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METHODOLOGY FOR INTEGRATED OPTIMAL CONTROL AND DESIGN OF BUILDINGS

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Abstract

A large potential exists to improve current practice of HVAC design and operation of buildings with respect to occupant comfort, energy use or energy cost, and investment costs for design and construction. More specifically, design and control processes can be improved through the use of contemporary optimisation algorithms such as Model Predictive Control (MPC). This paper presents a methodology for integrated optimal control and design of buildings using MPC. A possible implementation is presented and a case study application illustrates potential cost savings for a medium sized (10 000 m^2) office building. Opportunities for future work are outlined.

Keywords: Model predictive control, Design, Building, IDEAS, HVAC

1. Introduction

Building Heating, Ventilation and Air Conditioning (HVAC) equipment accounts for about 20 % of Europe's primary energy use [1] and the associated CO_2 emissions have a negative impact on our climate. The use of contemporary technology for optimal design and control of building systems can result in considerably reduced CO_2 emissions, while also achieving cost savings and increased thermal comfort. Many research studies therefore develop methodologies for optimising the control of building HVAC equipment using Model Predictive Control [2, 3, 4, 5, 6, 7, 8, 9, 10, 11], or develop methodologies for optimising the sizing or other design options of the building energy systems or the building envelope [12].
These studies however do not take into account the interaction between the building system design and the control, which can be important. The building *system* design determines what HVAC systems are present and thus what control actions are physically *possible*, while the building *envelope* design determines what heat or cooling loads exist and thus what control actions are *required*. The operational costs associated with a specific design thus depend directly on the design, but also on how the controller operates the building given the possible control actions. For complex buildings, the development of well-tuned building controllers is a labour-intensive process such that building controllers are often idealised during the design process. This can lead to a sub-optimal, conservative design, where the systems are oversized, or an inadequate design where the system is undersized. A systematic design methodology for complex buildings should thus take into account the building controller. We therefore present an integrated optimal control and design methodology for buildings.

This paper summarises work from the PhD thesis of Jorissen [13], which is here complemented with an extended discussion of future work. Section 2 presents the methodology for integrated optimal control and design

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and its implementation. Section 3 applies the methodology to a case study, the Solarwind office building. Section 4 discusses the results of this proof-of-concept. Section 5 elaborates on threats and opportunities for future work. Conclusions are formulated in Section 6.

2. Methodology and Implementation

Simultaneous optimisation of the operational and investment cost of both the design and the control variables of a building would lead to computationally expensive optimisation problems for two reasons. Firstly, the optimisation horizon has to be long (typically one year), to reflect the fact that the design variable values stay the same throughout the control horizon of interest. Secondly, there can be many control variables. Moreover, gradient-based optimisation algorithms may converge to a local minimum of the non-convex design problem. Heuristic optimisation algorithms that are usually able to cope better with non-convex optimisation problems may be intractable due to the large number of optimisation variables. Therefore we propose a nested optimisation loop that consists of an outer and an inner optimisation. The outer optimisation loop determines the design variable values and the investment cost using some heuristic optimisation algorithm. For these design variable values, a model predictive controller is generated, the inner loop, which evaluates the operational cost of the design using a computationally efficient gradient-based optimisation algorithm.

For the implementation of this methodology we rely on the equation-based modelling language Modelica [14], the Building Energy Simulation (BES) Modelica library IDEAS [15], which is an extension of the IBPSA (Annex 60) library [16, 17] and on TACO, a Toolchain for Automated Control and Optimisation of buildings [18]. We use Modelica since this equation-based language decouples model equations and methods for solving them, which allows the use of dedicated solvers. In this case an efficient optimisation solver is used, as implemented by TACO [18]. It exploits the linear nature [19] of the building envelope model dynamics and automatically generates an MPC with computationally efficient code using CasADi [20], which is optimised using IPOPT [21].
The practical implementation of our approach is now discussed in more detail. For this implementation we rely on Modelica-based concepts as much as possible. For usability reasons, we deliberately avoid spreading the design problem *definition* across multiple files and programming languages. The user thus interacts with a consistently defined Modelica model as much as possible.

2.1. Simulation model development

A first step is to develop a Modelica simulation model for the building of interest. Preferably, the IDEAS library is used since it has been configured [19] such that it is compatible with TACO. The building model should include HVAC equipment and the building envelope. Building system controllers should not be included. Internal heat gain models can be included, depending on how the user wants to set up the design problem.

2.2. Optimisation model development

A second Modelica model has to be developed that serves as a controller model for the MPC. The building envelope and HVAC models can be identical to the simulation model, insofar that the used Modelica specification constructs are supported by TACO. E.g. integer optimisation variables are not yet supported and algorithm sections are not supported either. Otherwise, the model must be modified such that it complies with the supported parts of the Modelica specification. Furthermore, the building HVAC models should be configured such that they are stationary by removing the optional model dynamics.

2.3. Model parametrisation

Next, the simulation and optimisation models are parametrised such that a change in design variables affects the model equations. This parametrisation has to be done consistently for the simulation and optimisation models, insofar that they do not already `extend` the same code, in which case the code is automatically consistent. Next, we create a Modelica `record` that summarises the design degrees of freedom. The record contains a

set of sub-records that each correspond to a `Boolean`, `Integer` or `Real` design variable. These sub-records contain fields that define the investment cost c_i, annual maintenance cost c_m, lifetime l and replacement cost c_r. The maintenance cost and replacement cost are defined as a fraction of the investment cost. For real design variables an upper and lower bound are specified. For integer variables, all allowed integer values must be specified. This record is instantiated in the simulation and optimisation models and its values are used to compute the earlier declared design variables of the model.
Using these cost values, each `record` automatically computes the Net Present Value (NPV) of the investment, maintenance and replacement as

$$r_c = \sum_{j=0}^{d-1} \frac{1}{(1+r)^j}, \tag{1}$$

$$c_{NPV,i} = c_i \left(1 + r_c c_m + c_r \text{floor}\left(\frac{d-\epsilon}{l}\right)\right), \tag{2}$$

where d is the depreciation period in years, r is the annual discount rate, r_c is a cumulative discount rate, ϵ is a small positive number that ensures that the replacement cost is zero when $l = d$, and floor$(\cdot)$ is a function that rounds a decimal value to the largest integer value that is smaller than or equal to this decimal value.
The simulation model is used to compute the NPV of the operational costs

$$c_{NPV,o} = r_c c_e, \tag{3}$$

where c_e is the annual energy cost. Note that this formulation implicitly assumes that energy prices are fixed throughout the years. Additional costs can be defined by the user.

2.4. Heuristic optimisation algorithm

A multi-objective heuristic optimisation algorithm is implemented using DEAP [22]. The main argument for using DEAP is its support for the automated parallelisation of its tasks on a computing cluster using SCOOP [23] and ZeroMQ [24]. The algorithm is based on NSGA-II, which was developed by Deb et al. [25].
Our algorithm automatically parses the design record and identifies how many design variables exist, what types they have and what upper bounds are defined for their values. The algorithm generates a set of design values and assigns them to the sub-records. The optimisation model is then translated for this set of design variables using TACO, after which it is translated by Dymola using the same set of parameters and using the MPC generated by TACO. Cost functions $c_{NPV,o}$ and $c_{NPV,i}$ are evaluated and saved to a text file that is read by the heuristic algorithm. This information is used by NSGA-II to choose a new set of design variables. Figure 1 presents a schematic overview of this implementation.

3. Case study

As a demonstration of our methodology, we apply it to Solarwind, a 10 000 m^2 highly insulated, GEOTABS [1] office building in Luxembourg. The building model consists of 32 zones of which 24 have individual Concrete Core Activation (CCA) systems and Variable Air Volumes (VAV) with a heating coil. The model further includes a borefield, two detailed, validated air handling unit models [26], multiple heat exchangers and four heat pumps. Valves, pumps, dampers, fans, pipes and ducts are modelled explicitly using pressure-driven flows such that mass flow rates are computed from a flow network, which was described in detail by Jorissen et al. [27, 28]. This allows the pump and fan electric power uses to be computed accurately, which can dominate the building electrical power use. Jorissen [29] validates and describes the model in more detail.

[1] GEOthermal borefield combined with Thermally Actived Building Systems (TABS)

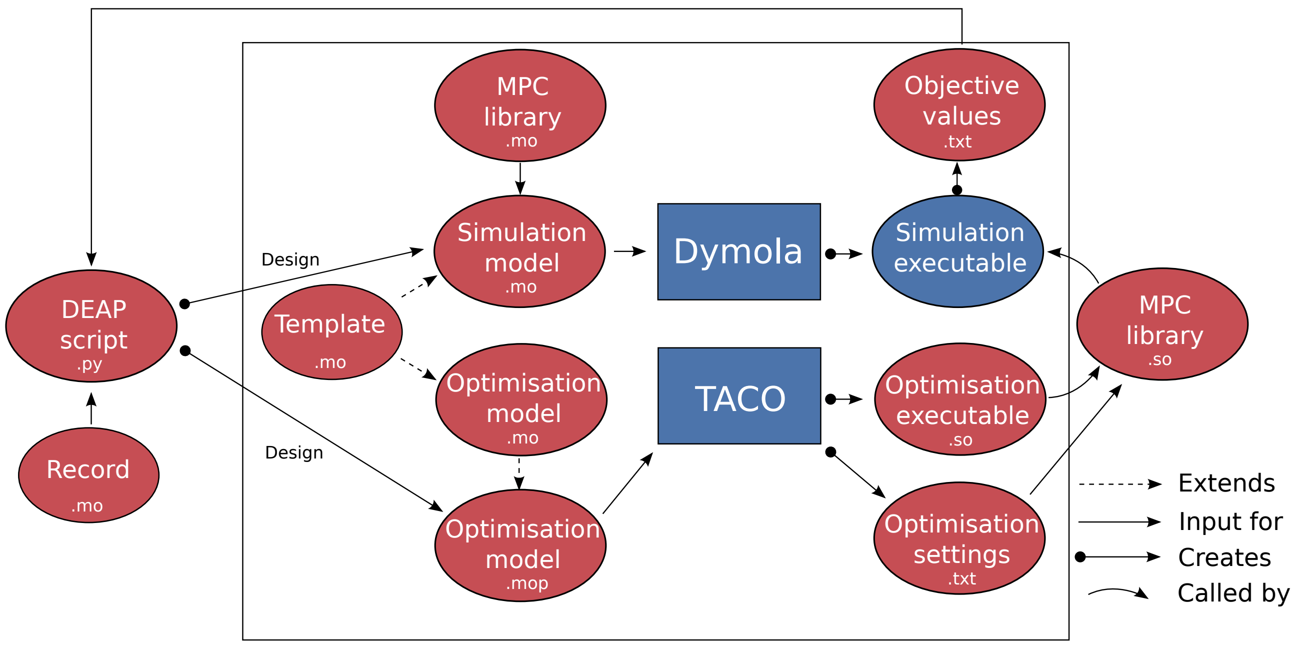

Figure 1: Schematic overview of optimal design algorithm. Executables indicated in blue are called by the DEAP script in this order: TACO, Dymola, Simulation. Files (ovals) with the extension `.so` are linux shared libraries. The template contains all models that are common to the simulation and the optimisation model.

Table 1: Summary of design variables, an indication of their type: boolean ($\mathcal{B}$), integer ($\mathcal{I}$), real ($\mathcal{R}$), their possible values, and investment cost c_i. Maintenance cost c_m and replacement cost c_r are presented as a fraction of the investment cost. The replacement cost is paid after each lifetime of l years. $A_w = 691$ m^2 is the total surface area of the window glazing.

Variable	Values	$c_i[EUR]$	c_m	c_r	l
AHU type	$\mathcal{I} \in \{0,1,2\}$	$2\{45000, 100000, 140000\}$	0.03	1	30
HP stages	$\mathcal{I} \in \{2,4,6,8\}$	$11725\mathcal{I}/2 + 11952\mathcal{I}/8$ [30]	0.03	1	20
VAV type	$\mathcal{B} \in \{0,1\}$	$24\{110, 650\}$	0.01	1	30
VAV coil	$\mathcal{B} \in \{0,1\}$	$24\{0, 1600\}$	0.01	1	30
Glazing type	$\mathcal{I} \in \{0,1,2\}$	$A_w\{50, 50, 0\}$	0	0	30

3.1. Design variables

Our methodology is now applied to Solarwind as a proof of concept. Design variables to be optimised are summarised in Table 1. The presented cost values are based on the work of Picard [30] and from real projects carried out by Boydens Engineering. We assume that the replacement cost is 100 % of the investment cost. We choose a depreciation period of $d = 30$ years and an interest rate of $r = 2$ %. Investment costs include delivery and installation. We now discuss the energy system design options in more detail.

Firstly, three air handling unit types are considered. The first type only has heat recovery and a bypass. The second type has an additional evaporative cooling function. The third type also has an active chiller such that the third type corresponds to the Menerga Adsolair type 58 unit of Solarwind. Secondly, we provide the option to reduce the number of heat pumps. This choice is somewhat simplified by optimising the number of heat pump *stages*, which is used to limit the maximum thermal power of the heat pump in the MPC. Thirdly, dampers with a fixed position, or controllable VAVs can be used. Fourthly, the VAV heating coils may or may not be present. Finally, three types of double or triple glazing can be installed.

The operational cost $c_e = p_{el}E_{el}$ is evaluated by computing the electrical energy cost of a full year, using the model predictive controller that is generated using TACO. We assume an energy cost of $p_{el} = 0.2$ EUR/kWh.

3.2. Model modifications for design parameter variations

We now summarise how the design variables are implemented in the simulation and in the optimisation models. The AHU types are implemented in the simulation model by disabling the IEH and chiller controllers. When there is no chiller, the pressure drops of the evaporator and condenser are removed. In the optimisation model, the respective control signals are replaced by zero if the IEH or chiller are not present. The pressure drops are also removed. The heat pump stages are implemented in the heat pump post-processing by limiting $y_{PI}(t)$ to the number of stages. In the optimisation model, the thermal power upper bound changes linearly with the available number of stages. When a damper is used instead of a VAV, the VAV models [28] are reparametrised using $\dot{V}_{max} = \dot{V}_{min} = 10\dot{V}_{nom}$. This causes the VAV internal damper to be opened fully. In the optimisation model, the control variables are replaced by ones. When the VAV heating coils are unused, the heating coil valve openings are forced to zero and the circulation pump is disabled. For windows that are not oriented north[2], three possible glazing types are selected. The first is the original triple glazing type, `GT401` [29]. The second is the triple glazing type with a lower g-value that is also used for the north façade, `GT404` [29]. The third type is double glazing type `Ins2ArGray` from the IDEAS library, which has a g-value of about 0.4, which is in between that of `GT401` and `GT404`, and a U-value of about 1.3 W/m^{2}K.

3.3. Solver configuration

Each design case is computed for a full year that is split up into twelve parts of 30.4 days such that the optimisation can be parallelised. Each part starts with the same default initial conditions, which are the same for all design cases. The required energy use is therefore probably underestimated, but this underestimation is consistent across all design cases. The results should thus be interpreted as relative trends rather than absolute numbers.
The design cases are evaluated on two computer systems. The first computer system is a Dell Precision T5810 workstation with Intel Xeon E5-1650 v4 3.6 GHz processor running Ubuntu 16.04 and GCC 4.8.5. The second computer system consists of four nodes of a computing cluster that each have two Intel Xeon E5-2630 2.3 GHz processors running Red Hat Enterprise 6.5 and GCC 4.9.2. Dymola 2018 does not natively support running in the headless[3] configuration of the cluster. This can be circumvented by using an X virtual framebuffer, Xvfb. Xvfb was only installed on four nodes such that we were unable to use the full cluster, which consists of 352 nodes. On both systems we use IPOPT [21] and HSL linear solver ma27 [31]. In our case there exist (only) 144 design options in total, such that we were able to evaluate all design options. A design case evaluation of Solarwind takes about six hours such that the entire optimisation can take a few weeks. Computation time however depends on the model complexity and the number of available computers, since the individual design cases can be evaluated in parallel.

4. Results and discussion

Results are summarised in Figure 2 where all subgraphs depict investment cost versus operational cost. The top left subgraph shows the results for all possible design variable combinations. The used color scale indicates the mean annual thermal discomfort per zone. The discomfort is computed relative to the MPC zone temperature constraints, which constrain the zone temperatures between 21.5 °C and 24.5 °C. Nights and weekends are included in the computation. The discomfort scale reaches up to 900 Kh/y, which corresponds to an average comfort violation of 0.1 K. However, for the near-optimal cases, the discomfort is in the same order of magnitude as the Solarwind design reference case. The cost-optimal result is indicated by the case on top of the

[2]These already have a different glazing type.
[3]Without display.

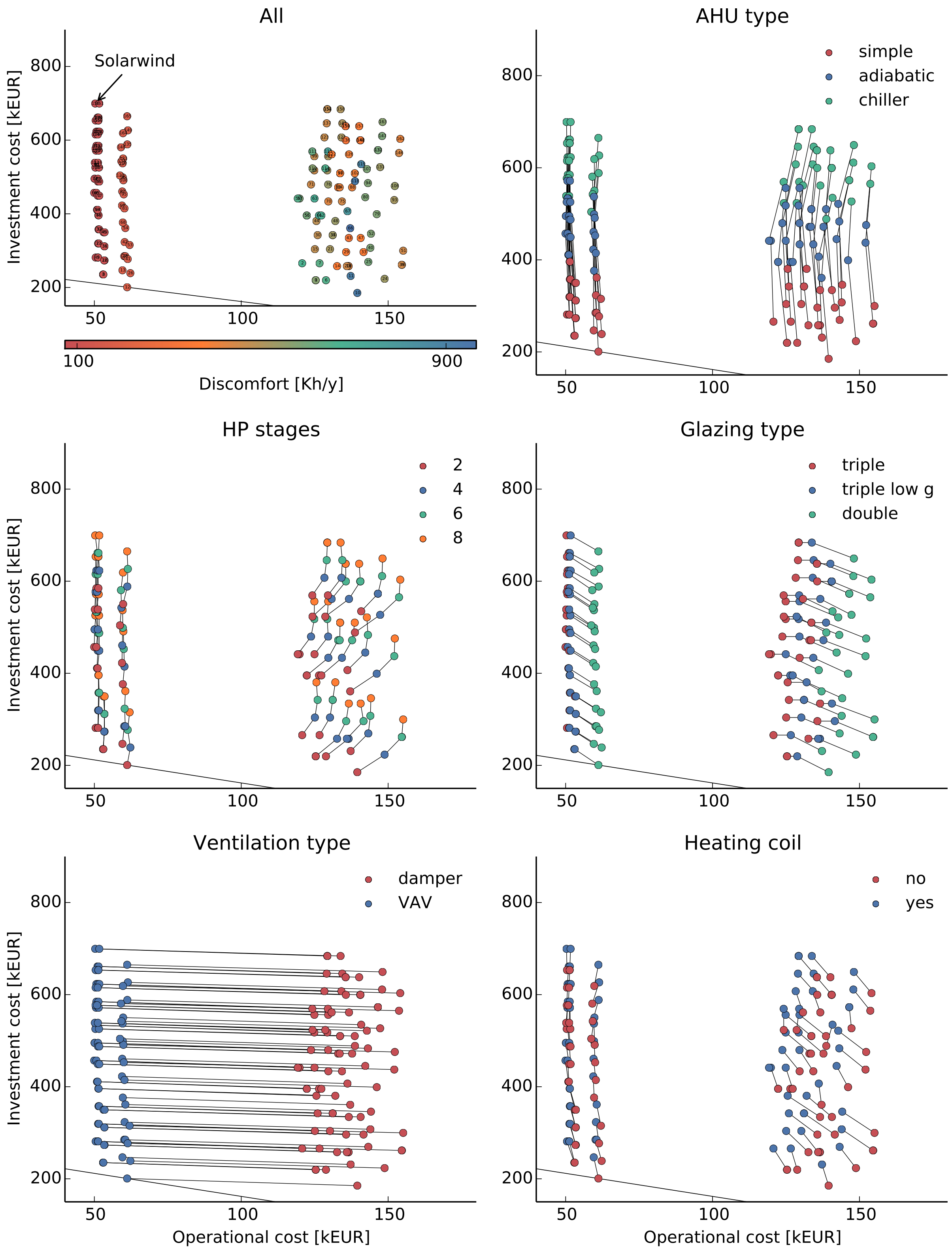

Figure 2: Summary of design results. The top left subgraph shows the annual mean (per zone) total (cold and heat) discomfort. Air quality is similar to or better than the MPC reference case that has the design of Solarwind. The remaining subgraphs show more detailed information for each design variable.

black line, which connects all points that have a combined investment and operational cost of EUR 261 852. See Appendix B of [13] for more detailed information for each case. This subgraph reveals only little structure in the results. Two vertical bands can be seen on the left and a larger blob of points is visible on the right. The structure of the results is better illustrated by the other five subgraphs, which each focus on one of the five design variables. For each design variable, the different possible design values are indicated using different colors. Moreover, for each subgraph we collect the design cases in groups for which each element has the same design variable values, except for the design variable on which is focussed in that subgraph. These groups are connected using black lines. These lines thus illustrate the sensitivity of the costs with respect to a single design variable. For a more detailed discussion of these results we refer the reader to Section 11.4 of [13].
The overall optimum is the design case that uses 1) simple AHUs without adiabatic or active cooling, 2) 2 heat pump stages, 3) double glazing, 4) VAVs, and 5) no heating coil. This case has an operational cost of EUR 61 162 and an investment cost of EUR 200 690 This is the design case with the lowest investment cost possible, except for the VAVs, which cost slightly more than dampers.
Compared to the original Solarwind design, the optimum design has an investment cost of EUR 200 690 instead of EUR 699 444 and an operational cost of EUR 61 162 instead of EUR 50 293 The total NPV *for the considered design variables*, which does not include the borefield, hence decreases by 65 % (EUR 487 885). This result shows that there is a strong economic case to be made for an integrated optimal control and design analysis for the design of buildings. This of course implies that MPC must be used in practice, for which an additional financial incentive exists: implementing MPC instead of RBC would by itself lead to additional operational cost savings in the order of EUR 218 000 over a period of 30 years, assuming that energy prices stay fixed at 0.2 EUR/kWh [32]. The numbers reported here are of course not applicable to every case, and they should be interpreted with care, as explained further in Section 5. Most notably, a thermal imbalance exists, which causes the borefield temperature to rise. Consequently, passive cooling may no longer be possible after several years. Future MPC versions can be designed to avoid this problem. In addition to economic incentives, we expect that MPC can lead to better thermal comfort, more systematic controller performance and other advantages such as reduced commissioning costs. Better thermal comfort in turn leads to higher productivity of the building users.

5. Threats and opportunities for future work

While the proof of concept leads to the conclusion that an economic potential clearly exists, our analysis is too simplified in its current form to be directly used in practice. Firstly, we neglect the impact of the thermal imbalance of the borefield, which means that the proposed design may not be able to supply the required cooling load for the entire period of 30 years. This could be resolved by initialising the borefield at a higher initial temperature, to reflect the heating caused over multiple years of dissipating heat into the borefield. Secondly, we use meteorological data for a single year, while extremely hot or cold years *could* be included in the analysis, especially with the onset of climate change. Thirdly, the building is almost completely occupied during the analysed period. In practice, this may not always be the case such that internal heat gains are lower, which can cause increased heating requirements. Having only two heat pump stages may then not suffice and a (low-cost) backup system could be included as a design option. Due to this third and fourth point, it would make sense to complement the design optimisation with a pass/fail type of test that checks whether the building systems are sized adequately to heat, cool and ventilate the building to a user-defined set of design conditions. Fourthly, a mismatch exists between the modelled behaviour of the building, and its actual behaviour. This must be taken into account when sizing the building thermal systems. Finally, two separate models must be developed. It would be more convenient if only a single model has to be developed by the users, which is then used both for simulation and optimisation purposes. IBPSA project 1 is working on a Modelica library for MPC, which could make this possible.

In addition to these threats, opportunities exist. Firstly, we did not yet optimise the size of the borefield, which has a large investment cost. Secondly, the building insulation thickness, window sizes or other elements of the building envelope can be optimised. The height of the photovoltaic overhangs or other shading types can also be optimised, which is essentially a degree of freedom that costs nothing. Thirdly, the location of the embedded pipes in the CCA can be changed, or multiple embedded pipes can be used at different depths in the concrete, which can increase the reaction speed of the CCA. Fourthly, the flexibility of MPC can be exploited by developing new hydronic configurations. E.g., thermal storage tanks can be added that can store residual heat or cold for later use in the building. Or, the solar thermal collectors can be used as a heat dissipater at night or during winter to regenerate the borefield for cooling dominated cases. Finally, our work does not consider time-dependent pricing and we do not consider the electrical power generation of photovoltaic panels. With the onset of smart grids, the building design could use existing or new thermal storage tanks to store low temperature heat, and/or convert this low temperature heat into high temperature heat when electrical energy prices are low. Similarly, the borefield and other components could be coupled to a district heating network to compensate the thermal imbalance if financial incentives exist to inject heat on the network using the heat pumps.

While the presented work has been designed with practical usability in mind, *implementing* (as opposed to *using*) the methodology requires a lot of expertise, especially when using a computing cluster to parallelise the computations. Future work could therefore focus on implementing a web-interface that allows the user to upload an optimisation problem, possibly complemented with additional pass/fail tests. The optimisations are then evaluated on a computing cluster and results are returned in several formats, e.g. as raw results or in a format similar to Figure 2.

Heuristic optimisation algorithms could be design to exploit the structure that is clearly illustrated in Figure 2. This is explained in more detail in Section 11.4.2 of [13]. The computed investment and operational costs are included in Appendix B of [13] such that these data can be used to test various types of heuristic optimisation algorithms and settings without performing the optimisations required for evaluating these costs.

6. Conclusion

This paper presents a methodology for integrated optimal control and design of buildings using Modelica simulation models and TACO. The user first creates a simulation and optimisation model of a building and declares all design variables and parameters that are required for evaluating the Net Present Value (NPV) of the investment (e.g. the investment and replacement costs). Our implementation automatically identifies the design variables of the Modelica model and a heuristic optimisation algorithm generates design cases for which the operational and investment cost are computed using 1) an MPC generated by TACO using the optimisation model and 2) the simulation model.

This methodology is applied to a case study, the Solarwind office building. Five design variables are defined and all 144 possible design cases are evaluated by computing the operational cost for a full year. The results show that the investment cost dominates the total NPV of the investment and that the operational cost is insensitive to many design variables, such that the investment cost can be reduced significantly by changing the building design. This results in cost savings of EUR 487 885 for the Solarwind case over 30 years.

These results show that there exists, at least for some buildings, a large potential to reduce the investment costs when using MPC as part of the design process. Future work is required to unlock this potential in practice. Moreover, the building operation can be optimised towards other objectives, such as CO_2 emissions, share of renewable energy sources, flexibility, ... as long as these can be defined using Modelica *equations*.

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