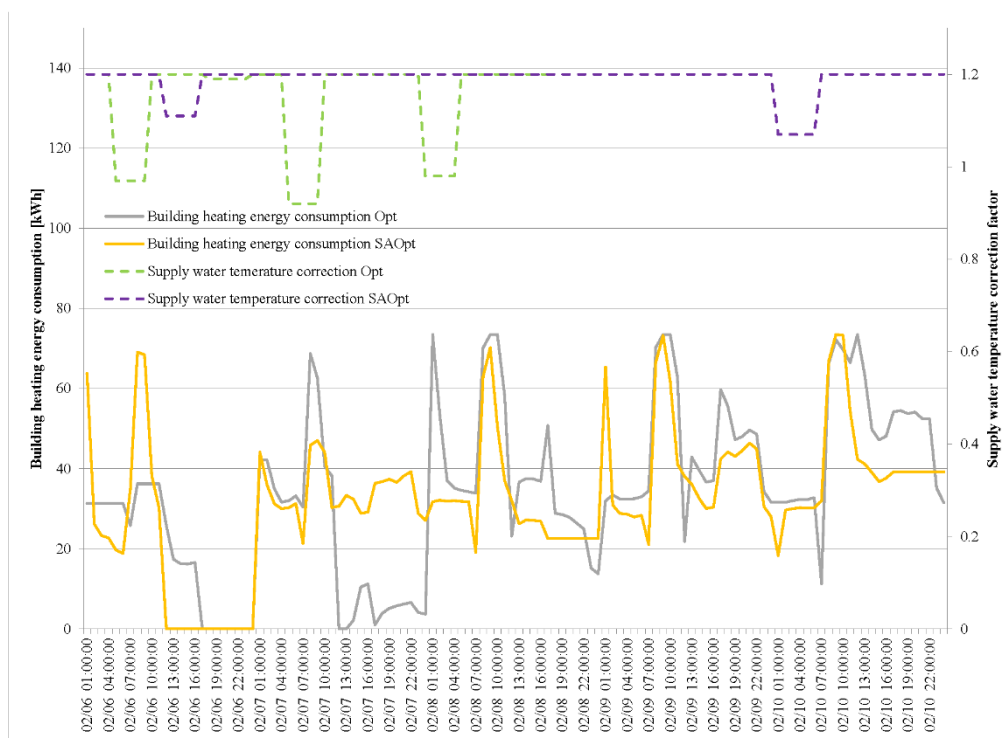


Fig. 11. Building heating energy consumption and supply water temperature correction.

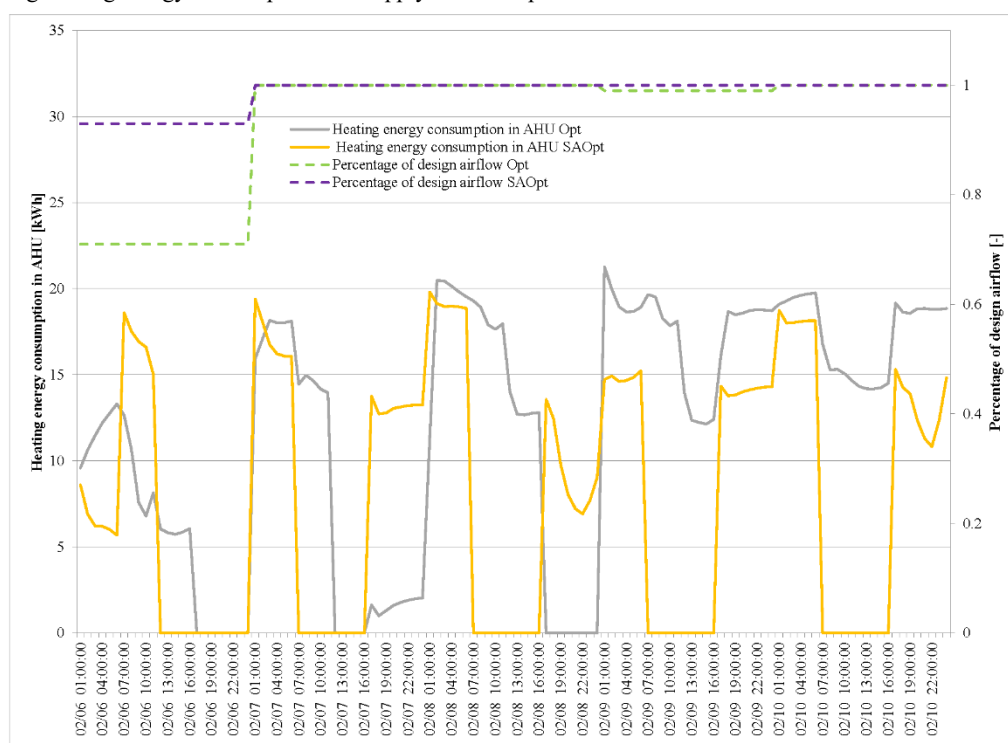


Fig. 12. Air conditioning system heating energy consumption and percentage of the design airflow.

Computation time for both cases and the difference between the two are given in table 1.

Table 1. Computation times and difference

Planning horizon	Full number [h]	Reduced number [h]	Difference [h]
06-07.02	43.0	14.8	28.2
07-08.02	33.2	15.0	18.2
08-09.02	55.8	15.1	40.7
09-10.02	55.2	15.5	39.7
10-11.02	55.5	12.4	43.1

Optimal operation strategies with full number of independent variables resulted in energy consumption of 4146 kWh for thermal comfort constraint set to $\varepsilon = 0.5$. Energy consumption in the air conditioning system accounts for 35%.

Sensitivity analysis had shown that energy consumption and/or thermal comfort function were sensitive to changes in inputs related to air conditioning system (airflow, system availability and supply air temperature setpoint), required heat capacity for the heating substation and partially to changes in radiator availability. From the total of 99 variables, for most planning horizons only 33-36 were influential and were treated as independent variables.

Furthermore, building energy consumption reduced by 5.02% (from 4146 kWh to 3937 kWh). By comparing required heat capacity of the heating substation and supply water temperature correction factors, it is seen that optimal values for correction factors were on the upper limit of the range (20% increased from the calculated supply temperature) in both cases, with shorter periods of heat supply intermittency for the sensitivity analysis approach, which leads to the conclusion that building thermal mass was better used with this approach. The latter statement is proven taking into consideration energy consumption within the air conditioning system as well as change in airflow within the system, since this energy consumption was reduced to 24% of total energy consumption for heating.

For approach with sensitivity analysis as the first step, the following was achieved:

- Resulting PMV in all offices was close to the values achieved with full number of variables, while for some there is a slight improvement,
- Energy consumption in air conditioning system was reduced due to building thermal mass usage and as a result of increased radiator heating,
- There is slight reduction in building energy consumption,
- Operation parameters for both available systems (supply water temperature correction factor, air flow and supply air temperature setpoint) are close to those obtained with full number of independent variables.

The main reason for this lies in the fact that reduced number of independent variables led to smaller population size in optimization process which further led to faster finding solutions that satisfy thermal comfort constraint thus having more generations for energy consumption reduction in the process. In addition, sensitivity analysis

approach resulted in significant computation time reduction.

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