APPLICATION OF AN OPTIMISATION APPROACH FOR THE CALIBRATION OF HIGH-FIDELITY BUILDING ENERGY MODELS TO SUPPORT MODEL-PREDICTIVE CONTROL (MPC) OF HVAC SYSTEMS

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ABSTRACT

Heating, ventilation and air-conditioning (HVAC) accounts for up to 50% of building energy consumption, and studies have shown significant potential for savings through the utilisation of fault detection and smart predictive control in place of traditional reactive based control systems. This paper proposes a strategy for implementing intelligent model-predictive control (MPC) of HVAC systems based on calibrated high-fidelity models and real-time performance data. A genetic optimisation algorithm is proposed to improve the initial calibration of the high-fidelity building energy models (BEM), and to generate, on a semi-automatic basis, the reduced-order models (ROM) on which the control optimisation algorithms are based. We also present a case study showing the application of the genetic optimisation approach on the development and calibration of a BEM for a 2,775m^2 commercial building in Helsinki, Finland.

INTRODUCTION

It is estimated that up to 90% of the buildings' life cycle carbon emissions occur during their operational phase, mainly as consequence of the HVAC, lighting and appliances' energy consumption (Ramesh et al. 2010), representing over 30% of CO_2 emissions and 35-40% of primary energy demand globally (International Energy Agency (IEA) 2014; Pérez-Lombard et al. 2008). Modern buildings typically incorporate extensive monitoring of systems and environmental conditions – and automated measurement-based control is becoming the norm. However, extensive smart metering and intelligent controls do not necessarily imply efficient or effective operation.

The development and implementation of effective control techniques, such as model predictive control (MPC) of HVAC systems, presents an opportunity to improve control performance in terms of energy consumption and thermal comfort. MPC techniques use a predictive system model to provide anticipatory control action rather than corrective controls, thus mitigating inefficiencies associated with classical control systems (Afram & Janabi-Sharifi 2014; Hazyuk et al. 2014). MPC also provides us with the ability to consider multi-objective optimised control, allowing the system to consider both comfort and the cost of energy. This is particularly relevant in a move towards a smart-grid, requiring active demand-response control in buildings.

For reliable and effective MPC, it is imperative to have a base model that is representative of the actual system operation and its behaviour under the influence of internal (e.g. occupancy, equipment and lighting) and external (e.g. outside temperature, humidity, solar irradiance, wind velocity, and cloud factor) disturbances (Afram & Janabi-Sharifi 2014):

This paper presents an approach for generating and calibrating high-fidelity models of buildings, utilising real system operational data (free-form profiles) combined with genetic optimisation techniques that help to reduce the discrepancies the model and actual system performance. Using this approach, it is possible improve the development time and accuracy of high-fidelity system models which can be used as a basis for an optimised MPC strategy. In order to improve computational efficiency and enable real-time MPC, we propose a semi-automatic procedure that generates a reduced-order model (ROM) based on a resistor-capacitor (RC) network representation (Staino et al. 2015), which is currently part of ongoing research work. The derivation of such a 'grey-box model' offers a number of significant advantages over alternative approaches:

i. the ROM can be derived quickly for a wide range of building configurations, without the need for extensive measured training data;
ii. the MPC control algorithm can be tested independently within the modelling environment;
iii. the ROM can be updated to reflect changes in the building fabric or operation, without the need for re-training on a new measured data set.

This research represents a significant enhancement to the capabilities of the existing VE simulation engine, providing the necessary framework and tools to enable the building design model to be used effectively throughout the building life cycle (BLC), as opposed to the traditional case where design considerations are often neglected during system installation, control specification and building commissioning. It is hoped that the outcomes of this work will help bridge the current gap that exists between building design intent and operational performance.

Computational Optimisation

Computational optimisation techniques aim to explore a design space and algorithms are designed to progress to the most appropriate solutions in a resource efficient manner. Single objective problems aim to determine one solution that corresponds to global minimum (or maximum) of the objective function. Multi-objective problems aim to maintain a population of many variants with the aim of finding the set for which there is no better performing variable combination across all objectives.

Figure 1 illustrates the results of a hypothetical two-objective optimisation problem. The plot shows the objective plane with each point representing a solution evaluated during the optimisation process. For the objective minimisation problem, solutions that lie to the lower left of the plot are better. In particular, the algorithm seeks to find points that are non-dominated and which form the Pareto front. The Pareto front represents the trade-off curve that highlights the balance between the two potentially conflicting objectives.

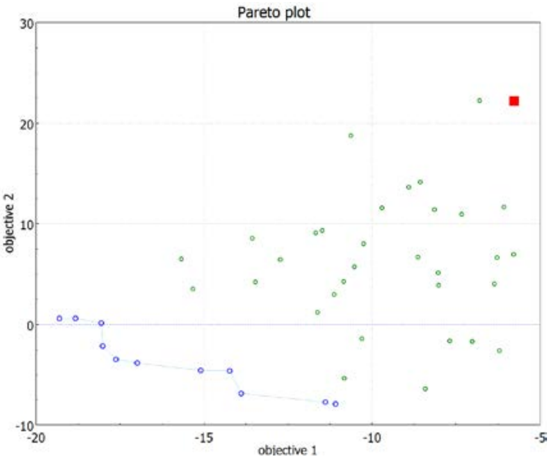

Figure 1: Example of a Pareto Front for a two objective optimisation problem. Blue circles are non-dominated points and form the Pareto front. Green circle are dominated points not on the Pareto front.

There are many approaches for exploring the design space (Evins 2013). Genetic Algorithms (GAs), which use the Darwinian concepts of 'evolution by natural selection', are one of the most commonly applied of these methods. GAs work by maintaining a population of individuals, with the fittest candidate solutions selected to progress to subsequent generations. Diversity in the set of individuals is maintained by means of two operators, crossover (combining the features of two individuals) and mutation (random changes to an individual).

Selection of individuals in algorithms based on a non-dominated ranking process (e.g. NSGA-II) (Deb et al. 2002) encourages the set of individuals to advance towards the optimum front. Furthermore, 'crowding distance', a measure of how closely individuals are packed on the optimal front, accounted for. This ensures that the spread of solutions along the front is even.

In this work, we make use of the Optimise tool, a new prototype application within IES <VE>. Optimise allows users to define optimisation problems, invoke the NSGA-II algorithm and monitor progress of the optimisation run.

METHODOLOGY

This paper explores the use of a GA as tool to help analyse suitable parameter settings to help with high-fidelity model calibration. Note that the same principles will apply to the subsequent optimisation of the building control algorithms, in terms of set points and schedules. In this case, we are illustrating a multi-objective optimisation based on calibration error (i.e. differences between measured and simulated values), while in the control scenario; the multi-objective optimisation focuses on minimising cost and energy consumption.

As part of this study, the optimisation algorithm has been applied to meet two different use cases identified during the calibration process.

1. Static parameter optimisation: Here the calibration engineer has identified a set of parameters for which there is uncertainty over the precise value. Uncertainty may exist in the model through incomplete information about the fabric or system configuration.
2. Dynamic profile optimisation: Automatic adjustment and fine-tuning of time-dependent variables and profiles (e.g. occupancy, lighting);

Static parameter calibration

Model parameterisation is a challenge for high fidelity thermal simulation engines such as the IES <VE> toolset. The reason for this is the large number of model parameters that need to be specified during model creation, and the typical lack of detailed information about the actual building, in combination with the fact that there are generally relatively few observed data-streams with which to calibrate or validate the model. For the purpose of this study, a pragmatic approach has been used to identify the model parameters of interest. An initial set of parameters have been identified by the building engineers based on experience and knowledge. The set of parameters is reduced further via a sensitivity analysis approach described in the case study. The parameters with most impact are taken as variables in the optimisation scheme for further adjustment.

Occupancy behaviour calibration

In the IES <VE> time-dependent behaviour is specified by assigning profiles to quantities in the model. For example, profiles are assigned to occupancy for each thermal zone in a model. As part of this work, it was identified that occupancy was not very well understood for the case studies. Data was collected via a survey in order to define the occupancy schedules for the calibration period. This was useful to defined key times in the building where occupancy changed, but not sufficient to detail the number of people at a particular time in any one room of the building. Therefore, an optimisation strategy was applied to adjust the occupancy profiles to get a better match for selected metered quantities in the model.

Parameterisation of the model was performed using an automated strategy. In a model there may be a number of different occupancy profiles assigned. For this work the profiles were restricted to have a step change form, as shown in Figure 2. Here the occupancy level is fixed for a period in time before a step change at a particular instance. Figure 2 shows a typical occupancy schedule, for one day, where the profile contains 5 different values corresponding to each interval of constant value.

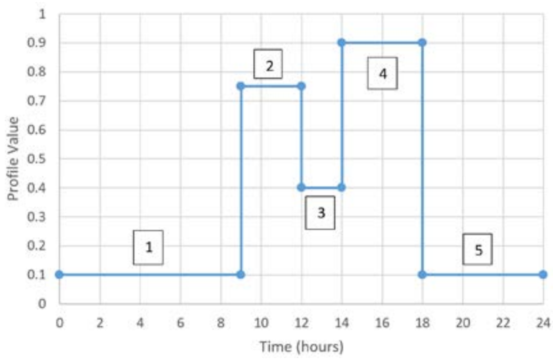

Figure 2: A generalised occupancy schedule for one day based on aggregated survey data.

The occupancy profiles assigned in the model can be determined by querying the model database. Each profile can be subdivided into days over the calibration period. For each profile day the number of discrete profile values can be identified and declared as variables in the optimisation process.

A further refinement to this parameterisation procedure was considered - Using a similar approach it is possible to define optimisation parameters based on the time of each step change. For the profile in figure 4, this would add a further 4 parameters. The profile defines first occupancy at 9:00, which would be in accordance with the data collected via survey. It may well be that the building is occupied earlier or later. Setting the times of occupancy changes as optimisation parameters was not considered in this work. The allowable range of each profile value is based on a user specified variation on the initial value. In this study each profile value was allowed to be changed by ±0.3. Profile values are restricted to the range 0 to 1.

Optimisation Objectives

A two-object optimisation problem was formulated for the calibration study based on measures defined in ASHRAE Guideline 14-2002. The optimisation objectives user are the coefficient of variation of the root mean square error, CVRSME, and the normalised mean bias error, NMBE. These indices are calculated for each variant model based on metered data and simulated results.

CASE STUDY

Sanomatalo is a commercial and office building in Kluuvi, the commercial centre of Helsinki, Finland (see Figure 3). It is the headquarters of Finland's largest newspaper group. Completed in July 1999, the building has a footprint of 2,775m^2 at ground level, an overall area of 42,734m^2 and a useful area of 38,190m^2.

Building Description

The building has twelve floors altogether consisting of nine above and three below ground. The south-west corner of the fourth floor, which faces on to Toolonlahdenkatu Street, is below-grade due to a higher ground level at this position. The building is comprised of a concrete core structure with a double-skin façade (double glaze inner with 70cm void before another glazing Panel) to the east, west and south, while the north face has a standard double-glazed façade. The north side has some external architectural support features in the form of vertical supports with cross bracing.

Figure 3: Sanomatalo case study building

The basement and below-grade floors comprise services areas, fitness suites, car parking, projector rooms, and conference rooms. The upper floors consist of large atriums with glazed walls and a corridor with a glazed roof giving good daylight penetration throughout. Each floor provides large open plan office space for the staff with access from multiple lifts and a central staircase. Three fire-rated stairwells provide emergency exits on the east, west and south facades. The top floor has roof terraces on three sides, south, east and west. The west-side roof terrace houses chiller equipment while the south and east provide space for occupant use.

Active chilled beams located at high level within each occupied zone provide space cooling. Perimeter radiators on each floor of the building provide for heating requirements. Air handling units (AHU) located at both basement and roof level provide fresh-air ventilation to all spaces in the building through supply ducts located on each floor. The AHU's also supply fresh air for cooling to the active chilled beam system. The building is broken up into four zones (A, B, C and D) as shown in Figure 4, where this study focuses on Zone C (highlighted in yellow) to present a simple demonstration of the application of this approach.

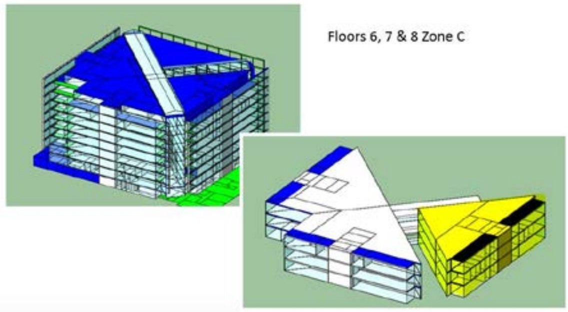

Figure 4: Sanomatalo Building Zoning

Data Collection

A detailed building audit was carried out, in accordance with standard audit guidelines (ASHRAE 2011), in order to collect information required to produce an accurate building energy model. A mobile application, the Virtual Audit Application (VAA) provides a repository for storing and tagging static building data (e.g. equipment information and photographs) during the audit process (see Figure 5). This data is used to define initial base-case estimates for model inputs, as well as the upper and lower bound values.

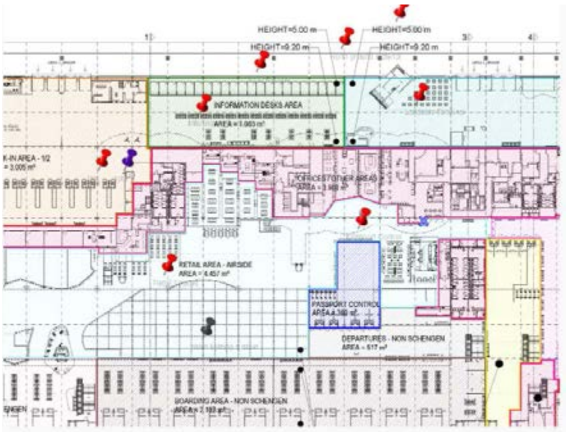

Figure 5: Virtual Auditing Application Interface (Static data collection and tagging)

The building management system (BMS) on-site monitors a combined total of over 20,000 points, comprising HVAC equipment, electrical metering, zone environmental conditions etc., Sub-metering on the primary heating, cooling and electrical circuits provide complimentary consumption information for the pilot case study area (Zone C). A web-based data management and analysis platform (see Figure 6) acts as an aggregator for both historic and live BMS and sub-meter data, as well as forecast information (e.g. occupancy and weather) necessary for model-predictive control. At this stage, all available building data points are logged as the associated computational and storage costs are insignificant when compared with the effort of filtering the dataset. Subsequent manual filtering and post-processing is required to eliminate redundant or faulty data logs.

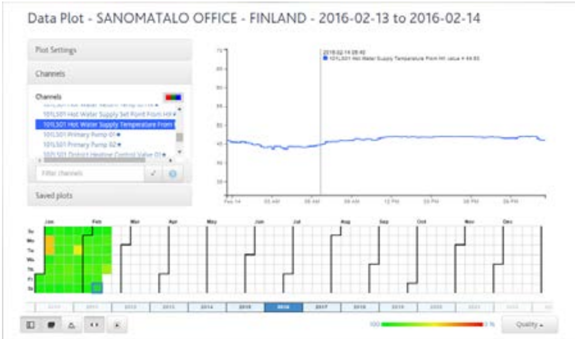

Figure 6: BMS data collection and analysis dashboard

Building energy model (BEM) development

The building energy model (BEM) for Sanomatalo, developed in IES <VE>, consists of a full-scale zonal model, complete with construction details, occupancy and equipment schedules as well as HVAC system information defined in the ApacheHVAC module of IES <VE> (see Figure 7).

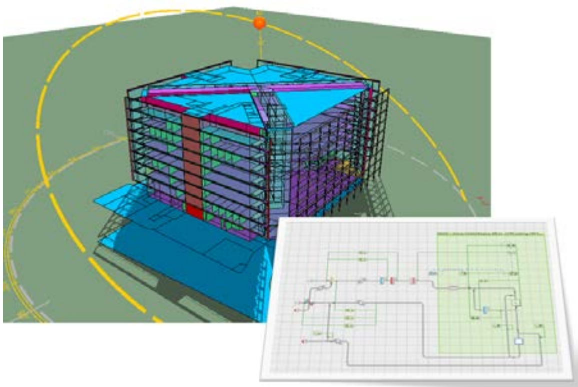

Figure 7: Sanomatalo building energy model and sample HVAC system schematic (IES <VE> and ApacheHVAC)

For the purpose of MPC, we are interested in achieving robust prediction accuracy at a high-frequency timescale (sub-hourly), particularly with respect to the following parameters that affect energy consumption, thermal comfort and dynamic system operation, respectively:

- Total System Energy [MWh]
- Room Air Temperature [ºC]
- System air flow rate [m^3/s]

In order to measure the performance of models with respect to these outputs, we use the following standard statistical indices to compare measured and simulated data (Coakley et al. 2014).

- Normalised Mean Bias Error, NMBE, (%): This is a non-dimensional bias measure (i.e. sum of errors), between measured and simulated data.

$$NMBE = 100 \times \frac{\sum_{i=1}^{N_p}(m_i - s_i)}{(N_p - 1)\bar{m}} \qquad (1)$$

- Coefficient of Variation of Root Mean Square Error, CV(RMSE), (%): This is essentially the root mean squared error divided by the measured mean of the data. CV(RMSE) allows one to determine how well a model fits the data; the lower the CV(RMSE), the better the calibration.

$$CV(RMSE) = 100 \times \frac{\sqrt{\frac{\sum_{i=1}^{N_p}(m_i - s_i)^2}{(N_p - 1)}}}{\bar{m}} \qquad (2)$$

Where; m_i and s_i are the respective measured and simulated data points for each model instance 'i'; N_p is the number of data points over the calibration period.

Model Calibration and Sensitivity Analysis

In order to improve model accuracy, we use a standard model calibration process to improve the 'goodness-of-fit' between model outputs and measured system performance (Coakley 2014). The approach uses sensitivity analysis during initial model calibration, optimisation and ROM development in order to help characterise the model in terms of primary influential variables. Using the standard deviation for each output variable (σ) and the coefficient of variation (CV) of each input parameter, we calculate the influence of each input on the overall model results relative to other parameters, using a normalised sensitivity index (NSI):

$$NSI = \frac{\sigma_{y(x)}}{Max\ \sigma_y} \Big/ CV_{i(x)} \qquad (3)$$

This provides a rank-order sensitivity index for each input parameter (see Figure 8), which is used to help improve the model calibration process.

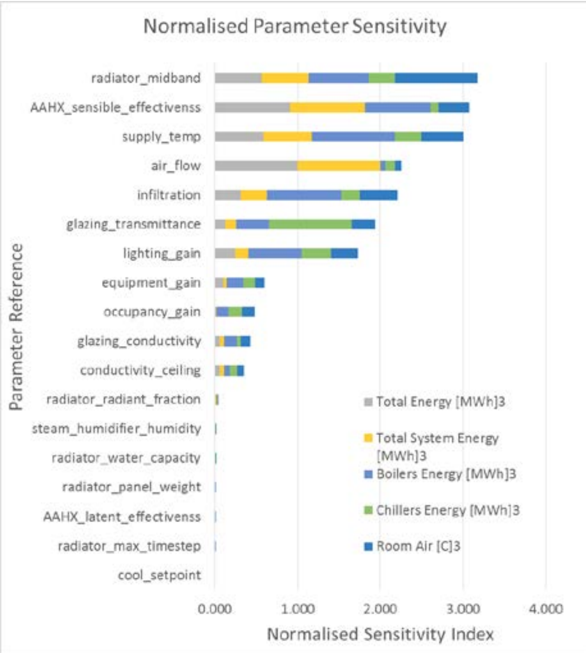

Figure 8: Sensitivity analysis results

Automated parameter optimisation

Once initial manual model updates are complete, the next step of the process is to use the Optimise tool with the aim of calibrating the final unknown parameters that have the biggest influence on the model as identified in the sensitivity analysis. Use of the optimise tool involved the following steps:

1. Optimise tool configuration;
2. Design parameter specification;
3. Objective function specification;
4. Result analysis and visualisation.

The Sanomatalo model was configured in the Optimise tool as shown in Figure 9.

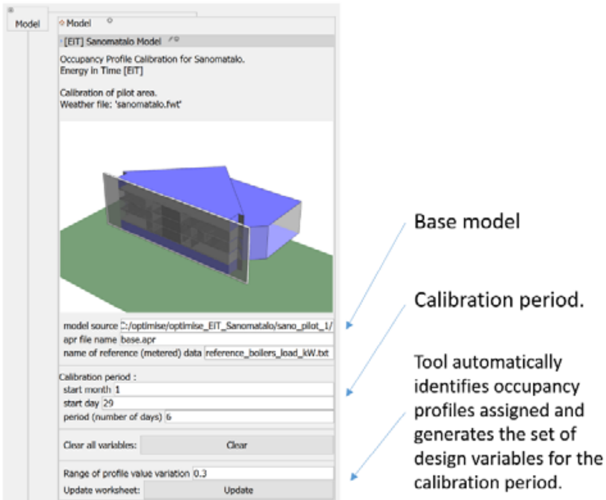

Figure 9: Optimise tool configuration window

The design parameters were set-up in Optimise as continuous variables with set lower and upper bounds. In the first instance, we focused on calibration of the dynamic occupancy profiles. In this configuration, 52 parameters were automatically identified from the 3 free-form profiles assigned to the zones in the model:

- FFP0043 – occupancy profile, floor 6;
- FFP0044 – occupancy profile, floor 7;
- FFP0655 – occupancy profile, floor 8.

Parameter ranges can be fine-tuned for each variable. In this case, we used a range of ±0.3 from the base model value. Occupancy profiles are modulating therefore the range is restricted to [0, 1].

Finally, we needed to specify the objectives for the optimisation run. A two-objective optimisation problem was defined with the aim of minimising both the CV(RMSE) and the absolute value of the NMBE. These indices are calculated for each mode based on total boilers energy. Equation (4) is used to combing objectives and allow the ranking of models in the optimal set, with better models corresponding to a lower F.

$$F = 0.5 \times CV(RMSE) + 0.5 \times |NMBE| \quad (4)$$

RESULTS

Occupancy behaviour calibration

Once set-up was complete, optimisation of the occupancy profiles was performed. A total number of 29,000 simulations were run for the Sanomatalo building on multi-CPU server. Figure 10 shows a plot of the objectives for all simulations run for Sanomatalo. It can be seen in the graph where the objectives start to converge. The plot in Figure 11 focuses in on the Pareto curve for the optimisation.

Static parameter optimisation – Study 1

Furthering the calibration, the 'best' model from the occupancy profile calibration run, ie the model with the lowest combined objective value as defined by expression (4), was taken as the base model for a secondary optimisation. This second run focused on the 6 'most significant' variables, as identified during the sensitivity analysis (see Table 1).

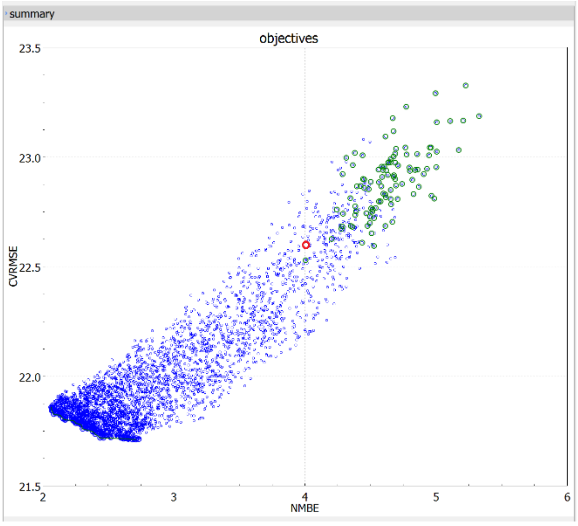

Figure 10: Initial optimisation result. Green initial points from first generation. Red CV(RMSE)(22.6%) and NMBE(3.9%) for base model.

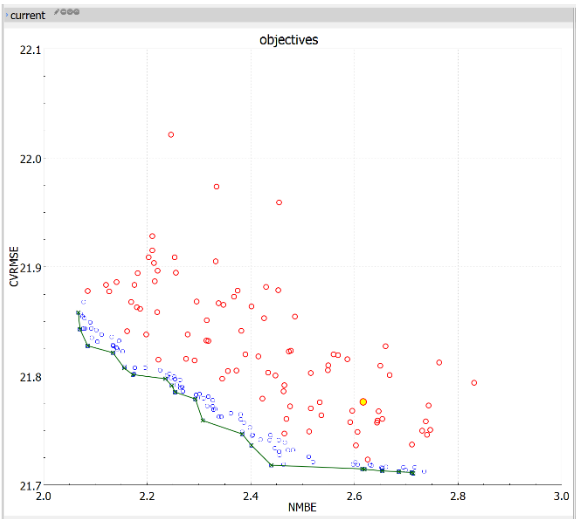

Figure 11: Initial Optimisation Pareto Curve

Table 1

PARAMETER	DESCRIPTION	RANGE
supply_temp	Scaling factor applied to supplied air temperature.	[0.5,1.5]
infiltration	Scaling factor applied to each zone level infiltration rate.	[0.5,1.5]
lighting_gain	Scaling factor applied to lighting gain defined in each zone.	[0.5,1.5]
AAHX_sensible_effectiveness	Sensible effectiveness of air-to-air heat exchanger. Percentage value.	[42,78]
air_flow	Scaling factor applied system air supply flow rate for each conditioned zone.	[0.8,1.2]
radiator_midband	Radiator set point (°C)	[18.9,23.1]

The results for the most promising simulations after 114 generations (100 simulations per generation) are shown in Figure 12. For the 45 models on the Pareto curve table 2 provides a summary of the parameter values.

Table 2

PARAMETER	MEAN	RANGE (MAX-MIN)	RANGE / MEAN
supply_temp	1.48	0.07	0.05
infiltration	1.01	0.59	0.59
lighting_gain	0.77	0.81	1.04
AAHX_sensible_effectiveness	45.43	2.72	0.06
air_flow	0.92	0.11	0.12
radiator_midband	22.89	0.11	0.005

There are a few points to note from these results:

- For the Sanomatalo test case model, NMBE values of 0% can be obtained. A negative NMBE means we are, in general, overestimating energy consumption while a positive result indicates an underestimate. A zero value may simply indicate that our simulated results are above the metered values just as much as they are below. This highlights the importance of including the CV(RMSE) as an objective to give a better indication of model performance.
- With regards to optimisation of the CV(RMSE) index, we can achieve results in the range of 19.92% to 20.55% for the Sanomatalo model. The base model gave a CV(RMSE) of 22.6%, indicating a relative improvement of up to 12% by using the optimisation tool.

  Finally, by examining the parameter values of the optimal models, summarised in table 2, it can be noted that there is little variation in some parameters across all the models. This would suggest that these variables have a well-defined optimum value, and further variation is not required or recommended. A further optimisation run was performed with a reduced set of parameters.

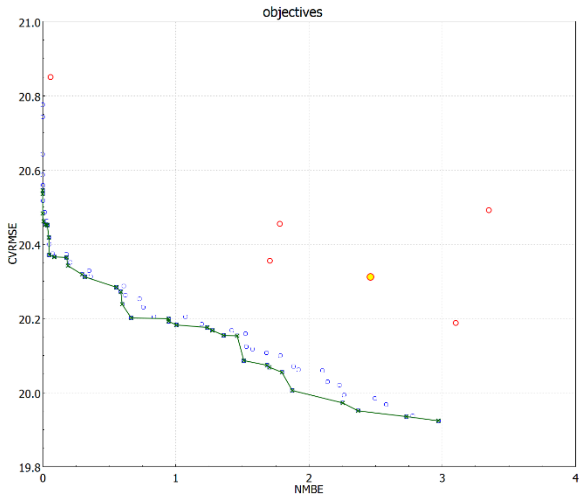

Figure 12: Pareto curve for static parameter optimisation study 1

Static parameter optimisation – Study 2

Refining the optimisation performed as part of study 1, the following changes were made:

- Reduced the range on the *supply_temp* scaling factor to [0.9, 1.1]. Range defined for study 1 was too large allowing unrealistic values.
- Reduced the range on the *infiltration* scaling factor to [0.8, 1.2]
- Removed *'radiator_midband'* as a variable, value fixed: 22.89^{o}C
- Removed *'air_flow'* as a variable, value fixed: 0.92

The Pareto curve for this second run is shown in Figure 13. The improvement in CV(RMSE) and NMBE is not as good when compared to study 1. This may be due to the fact that we have removed some degrees of freedom and restricted the permitted range of some parameters. The best fit final calibrated model for the Sanomatalo case study was determined by taking the model from the optimal set that minimised equation (4). Using the optimise tool, we achieved the following performance results for boiler energy simulation accuracy:

- CV(RMSE) : 20.75%
- NMBE : 0.76%

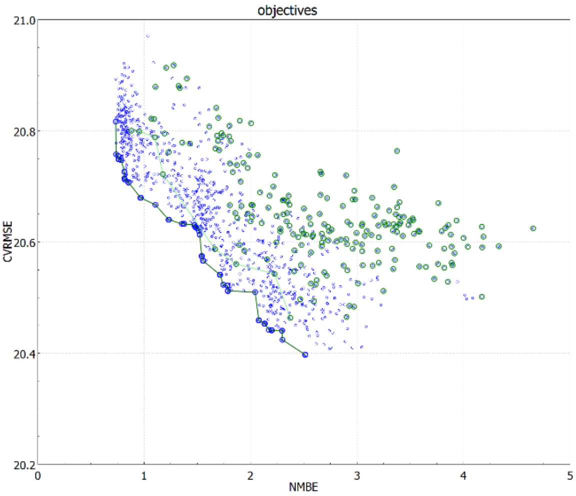

Figure 13: Pareto curve for static parameter optimisation study 2. All variant model evaluations shown. Green indicates first generation.

CONCLUSION

In this paper, we have demonstrated the initial application of a genetic optimisation algorithm to a multi-objective model calibration problem. The approach may be used to automatically refine high-fidelity models for use in model-predictive control (MPC). While the paper focuses on the model calibration optimisation, the same approach can be used to optimise the control variables once an accurate high-fidelity model is available.

The findings illustrate the advantage of incorporating genetic optimisation within the model calibration process to improve model parameter estimation and hone in on promising values/ranges for particular parameters.

Future work will focus on the extension of the optimisation system to include automatic filtering of input parameters based on a linked sensitivity analysis. In addition, further work is needed on the implementation of the automated extraction of a reduced order model (ROM) from the detailed building energy simulation model.

We also wish to extend the tests to include real control results based on optimisation of economic/comfort criteria. Furthermore, the optimisation process outlined is highly dependent on having reasonably good base-case estimates and thresholds for building parameters. Therefore, further investigation is needed into real building data repositories for provision of this information.

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