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EMPA
Materials Science & Technology

PROCEEDINGS

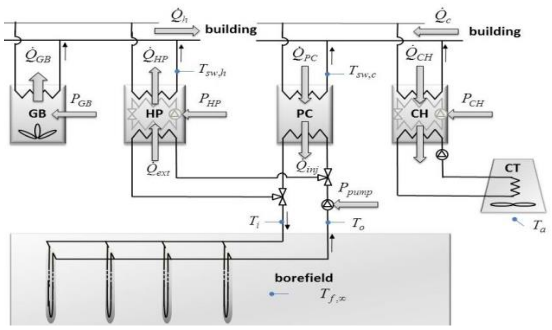
OF THE

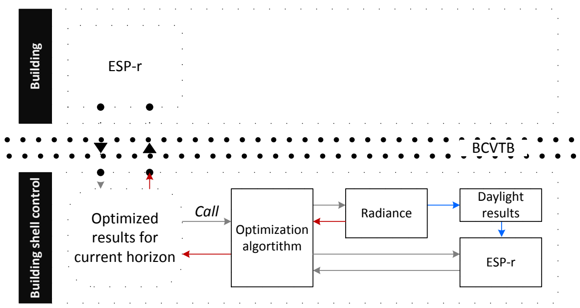
COLEB 2014 Workshop

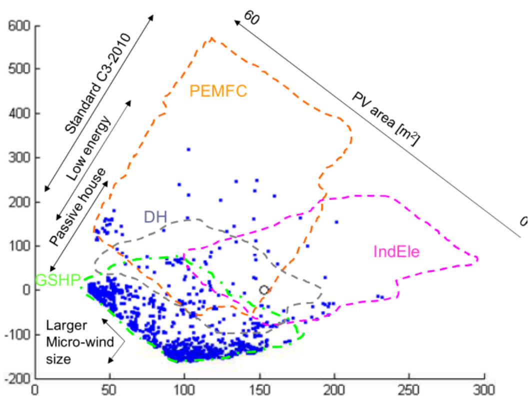
Computational Optimisation of Low-Energy Buildings

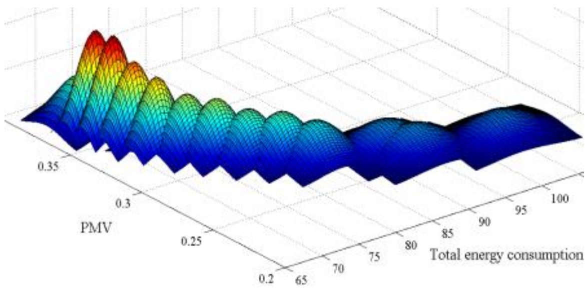
6 & 7 March 2014

ETH Zürich









These proceedings collate the contributions presented at a two-day workshop covering the application of computational optimisation to low-energy buildings, including algorithmic approaches, multiple objectives, building design and operational control.

The workshop was kindly supported by the Chair of Building Physics at ETH Zürich and the Swiss Competence Centre - Energy and Mobility project "Integration of Decentralized Energy Adaptive Systems for cities".

Ralph Evins, Viktor Dorer & Jan Carmeliet
ETH Zürich & Empa, Switzerland

Thursday 6th March

09:30	Coffee	
10:00	Welcome	Prof Jan Carmeliet
10:15	Introductions	All
	Session: Design optimisation	
10:30	Considerations regarding optimization of dynamic facades for improved energy performance and visual comfort	Dr Roel Loonen
10:45	The route to an ideal adaptive glazing facade	Fabio Favoino
11:00	Exploratory computational tools for holistic building design and optimisation	James Ramsden
11:15	Optimal design and control of technical building systems	Prof Cheol-Soo Park
11:30	Interactions between different levels of the building system to be optimised	Dr Ralph Evins
11:45	*Discussion*	
12:00	**Keynote: The model-based optimization of buildings - an optimization workflow and reflection on the state-of-the-art**	**Prof Jonathan Wright**
13:00	Lunch (Dozentenfoyer)	
	Session: Control optimisation	
14:00	Modeling, identification and control of building thermal systems	Prof Roy Smith
14:15	Simultaneous optimal design and control of future building energy systems under various pricing systems and governmental directives	Araz Ashouri
14:30	A tool chain for constructing reduced order building models using modelica	Filip Jorissen
14:45	Benchmark and competition for climate control algorithms of office buildings	Damien Picard
15:00	Lessons learned from modelling and control of hybrid GCHP systems for energy use minimization	Ercan Atam
15:15	*Discussion*	
15:30	Coffee	
	Session: Multi-objective optimisation	
16:00	Combining simulation and optimisation for maximum building performance	Prof Kai Siren
16:15	Pareto optimization and aggregation: a new approach to integrate optimization with user criteria in BPS	Dr Christina Hopfe
16:30	Multi-objective optimisation to simultaneously address energy hub sizing and scheduling using a linear formulation	Georgios Mavromatidis
16:45	Implementations of the Multi-Objective Building Performance Optimization Software MOBO	Dr Ala Hasan
17:00	*Discussion*	
17:15	*Discussion summarising the day: how design meets control*	
19:30	Workshop dinner (Brasserie Schiller)	

Friday 7th March

	Session: District-level optimisation	
09:00	District-scale energy optimization	Dr Ruchi Choudhary
09:15	Optimized renewable energy integration at neighborhood scale	Dr Kristina Orehounig
09:30	District heating and cooling with low temperature networks - sketch of an optimization problem	Florian Ruesch
09:45	Optimisation methods for the design of integrated urban energy systems	Prof François Maréchal
10:00	Proposition on how to integrate technical uncertainties into the design of district energy systems	Jakob Rager
10:15	*Discussion*	
10:30	Coffee	
	Session: System optimisation	
11:00	Optimal design of HVAC systems as part of the future energy system	Dieter Patteeuw
11:15	Exploring the potential of buildings in Switzerland ancillary service market	Evangelos Vrettos
11:30	Population of thermostatically controlled loads for the Swiss ancillary service market	Dr Maryam Kamgarpour
11:45	*Discussion*	
12:00	**Keynote: Advanced control for energy efficient buildings: challenges and opportunities**	**Prof Francesco Borrelli**
13:00	Lunch (Dozentenfoyer)	
14:00	*Discussion: A Horizon 2020 project*	*Chair: Prof Kai Siren*
14:30	*Concluding discussion: current position and future directions….*	*All*
15:30	Coffee	

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Contents

CONSIDERATIONS REGARDING OPTIMIZATION OF DYNAMIC FACADES FOR IMPROVED ENERGY PERFORMANCE AND VISUAL COMFORT

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ABSTRACT

This contribution discusses requirements, challenges and solutions for simulation-based design optimization of climate adaptive building shells. We compare the different needs of this approach with design optimization of conventional, static facades, and do this with a focus on achieving energy savings while improving indoor environmental quality in terms of thermal comfort and dynamic daylight performance. The solution we propose couples ESP-r with Radiance through the Building Controls Virtual Test Bed, and employs a receding horizon model-based control approach with evolutionary optimization algorithms to ensure high-performance operational façade adaptation.

INTRODUCTION

Climate adaptive building shells (CABS) are seen as a promising design concept for achieving low-energy building operation, while offering potential for improving levels of indoor environmental quality (Davies 1981; Heiselberg 2009). The number of CABS applications in the current building stock is nevertheless limited, with a focus on bespoke projects rather than larger-scale solutions (Loonen et al. 2013). In research and development settings, however, efforts that investigate the potential of innovative adaptable facade components are rapidly increasing. Furthermore, in many technology roadmaps, CABS are recognized as a notable strategy for achieving forthcoming targets for design and operation of nearly zero-energy buildings (IEA 2013; EC 2013).

To facilitate the transition to a more prominent future role for CABS, there is a need to move away from costly, custom-built solutions towards concepts that enable affordable application of adaptable building envelope components at a much wider scale. Computational performance prediction can form an essential resource in supporting, stimulating and accelerating this development process, by functioning as a virtual test-bed for new technologies (Loonen et al. 2014). Optimization methods can, in addition, support design space explorations and help in getting a better understanding of the theoretical performance potential that is achievable with CABS.

In the context of static facades, numerous studies have successfully demonstrated the potential value of combining building performance simulation (BPS) tools with optimization techniques, such as genetic algorithms (GA), to find the set of building envelope design parameters that leads to the best performance with respect to a specified cost function (Evins, 2013). Currently, however, there is no framework available for extending this type of multi-criteria performance optimization to the domain of CABS.

CHALLENGES AND REQUIREMENTS FOR OPTIMIZATION OF CABS

The multi-domain, multi-scale and inherently time-dependent nature of the problem makes that the assessment of CABS' performance potential by means of optimization is a complex task. Instead of optimizing for a single facade configuration, the goal of the optimization procedure in CABS is to find the sequence (i.e. time series) of dynamic facade properties that best satisfies a set of performance criteria over time. Such information can then be used to identify high-potential CABS design concepts. Compared to design optimization of conventional, static facades, this poses unique requirements for the performance prediction framework:

- <u>Modelling dynamic facade properties</u>: Facade properties need to be changeable during simulation run-time to properly account for transient heat transfer and energy storage effects (Loonen, Hoes, and Hensen 2014). In the majority of BPS tools, the options for modelling of adaptable facade actuators are limited (Crawley et al. 2008); ESP-r forms an exception although code modifications are required for more flexibility.
- <u>Modelling the operation of facade adaptation</u>: The dynamic interactions in CABS introduce a strong mutual dependence between design and control aspects. Performance of CABS fully depends on the control strategy for facade adaptation during operation. To identify the characteristics of optimal CABS concepts, not only design considerations, but also insights into high-performance operation of the dynamic facade shall be taken into account. Previously developed workflow procedures for optimization of building

envelope design, however, lack capabilities to support performance optimization of the short-term adaptability in CABS, as they are focused on the optimization of properties that remain constant throughout the year (Evins 2013).

PROPOSED OPTIMIZATION APPROACH

Figure 1 introduces the principles of the optimization framework that we developed in response to the points raised above. Various components of the framework can be distinguished:

- Integrated performance prediction with time-varying construction properties by coupling ESP-r with the Radiance three-phase method through the building controls virtual test bed (BCVTB) (Wetter, 2011).
- Model-based building shell control with receding optimization horizons, coordinated by algorithms implemented in Matlab, to optimize façade adaptation in multiple successive steps. Explicit state initialization in ESP-r ensures consistency of thermal history effects between the different models.
- Multi-objective optimization with an evolutionary algorithm, enhanced with seeding of initial populations and soft constraints to aid optimization efficiency.

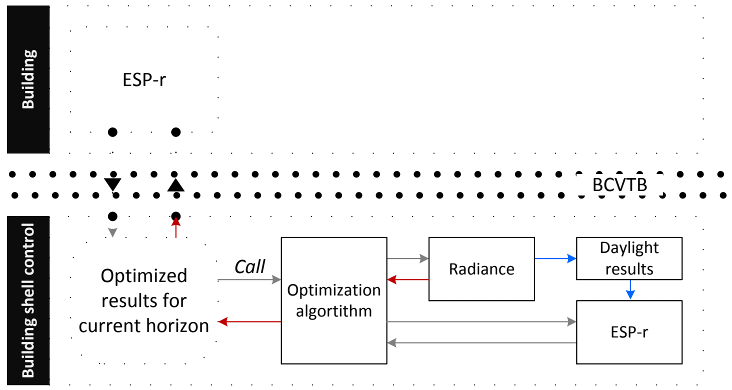

Figure 1. Overview of the optimization framework for CABS.

CONCLUSION

This short paper has introduced the considerations and requirements for simulation-based performance optimization of buildings with adaptable facades. The presentation during the workshop will provide more details on implementation aspects, the implications for optimization algorithms, and will present further points of attention on the basis of results from a case study.

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THE ROUTE TO IDEAL ADAPTIVE GLAZING FACADE

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Abstract

The development of adaptive building envelope technologies is considered a crucial step towards the achievement of the nZEB target. This paper presents a method to devise an ideal adaptive façade and evaluate its energy saving potential. This is based on the minimization of the total primary energy consumption, by means of single-objective optimization, and applied to a case study of an office reference room in the climate of London. The results show that the shorter the time scale of the adaptive façade mechanism is of higher energy saving potential. A more accurate method is required for devising a product for a faster adaptiveness.

Introduction

The requirements for the façade elements are conflicting and transient, e.g. maximising natural light transmittance whilst minimising unwanted solar heat gain in the cooling season, while allowing solar heat gains and minimising heat loss in the heating season. It is evident that an exclusive approach, aimed at excluding the outdoor environment from the indoor one, achieved by means of an optimized static facade cannot successfully satisfy all these conflicting and transient performance requirements. Thus the employment of smart materials/technologies, in order to adapt to varying outdoor and indoor boundary conditions/requirements, is considered a necessary development towards the achievement of the Zero Energy/Emission building target (Perino et al., 2007).

Many research efforts are currently being carried out in the area of adaptive facades, but many issues remain unaddressed. In particular it is not yet clear: (a) to which extent the adaptiveness of the façade can reduce the energy demand of a building compared to a static façade; (b) to which building properties and time-scale of the adaptive mechanism of the façade is the building energy consumption more sensitive to. The answer to these issues could provide a significant step towards the definition of an ideal adaptive façade: a façade which is able to minimize the total energy consumption of the indoor space by means of adapting to varying outdoor/indoor environmental conditions (i.e. solar radiation, air temperature, wind velocity, internal loads, etc…). To date most of the research efforts aimed at evaluating the performance of adaptive building envelopes are technology specific, that is they numerically and/or experimentally compare the performance of a specific adaptive system with a state-of-the-art static façade technology. This approach is not able to give an answer to the research issues above, as it evaluates a specific case of adaptive mechanisms (in terms of time scale of adaptive mechanisms and adaptive façade properties) and technology. In contrast an inverse approach could be used: given a climatic and building context, the optimal adaptive façade properties and reactivity of the façade are found.

Method

The evaluation of the ideal combination of adaptive façade properties, in terms *of U-value [W/m²K], g-value [-]* and τ_{vis} *[-]*, is performed by means of a single objective optimization with a variable time horizon. The optimization problem for the whole year is considered as a summation of subsequent equilibrium ideal states with a shorter duration (i.e. monthly and daily), which can be simulated separately, as shown in equation (1):

$$min \sum f(t_i, \mathrm{X}) = \min f(t_1, X) + \min f(t_2, X) + \ldots + \min f(t_i, X) \qquad (1)$$

where $X=[x_1,x_2,..,x_n]$ is the vector identifying the ideal façade properties at each time horizon t_i, and f is the cost function (i.e. the energy consumption of the building enclosed by the façade with property X). This is based on the assumption that the effect of the thermal mass of the building is negligible (ISO EN 13790, 2008). This method can quantify in sufficient details the potential of adaptive facades only for long time scale adaptiveness of the façade (seasonal and monthly), while it can be used to highlight the trends towards increasing energy saving if a faster reactive façade is employed (daily). The definition of the constraints on the control variables (Loonen et al., 2011) as well as the definition of the cost function is of primary importance. The ranges of ideal adaptive properties of the façade are defined so that each single property can vary in a domain that is physically feasible: U-value ranges between 0.2 and 5.14 W/m^{2}K, g-value between 0.01 and 0.84, τ_{vis} ranges between 0.01 and 0.98. The cost function is the total primary energy consumption of a South oriented enclosed office room located in London, as in equation (2). The cost function is modified by a barrier function in order to include the physical limit in the ratio τ_{vis}/*g-value* (3):

$$f(X) = E_p + z = E_{p,heat} + E_{p,cool} + E_{p,light} + z \quad (2)$$

$$z(X) = -\,\mu \log\left(\frac{g\text{-}value}{0.428} - T_{vis} + \epsilon\right) \quad (3)$$

The workflow for the optimization is described as follows: (a) Matlab RA2013 is used to generate the parametric model with variable time horizon and to analyze the results; (b) the parametric model is fed to GenOpt (Wetter, 2011), which runs the optimization; (c) the objective function is evaluated by EnergyPlus. PSOGPSHJ (Particle Swarm Optimization with Generalized Pattern Search Hookes and Jeeves implementation is used in GenOpt. The evaluation is carried out for different time scales of the adaptive mechanism, namely, monthly (M) and daily (D). As a term of comparison the primary energy consumption of a reference office with a reference façade (R), and of a reference office with the yearly optimized façade (Y) is considered.

Results and conclusions

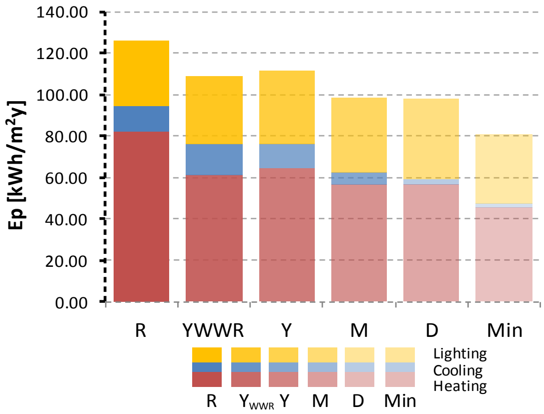

Figure 1. Specific primary energy consumption.

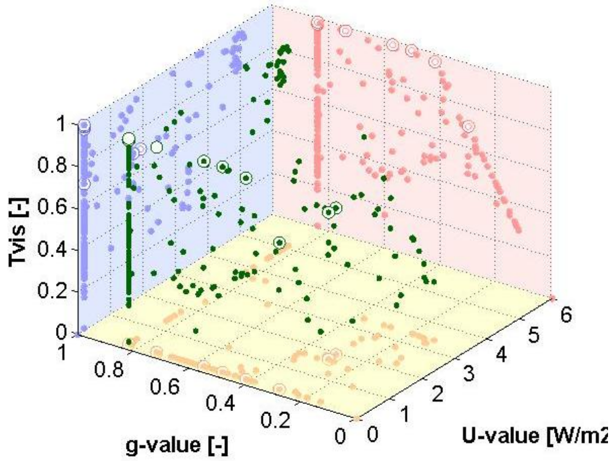

Fig. 2. 3D plot of M (white) and Min adaptive properties..

An ideal static glazing façade technology (Y) could decrease the primary energy consumption of the enclosed office room located in London with 40% WWR by 12%. While a monthly ideal adaptive glazing façade (M) is able to provide an additional 10% energy saving compared to the yearly one. The limitations of the proposed method are highlighted in the case of a daily adaptation of the façade (D), in particular the difference in the air and mean radiant temperature among one optimization starting conditions and the precedent optimization ending conditions does not assure optimal results to be reached. Therefore an approximation method is proposed in order to reach a result (Min) which is closer to the daily optimal solution, by means of choosing the control variables resulting in always the minimum daily primary energy consumption comparing the monthly (M) and daily (D) optimizations. Finally a daily ideal adaptive glazing façade (Min) is potentially able to save an additional 14% energy compared to the monthly case study, 24% compared to the ideal static glazing (Y) and 36% compared to the reference static façade (R). Future work will expand the case studies analyzed to different climatic conditions, *WWR*s and orientations. Moreover different time frame of the adaptive mechanisms could be analyzed, i.e. seasonal, or with different starting/ending days (for the monthly adaptiveness). In order to provide more accurate results for the daily adaptiveness a method will be proposed to reduce the effect of the difference of starting boundary conditions, while in order to evaluate the effect of the reduction of the time-scale of the adaptive mechanisms, model-base predictive control of the façade thermo-optical property will be explored.

Acknowledgement

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MODELLING AND OPTIMISATION OF HOLISTIC BUILDING PERFORMANCE

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ABSTRACT

The complexity of modern buildings requires that a significant number of specialised disciplines are able to collaborate to ensure the success of a building's design. Furthermore, within teams, there is a need to be able to efficiently design various aspects and components to conflicting requirements. By performing research within a practising engineering consultancy, the aim is to develop an understanding of how computational methods can be used more effectively to find optimised solutions to multi-objective problems in the early design stages. To explore this, a prototype framework using Grasshopper for Rhino has been outlined.

INTRODUCTION

Modern buildings are highly complicated structures. There are many often-conflicting constraints in their design, including cost, structural strength and durability, environmental footprint, and comfort. BIM exists in part to help manage the large amount of data, but the complexity and detail that BIM offers does not favour rapid exploration of ideas in the earlier stages of design. In industry, there remains a gap for early-stage, multi-objective, multi-disciplinary optimisation tools and frameworks at the intra- and low-level inter-team levels.

This research is being carried out within a multi-discipline engineering consultancy environment. The wider aim of this research is to integrate the most relevant existing tools (Attiaa et al., 2013) and methodologies (Lapinskiene & Martinaitis, 2013) using a Systems-based approach, as discussed by Geyer (2012), into a general framework that will assist consultancies in generating a range of optimised solutions for a given design problem early into a conceptual design stage.

DISCUSSION

A prototype framework is being developed (Figure 1) that will allow geometry and construction properties to be defined parametrically, and for an optimisation loop to improve a user-specified range of these parameters. This loop currently supports multi-objective optimisation with scalarisation, and can be adapted to optimise based upon a Pareto analysis, but in order to fully balance the conflicting needs that occur in holistic design, a strategy such as MDO (Multi-Disciplinary Optimisation) is required, as summarised in (Ren et al., 2011). However, because of the requirement to ensure that any solution remains accessible and ultimately time-saving for end users, the focus for the immediate future shall be to employ the simpler system in Figure 1 on a number of projects and studies, and to use learning from this experience to drive the next stage of research.

Grasshopper studies

Grasshopper is a plugin for the Rhino NURBS modelling tool that provides an intuitive, visual way of parametrically defining geometry through graphical programming. It has a wide community developing third-party tools for analysis and creating geometry, including tools which link to existing analysis packages. These benefits have made Grasshopper a prime candidate for applying the framework above. An example of how Grasshopper has been used to optimise simple structures is shown in Figure 2. Arbitrary cost functions were applied to geometry and scalarised to solar gain, and the geometry was optimised to minimise the total cost. A key outcome of this was the challenge of concisely and rapidly defining geometry; a number of components were consequently developed to allow users to quickly define rooms and windows.

To further enhance geometry creation and analysis, a platform-independent geometry DLL SMART Form has been written in-house at Buro Happold, and links are being made between this library and Grasshopper, and with Dynamo for Revit. The generic nature of this library means that it is relatively simple to create new analysis links with other external programs as required in the future. The components written for Grasshopper as a result of this development have been applied on a number of projects, including panel analysis on a major development for Singapore Changi Airport (Figure 2). These components can be used seamlessly with all other components available in Grasshopper, including the Galapagos optimisation component.

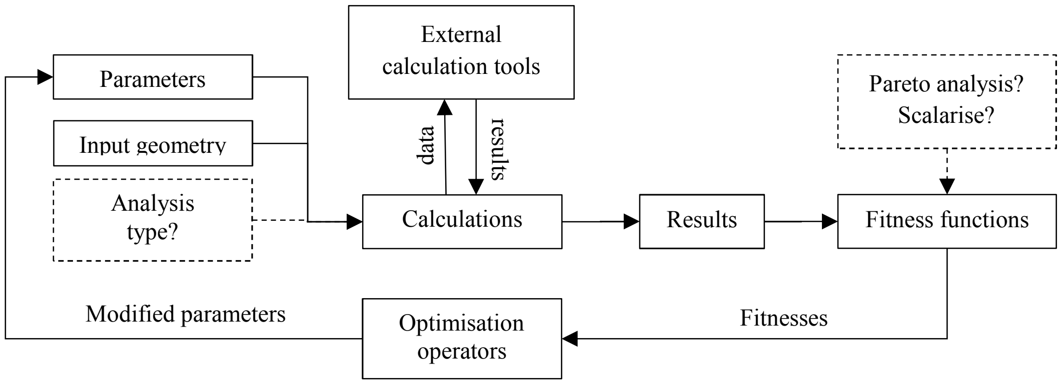

Figure 1A simple optimisation procedure to be used as the basis for current and future work

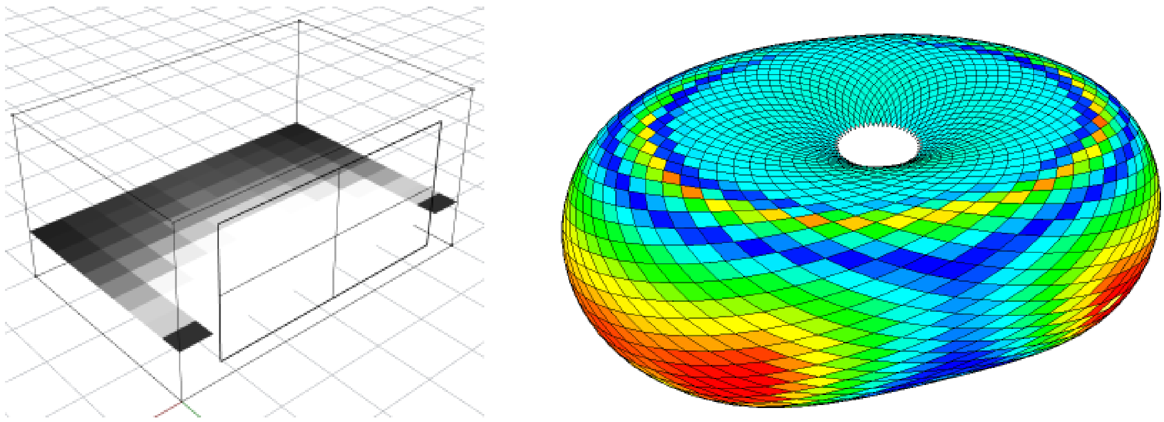

Figure 2 Analysis of a parametically-defined structure using DIVA daylighting analysis of a room with one window (left) and using in-house software to analyse panel planarity on a real project (right)

CONCLUSION

A gap has been found in industry in using computational tools and frameworks to assist in early stage multi-disciplinary design process. An optimisation procedure has been demonstrated and implemented in Grasshopper, and the benefits of this are currently being explored. Future work will include exploring more sophisticated frameworks to handle the conflicting requirements that come with holistic design.

ACKNOWLEDGEMENTS

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CASE STUDIES OF COMPUTATIONAL OPTIMIZATION FOR DESIGN AND CONTROL

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ABSTRACT

This paper discusses several case studies of simulation-assisted optimal design and control: office-building design, blinds control, double-skin control and selection of double-glazing system. The optimization algorithms used in the case studies are Genetic algorithm, gradient-based search, Pareto, etc. In the paper, the following are discussed: issues, limitations, and lessons learned by the use of simulation-assisted optimization.

CASE STUDIES

Case study #1: Heuristic vs. meta-heuristic approaches for energy optimization of a post office building

In this study, application of heuristic and meta-heuristic to energy optimization of a post office building is presented. The target building was first optimized by a heuristic approach which was based on the expertise, experience and intuition of experts as well as the use of a whole building simulation tool, EnergyPlus. Then, such heuristic approach was compared to one of the meta-heuristic approaches, Genetic Algorithm (GA). The meta-heuristic approach was conducted in MATLAB platform where EnergyPlus and GA are coupled. M-script files were made by the authors to automate execution of simulation runs (reading output files and writing input files) with GA. It should be noted that in this study, most design and simulation parameters were fixed and given by the client. Therefore, the authors were not allowed to make any significant change to the original design of the building. It is not surprising that GA performs much better in finding a global optimum than the heuristic approach but it takes significant simulation run times and programming effort. The heuristic approach has advantages that it considers design context in decision-making and allow fast result analysis between building stakeholders (Suh et al, 2011).

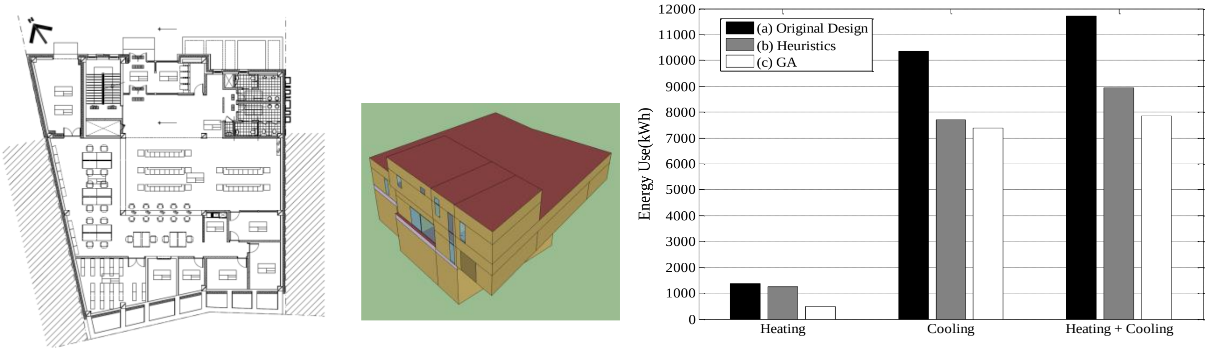

Figure1Comparison of annual heating and cooling energy (post office building)

Case study #2: Static vs. optimal control for interior and exterior blinds

Blind systems have been introduced to provide visual and thermal comfort, as well as to reduce energy use in buildings. A wide variety of such systems exist in terms of thermal and optical properties, location (exterior, interior), and physical configuration (size, distance between blind slats). The current problem with blinds is that their operation is not based on the dynamics of the room (space), but on the static or manual control operated by occupants, although many studies have recognized that dynamic control can far outperform static control. One reason for the lack of dynamic control is that it is not easy to combine the room dynamics with any possible optimization algorithm. Hence, in this study, a whole building simulation tool, EnergyPlus, was integrated with MATLAB optimization toolbox to solve for optimal control of blind systems. This study addresses the difference between static vs. optimal control of interior and exterior blind systems in office buildings. (Kim and Park 2012)

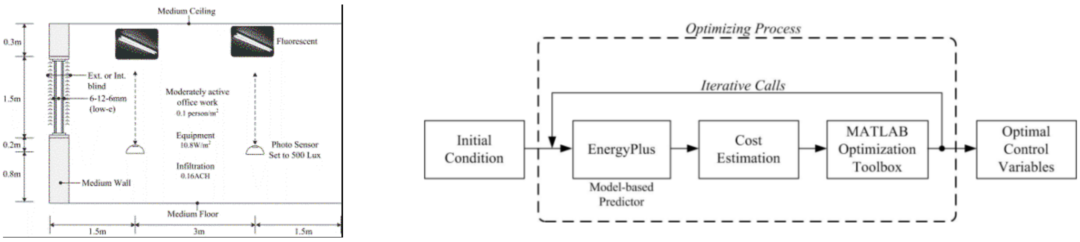

Figure 2 Simulation model and optimal control approach

Case study #3: Local vs. integrated optimal control of double-skins

This study presents the follow-up in the development of occupant responsive optimal control for double-skin systems that was previously published. In the aforementioned approach, the double-skin façade system was viewed as an 'isolated' system and hence treated as a local control problem, i.e., based purely on information about the state of the façade and its immediate environment. This study extends the local control problem to an integrated control problem in which room environmental control and façade control are dealt with simultaneously. It was found that the local control leads to sub-optimality, albeit of moderate proportions (Park and Augenbroe 2013).

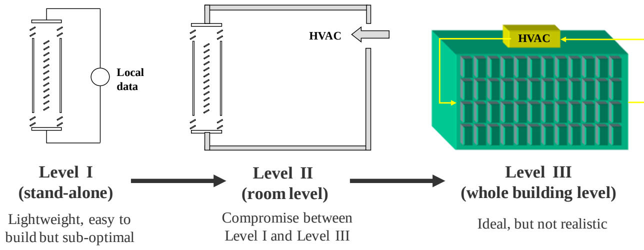

Figure 3 Various levels of couplings for façade control

Case study #4: Gaussian emulator for stochastic optimal design of a double glazing system

This case study presents the use of a Gaussian Process (GP) emulator for optimal design of a double glazing system. In general, stochastic Pareto optimization requires significant simulation run-time. With this in mind, the authors developed a simple and quick prediction model based on Gaussian Stochastic Process (GASP), Bayesian approach, and a dataset of observations. The GP emulator can be regarded as a surrogate model of Building Performance Simulation (BPS) tools. For design optimization, the Gaussian process regression model was iteratively computed inside an optimization routine in MATLAB optimization toolbox. It was found that (1) the GP emulator produces outputs almost identical to BPS tools, (2) requires significantly less computation time than BPS tools, (3) thus can be used beneficially for stochastic Pareto optimization. The approach reduces computational demand for stochastic optimization and contributes to rational decision making (Kim et al 2013).

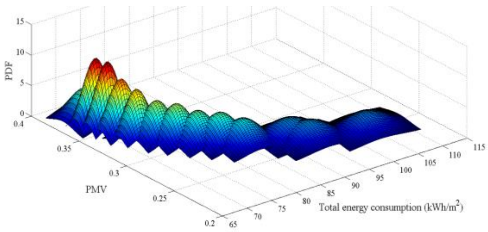

Figure 4 Non-dominated Pareto solutions

ACKNOWLEDGEMENTS

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INTERACTIONS BETWEEN DIFFERENT LEVELS OF THE BUILDING SYSTEM TO BE OPTIMISED

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ABSTRACT

Different aspects of building performance should be simulated using appropriate methods, and similarly different the optimisation of different aspects of performance are best approached with specific types of algorithm. One aspect of performance (e.g. annual performance of a proposed design) may depend on another (e.g. the way in which the building is controlled), leading to a nested or hierarchical problem. This paper discusses the implications of such system-level interactions in the phrasing of optimisation problems.

INTRODUCTION

For design problems, heuristic methods like genetic algorithms provide a powerful means of optimising black-box problems. This is particularly true for multi-objective problems, where the NSGA-II algorithm [1] is a popular choice.

For scheduling problems with many timesteps, programmatic methods like Mixed Integer Linear Programming (MILP) provide a more robust and rapid means of optimisation. The energy hub model [2] formulates a MILP problem to describe the energy conversion and storage between multiple energy carriers, such as in a co- or tri-generation scheme.

Deb and Sinha [3] have developed the idea of bi-level optimisation, where the objectives or constraints of one optimisation problem depend on a nested sub-problem. They used a multi-objective evolutionary algorithm for both levels, adapting the selection procedure of the NSGA-II algorithm to account for non-domination rank and crowding distances at the two distinct levels.

EXISTING FORMULATION

Figure 1 shows a bi-level arrangement combining a multi-objective genetic algorithm for plant, storage and renewables at the design-level, and an energy hub model for scheduling at the operational level [4]. The MILP energy hub formulation is used as the evaluation step in the GA iterations, taking the variable values for capacities to use as constraints. Because the demands to be supplied are fixed, these are given as external information to the energy hub process, along with data on efficiencies, carbon factors, storage losses etc. The process is also shown in simplified form in Figure 2(a), with the causality highlighted: fixed demands are used to calculate operational schedules, which are aggregated to get annual energy use.

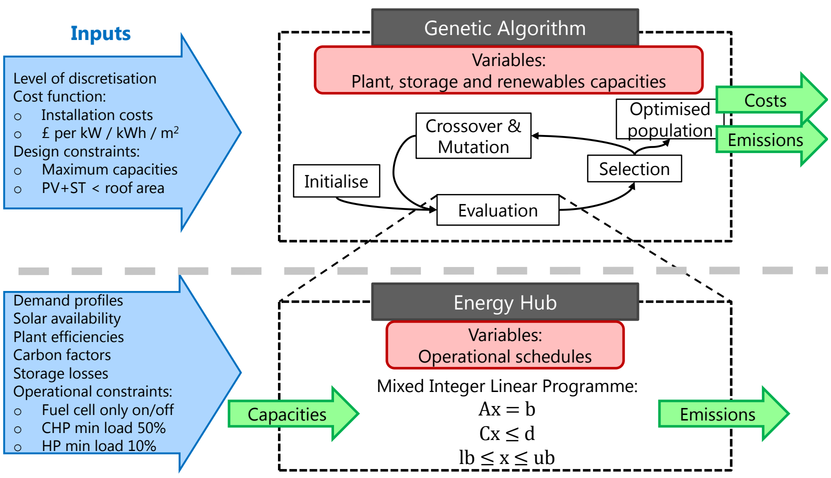

Figure 1. Bi-level optimisation of plant design (GA) and scheduling (MILP) [4].

ALTERNATIVE FORMULATIONS

Two alternative formulations are proposed, which add the ability to optimise building demands using the GA, and the coupling of control and scheduling.

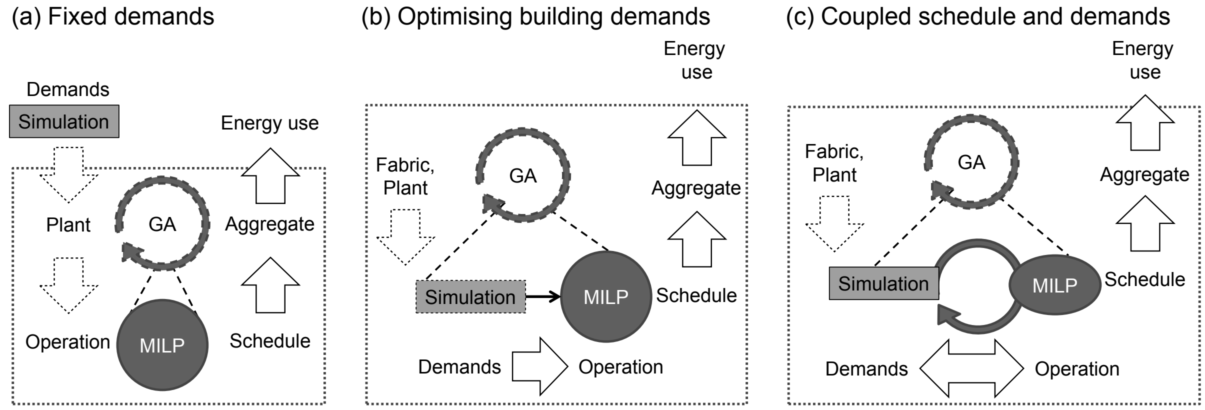

Figure 2. Three ways of formulating the system to be optimised. Dashed line shows the optimisation process.

Optimising building demands

Figure 2(b) extends the formulation so that design variables which affect demands (fabric properties, geometry etc) can also be optimised, as the demands are calculated at each GA iteration using EnergyPlus, as in many building optimisation formulations. The specific demands of each building configuration are then used for the operational optimisation using the energy hub model. An archiving strategy can be used to avoid rerunning costly EnergyPlus simulations when only plant options are changed.

Coupled schedule and demands

The above approaches are only suitable when specific energy demands can be calculated for a particular building design, i.e. when fixed set points and control choices are used within the building. The energy hub model can then find a schedule that optimally supplies these demands. Figure 2(c) includes a coupling between the demand and scheduling calculations, such that building operation can be adjusted in order to facilitate a better energy supply schedule within the constraints of thermal comfort.

CONCLUSIONS

A variety of formulations are proposed for multi-level building optimisation problems. The coupling of demand-side and supply-side performance optimisation is highlighted as an important aspect of the scheduling problem. An iterative process could be used to link building control with energy supply scheduling. The nature of such an iterative process should take advantage of the information available from MILP solutions regarding binding constraints and sensitivities.

ACKNOWLEDGEMENTS

The author is the recipient of an EU Marie Curie CoFund fellowship.

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THE MODEL-BASED OPTIMIZATION OF BUILDINGS: AN OPTIMIZATION WORKFLOW AND REFLECTION ON THE STATE-OF-THE-ART

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ABSTRACT

The building design optimization process should result in a number of robust and innovative design solutions that simultaneously optimize one or more design criteria and provide the designer with information that aids the selection of a particular design solution for construction. This paper describes a four-stage optimization workflow: problem identification, implementation, solution, and analysis. The state-of-the-art and possible future research directions are considered in each of the four stages. In particular, future research should focus on optimization during the early design stage, on the integration of model uncertainty within the optimization, and methods of solution analysis that aid decision-making.

INTRODUCTION

Early research into the model-based optimization of buildings was often driven by the desire to find design solutions that minimised the buildings annual energy use or capital cost. A recognition that the design process involves the resolution of conflicting design goals resulted in the research shifting towards a multi-objective optimization approach. Even though there has been a six-fold increase in the number of research publications per annum over the last two decades (Nguyen et al, 2013), a number of open research questions remain unanswered. The questions are a result of: an increasing acknowledgement of the range of useful information obtainable from the optimization process; the differences in the design focus and problem specification across the design life-cycle and the application of the optimization process to both an urban as well as single building scale; and the continuing need for an improvement in the computational effectiveness and robustness of the optimization tools. This paper presents a reflective summary of the state-of-the-art of building optimization research. The summary is presented in three parts: a commentary on the output required from the optimization process; the specification of a simplified generic framework for the optimization process; and a summary of the state-of-the-art in each element of the framework.

DISCUSSION AND CONCLUSIONS

Over the last two decades, building optimization research has been focused on the solution of multi-objective optimization problems in which two design criteria are simultaneously optimized. The approach results in multiple optima that lie on the trade-off between the design criteria. These provide the designer with a **choice of solutions**, with the selection of a single design for construction being made *a posteriori* to the optimization; the design-decision is derived from the **information** extracted from the candidate solutions. Implicit in this approach is an expectation that **innovative design solutions** will also result from the process. However, since by its nature, an innovative solution is atypical and perhaps beyond the designers' experience, the decision-maker needs to be confident that the solution is robust and is not a result of a computational or modelling error. The **robustness** of the design solutions is a function of the **uncertainty** in the performance predictions (de Wit, 2001) and the **sensitivity** of the solutions to changes in the design parameters. Therefore, at any stage of the design life-cycle, the optimization process should result in a number of robust and innovative design solutions that simultaneously optimize one or more of design criteria, and provides the designer with information that aids the selection of a particular design solution for construction.

The state-of-the-art in model-based optimization is considered here through a four-stage optimization process of: **P**roblem identification, **I**mplementation, **S**olution, and **A**nalysis (PISA). Although in general the process is followed sequentially, the four-stages are not independent (Figure 1), and can involve iteration between the stages. The simplicity of the PISA optimization process means that it is applicable to any stage of the building design life-cycle.

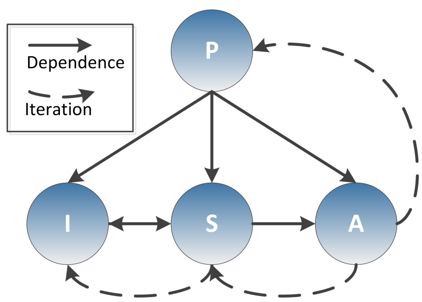

Figure 1, PISA Optimization Workflow

Problem identification: is concerned with a high-level definition the design variables, the design criteria to be optimized, and the design constraints. Both topological and parametric optimization problems can be found in building optimization literature. The topological optimization includes layout-planning optimization, HVAC system configuration optimization, and district energy network optimization. Parametric optimization has been the most widely applied in the specification of design detail (the choice of construction materials, glazed areas, supervisory control setpoint, etc). There is a wide range in the scale of optimization problems found in the literature, with the majority of research focusing on problems having fewer than 100 problem variables. Problems that attempt to optimize the control setpoints, or multiple buildings on an urban scale, can however result in hundreds or thousands of problem variables. More research is required for the efficient solution of large-scale (many variable) building optimization problems. There are generally three categories of design criteria: a criteria relating to capital expenditure, a second relating to the operation of the building (operating cost, energy use, or carbon emissions), and a third for client/occupant satisfaction (which includes occupant thermal comfort for instance). The specification of sub-criteria in each of these categories requires more research. Further, there are two key design stages: the early concept design stage in which the form and layout of the building are designed; and the second stage in which design detail is optimized. The two stages are distinct in that during the early concept design, the criteria may include subjective measures such as the aesthetic appearance of the building, with a desire by the designer to interactively guide the direction of the search. The criteria during the scheme and detailed design stages are quantitative with the designer only interacting with the process at the problem **I**dentification and **A**nalysis stages. The majority of the research to date has been focused on the scheme-detailed parametric design optimization, with more research required on early design stage optimization. Finally, while there is some progress on integrated design (Meuller et al, 2013), there is a need for research on design optimization that simultaneously considers multiple domains (the form, structure, and thermal performance for instance).

The **I**mplementation stage: is concerned with a low-level specification of the optimization problem and the development of models for quantifying the design criteria (including the uncertainty in the modelling process). The form of **S**olution process is often the drives the specific **I**mplementation (particularly in the case of topological problems). In the case of a parametric optimization, there is scope for research into categorizing the problem variables, and implementing the problem in a way that allows problem-specific operators to inform the search direction (for instance, established control rules could be used to seed the search with viable control setpoints). More research is also required on the development of capital cost models that incorporate model uncertainty.

The **S**olution process: is concerned with solving the optimization problem, evaluating the solution uncertainty and the sensitivity of the solutions to changes in the design variables. The majority of research to date has been focused on the use of Evolutionary Algorithms, most commonly in the solution of bi-objective problems. The computational load associated with simulating the building performance has also resulted in the use of a number of fast executing surrogate models. Although some work exists (Hoes et al, 2011), more research is required on integrating the solution uncertainty and sensitivity analysis within the optimization. More research is also required into suitable methods for solving problems having more than two objectives

The **A**nalysis: of the solutions provides information in a form that aids decision-making. This includes the trade-off between the design criteria, the function of the variables in driving the trade-off (Brownlee and Wright, 2012), the sensitivity of the criteria to changes in the design variables and the uncertainty in the criteria. To date, the analysis has been focused on the analysis of bi-objective problems, with more research required for problems having three or more objectives, and for integrating the analysis of the solutions uncertainty and sensitivity to the design variables.

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MODELING, IDENTIFICATION AND CONTROL OF BUILDING THERMAL SYSTEMS

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ABSTRACT

In this paper we report on our work in the past years on model predictive control of office buildings with focus on experimental applications and the modeling of buildings.

INTRODUCTION

Model Predictive Control (MPC) is a promising alternative to standard strategies for building control. MPC uses a mathematical model of the building and predictions of disturbances (e.g., ambient temperature) over a given prediction horizon (e.g., two days) for defining an optimization problem that is solved such as to maintain thermal comfort for the occupants while minimizing some objective (e.g., energy use or monetary cost). This makes it possible to integrate all available actuators and their interactions as well as predictions of weather, internal gains and electricity prices into a coherent, mathematical control framework that can handle constraints on control inputs and room temperatures. MPC relies on having a model of the building dynamics.

SIMULATIONS, EXPERIMENTS AND SOFTWARE

Simulation-based potential assessment of MPC [Oldewurtel 2012]

In a first project (OptiControl-I, www.opticontrol.ethz.ch), the potential of model predictive control strategies was assessed in simulations. For a large set of building/systems/weather combinations, whole year simulations of industry standard rule-based controller (RBC) and MPC were performed. Validated one-zone bilinear resistance-capacitance type models developed at EMPA [Lehmann 2013] were used. The simulations showed that (assuming no model-mismatch), MPC can in many cases save significant amounts (~20%) of control energy compared to conventional RBC.

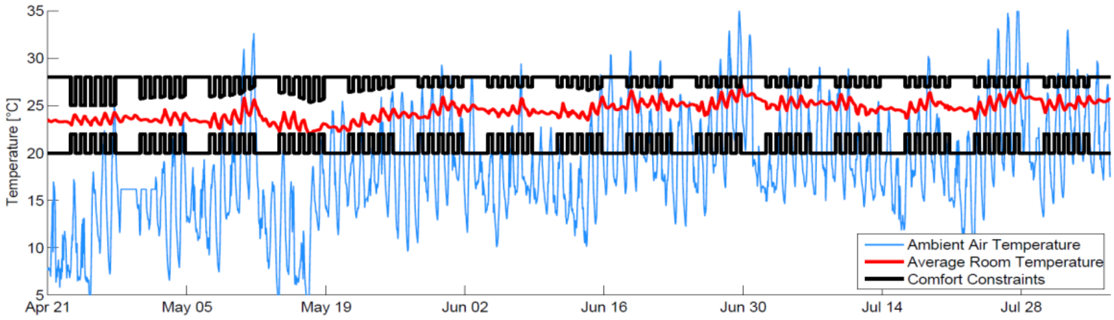

Figure 1: MPC room temperature performance (2012). EN15251 comfort constraints shown.

Model predictive control of a Swiss office building [Sturzenegger 2013]

The OptiControl-II project (www.opticontrol.ethz.ch) provided a proof-of-concept for the integrated control of a whole office building. It addressed problems such as the modeling of real buildings, plant-model mismatch and compatibility with pre-installed control systems. On a typical Swiss office building with a conditioned floor area of ca. 6000 m^2, five office floors were controlled for a total period of seven months. The MPC provided integrated control of the TABS, the air handling unit (including energy recovery/heating coil/evaporative cooler), radiators and centrally controlled blinds. The modeling approach is described in the next section. MPC was implemented as a high-level controller, sending set-points and operating modes to the existing low-level control. The control algorithm ran in Matlab on a PC, connected through a BACnet-OPC client to the building automation system. Figure 1 shows the spring/summer experimental period. The maximum (over all rooms) measured integrated comfort violations were approximately 10 Kelvin-hours, mostly stemming from the end of June when the cooling system was overwhelmed. Comfort also was maintained in the heating season experiments (not shown). This was underlined by the facility manager’s feedback.

BRCM Matlab Toolbox: Model Generation for Model Predictive Building Control [Sturzenegger 2014a]

Creating an accurate building model that is simple enough to allow the resulting MPC problem to be tractable is a crucial task in the control development. The building resistance-capacitance modeling (BRCM) Toolbox (www.brcm.ethz.ch) provides a means for the fast generation of bilinear resistance-capacitance type models from basic geometry, construction and building systems data. It also supports the generation of the corresponding potentially time-varying costs and constraints. The full building model is constructed in a stepwise procedure: i) Automated generation of the building's linear thermal model (describing the heat transfer between zones, walls and ceilings) from construction and geometry data; ii) modeling of external heat fluxes (e.g. solar gains, building systems, internal gains etc.) using parameterizable modular sub-models; iii) discretization. Several comparisons with the widely used building simulation software EnergyPlus have shown average model discrepancies of around 0.5K over three days (a typical MPC horizon). Moreover it is possible to construct the thermal model directly from EnergyPlus input data files.

Frequency-Domain Identication of a Ventilated Room for MPC [Sturzenegger 2014b]

System identification methods have been used to model a ventilated room (with either constant air flow or constant supply temperature). An office type test room was instrumented for experiments and three models for the room were derived: i) an empirical transfer function estimate (ETFE) derived from a pseudo-random binary sequence input signal; ii) an ETFE derived from a relay feedback approach; iii) a model generated with the BRCM Toolbox. Using additional validation data, the different models and approaches were compared in terms of accuracy and efficiency. The effect of air mixing dynamics was demonstrated in a further experiment to be one of the main differences between the experimentally identified and the RC model. An additional pole can be added to the RC model in order to compensate for the differences.

DISCUSSION

For MPC to become an interesting alternative for wide-spread commercial use, the modeling effort must be small. Hence, there is need for reliable and efficient methods for generating MPC suitable models of buildings. Key decisions in building MPC are the form of the model (linear / bilinear / nonlinear) and how it is obtained (physical modeling / identification). The obvious downsides of nonlinear models are that in the resulting MPC problem the "solution" time is long and it is usually intractable to find the global optimum. This makes it hard to test the algorithms in longer simulations. However, while modeling the building's thermal dynamics linearly is usually a good approximation, some of the necessary simplifications in modeling building systems linearly may be too inaccurate. The best choice depends on the problem at hand but many cases can be covered by bilinear models. We believe that a physics-based modeling approach is better suited for integrated MPC of multiple actuators because it avoids time consuming identification experiments for potentially nonlinear multi-input multi-output systems. Moreover, it allows the physical interpretation of input-output relationships and can be easily adapted to changing zone geometries, HVAC systems etc. The obvious downside is that building data must be available. However, we believe that – if unavailable - the use of "best guess" data is sufficient to set up a conservatively tuned MPC that can be refined during operation once measurements become available.

MPC has been shown in simulations to be a promising alternative to standard building control. However, upfront development costs – in particular for modeling - are currently too high for a widespread adoption in industry. A potential solution is the automated modeling implemented in the BRCM Toolbox. It was used in a proof-of-concept project for the long-term integrated control of an operational office building under fully realistic conditions.

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SIMULTANEOUS OPTIMAL DESIGN AND CONTROL OF FUTURE BUILDING ENERGY SYSTEMS UNDER VARIOUS PRICING SYSTEMS AND GOVERNMENTAL DIRECTIVES

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ABSTRACT

As mandated by several directives issued by the European Union, starting from 2020, new buildings have to fulfil demanding low-energy standards. This new restrictions require the installation of renewable energy technologies, storage systems, and improved insulations. Due to the stringent requirements for such future building systems, the complexity of the design process will increase inevitably. Therefore, this paper presents a design framework for the optimal selection and sizing of such building systems. Various building components are implemented in the framework using mixed-integer linear programming techniques. In order to enable a reasonable comparison of various configurations, the problem solver computes an optimal operating strategy simultaneously. Finally, the impact of regulatory policies and variable pricing systems on the design of the building components are examined.

INTRODUCTION

Increasing energy prices and the more stringent legal regulations for the use of fossil fuels and CO2 emissions of buildings will result in the introduction of more building-integrated production. In Addition, with the introduction of a “smart grid” on the supply side, the impact of the interactions between the building and the supply grid increases. Introducing renewable energy sources such as wind and solar power plants will result in a fluctuating electricity production, raising a significant need for balancing power. The so-called “smart buildings” could provide a significant part of this ancillary service.

The design of such smart building systems and its services is a computationally complex task. The variety of building applications, local weather conditions, governmental restrictions and energy tariffs makes it even more difficult to generalize the process of optimal component design. Based on these conditions, the building designer must assure an optimal selection and sizing of the building components, while pursuing the goal of an optimal operation of them.

MODEL FRAMEWORK

The process of simultaneous design and selection of building services is based on a framework previously described by the authors in [Ashouri et al., 2013]. The tool is called the smart building designer (SBD). Figure 1a shows the implemented devices in the SBD framework and the interconnections among them. Certain devices are installed in the building in order to convert the available resources into the appropriate deliverable types of energy. The outputs of the converters are transferred to the building envelope in the form of heating or cooling power, or electricity. However, the energy management system or the optimizer (in the design phase) decides how the power flows are distributed among the converter devices and other parts of the system. The optimizer controls the total input and output energy flows, as well as the internal flows between any two converters.

The storage devices provide an energy buffer between the converters and the consuming devices. In addition, the external block provides gas and electricity to the building system.

The principal optimization problem of the SBD framework is to find the optimal selection and sizing of building components in order to minimize a multi-criterion cost function. Since the optimal design and the corresponding operating problem are correlated, the SBD uses an optimal control approach. Hence, the design process is separated from the control problem. This separation means that if the suggested design is used, no other control strategy yields better results (i.e. a lower cost function). Vice versa, if the building is operated using the suggested optimal control strategy, no other component design is advantageous. Such an approach is referred to as a simultaneous optimization of control and design [Bansal et al., 2002]. The simultaneous optimization of the design and operation is performed for a full year, while the objective is extended to 20 years, which represents a typical life-time of the building services. The total objective function to be minimized consists of three monetary cost terms associated with investment (O_{inv}), operating (O_{opr}), and discomfort (O_{dcm}), as well as a term

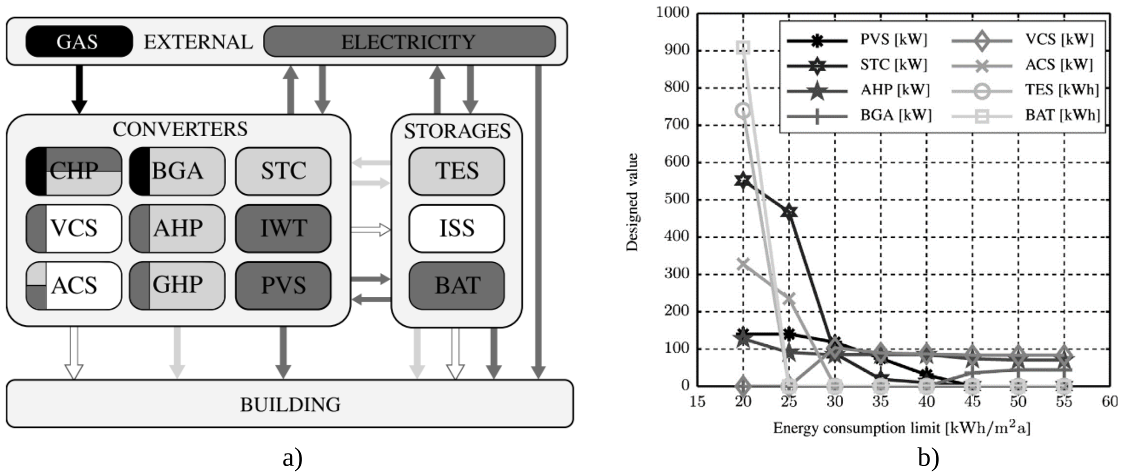

Figure 1 a) Overview of the SBD blocks, subsystems and energy flows: gas flow (black), electricity flow (dark grey), heating flow (light grey) and cooling flow (white). b) Component selection and sizing for different restrictions on maximum energy consumption.

representing the subsidies (S) for all devices:

$$O_{tot} = O_{inv} + O_{opr} + O_{dcm} - S \quad (1)$$

RESULTS AND DISCUSSION

As concepts such as zero-energy buildings are being introduced by governments, a constraint on the annual energy consumption (L_E) is introduced. This constraint ensures that all calculated optimal control strategies lead to a maximum annual energy consumption smaller than or equal to the energy limit, within the building envelope. The effect of applying such limitations on the design of the building is shown in Figure 1b. For values of L_E greater than $50\frac{kWh}{m^2 \cdot a}$, the constraint is not affecting the optimization results considerably. Standard devices such as gas boilers (BGA) and heat pumps (AHP) and vapour compressions systems (VCS) are selected. As the external consumption limit becomes tighter, local energy production is needed. For a value of L_E smaller than $40\frac{kWh}{m^2 \cdot a}$, a photovoltaic system (PVS) and solar thermal collectors (STC) are integrated. However, the installation of storage devices such as battery systems (BAT) or thermal energy storages (TES) does not seem to be necessary until a very bounding constraint of L_E smaller than $20\frac{kWh}{m^2 \cdot a}$ is applied. In addition, when the dimension of the STC becomes large enough, an absorption chiller system (ACS) replaces the vapour compression system (VCS).

CONCLUSION

The potential for the optimization of building services is increased due to the development of renewable energy sources and storage technologies. In this paper, a modular framework called the Smart Building Designer is described, which enables the derivation of an optimal component design and operation strategy of the building system. The investigations show that the SBD is able to solve the optimization problem for one year in less than 10min on a typical computer. This ability is mainly due to the accurate but control-oriented formulation of MILP models. The SBD precalculates the required boundary conditions using the raw data such as those gained from meteorological measurements (temperature and solar irradiation), occupancy schedule, and spot-market electricity rates. Due to the modular and flexible framework, the user of SBD are able to optimize arbitrary building systems. The sensitivity analyses also demonstrate how increasing energy-carrier prices or governmental legislation results in different optimal designs.

ACKNOWLEDGEMENTS

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A TOOL CHAIN FOR CONSTRUCTING REDUCED ORDER BUILDING MODELS USING MODELICA

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ABSTRACT

A toolbox for performing system identification on reduced order building models is presented. It allows automating the different steps in the system identification procedure such as data handling, model selection, parameter estimation and validation. A Modelica package, *FastBuildings*, containing a set of low order models is included in the toolbox. The toolbox is implemented as a Python module that wraps the functionality of *JModelica.org* to perform the optimization. This on-going work is followed by future plans to derive reduced order models directly from a Modelica model's system of equations.

INTRODUCTION

As more computing power and low-cost sensors become available, more sophisticated methods can be used to design and control buildings. Model Predictive Control (MPC) is such a method. This methodology incorporates a controller model into the optimal control problem (OCP), which contains the most important characteristics of the controlled system. Constructing these low-order controller models often requires a lot of manual work. Ways to automatically derive controller models could therefore improve the practical usability of these methods.

In this paper we discuss two approaches to do this. The first is a newly developed data-driven grey-box toolbox that fits parameters of low-order models to measurement data. The second is future work: a methodology for deriving low-order models from detailed Modelica models.

GREY-BOX BUILDING MODELS FOR MODEL ORDER REDUCTION AND CONTROL

In this section a toolbox is described that facilitates and automates the different steps of a system identification procedure. It estimates the parameters of a series of low-order building models using easily obtainable measurement data such as the ambient and zone temperature and electricity consumption.

The toolbox consists of four major components:

1. a Modelica library *FastBuildings* which contains predefined low-order models for thermal zones, HVAC components and buildings;
2. several *.mop files* specifying the possible model structures and parameters to estimate;
3. *JModelica.org* is used for compilation of the *.mop* files and solving the optimisation problem;
4. the Python module *greybox.py* that contains the user interface and top-level functionality.

The relation between these components is shown in Figure 1 and is further explained.

The FastBuildings library contains multiple low-order Modelica components, typically using RC-networks. These components serve as the building blocks for the construction of the *.mop* files. The *.mop* files are very similar to ordinary *.mo* files but they contain two models: one for optimizing, called *Parest* and one for simulating, called *Sim*. Custom *.mop* files can be added using this structure. The *FastBuildings* library is distributed with the *Modelica license 2* and can be found in the open-IDEAS source code repository on Github (KU Leuven and 3E).

The *Parest* model contains the parameter estimation problem. The model parameters are free optimization variables and measurement data serves as input. The optimization problem is solved using JModelica

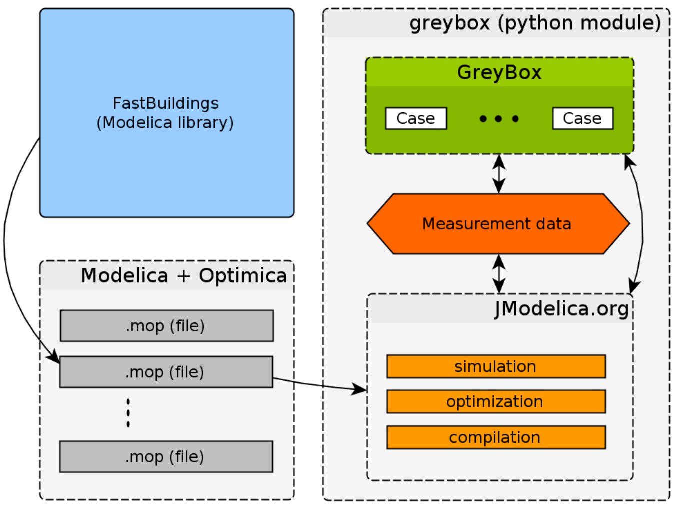

Figure 1: Overview of the grey-box buildings toolbox (De Coninck, 2014)

(Åkesson et al., 2010). The optimization algorithm is collocation-based and is discussed in more detail by Magnusson et al. (2012).

The *Sim* model has fixed parameters and is used to evaluate the performance of the estimated parameters based on a set of measurement data, which may or may not be the same data as used for the parameter estimation.

The Python module greybox.py defines the *GreyBox* class. An instance of this class is made for the system identification of every building. This class keeps track of all attempts to identify the model using the *Case* class. Cases can for instance use different *.mop* files or can use different initial guesses for the parameter estimation problem. Cases can also be generated automatically by exploring the parameter initial guess solution space using Latin hypercube sampling.

The cases of a *GreyBox* instance can be compared using the *Sim* model. The comparison includes predefined graphical and quantitative validation methods. Based on these methods the best set of parameters and type of model is then selected. This solution can then be used as the low order model for an MPC controller.

For a more detailed description of the toolbox, its further possibilities and results we refer to De Coninck et al. (2014).

REDUCED ORDER MODEL EXTRACTION FROM MODELICA MODELS

Secondly we present future plans to derive a methodology to complement the *data*-driven approach described above with a methodology that uses the equations from a detailed Modelica *model* to construct a reduced order controller model.

Modelica allows describing component and system models of buildings in high detail. This amount of details can be necessary to be able to assess the performance of a system accurately. However it is computationally impractical to use these detailed models to perform optimal control. Therefore a controller reduced order model needs to be derived, which can be obtained in different ways. The Modelica model could for instance be used to generate 'measurement data' that can serve as an input for the toolbox described above.

However, since the Differential Algebraic Equation (DAE) system is available in Modelica, mathematical techniques such as model order reduction could be applied. The resulting reduced order system model or a collection of reduced order component models can then be used as the controller model in an MPC problem.

Using this methodology the same Modelica model can serve as the basis for both the emulator and controller model of a typical MPC problem. Ideally the objective function and constraints for this MPC problem can also be incorporated into the same Modelica file. This would allow automating the setup of MPC for building models, as components can be switched in and out of the model and the correct MPC problem is derived automatically.

Eventually these methodologies and further developments could evolve towards a collection of packages that form a tool chain for easily evaluating the performance of buildings based on dynamic simulations using optimal control in Modelica models.

CONCLUSION

This extended abstract first presents a toolbox for deriving grey-box low-order building models based on measurement data. Its different components are explained. Secondly future plans to complement this data-driven approach with a model-based approach are discussed. The goal of these methods is to be able to easily derive building MPC problem formulations based on Modelica models.

ACKNOWLEDGEMENTS

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BENCHMARK AND COMPETITION FOR CLIMATE CONTROL ALGORITHMS OF OFFICE BUILDINGS

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ABSTRACT

Assessing the performance of advanced climate controllers for a complex building is a difficult task. Experimenting in occupied buildings is cumbersome and accurate comparison of the performance of different control algorithms is often impossible, due to different boundary conditions and assumptions. An alternative is to test the algorithms on dynamic building models using energy simulation platforms. However, until now no benchmark for climate control of complex buildings seems to exist with which academics and companies could compare their algorithms in an objective and unbiased way. The purpose of this extended abstract is to propose such a benchmark model, written in Modelica©, that would be freely available and that can be run in the open-source software OpenModelica. The authors will also organize a competition, including both companies and universities, where the energy use or cost and thermal comfort of the office building will be compared for the different control algorithms developed. An online platform should also be created in order to share the results and information about the control strategies.

INTRODUCTION

In the last decades, building design and climate control have received increasing attention, in order to reduce primary energy use or in order to shift the peak energy loads. This trend results in more and more sophisticated buildings, with hybrid heat and cold production (e.g. the combination of a geothermal heat pump, a gas boiler and a dry-cooler), the use of thermal storage (e.g. storage tank, thermal use of the building structure, etc.) or special attention to the building envelope and solar shading. Traditional rule-based-controllers struggle to control this level of complexity with satisfactory results regarding both the users' thermal comfort and the minimization of energy use.

(Near) Optimal Controllers such as Model Predictive Control have been developed in order to use the dynamics of the building in a smart way, as well as the possibilities offered by hybrid systems or the information provided by weather forecast. Even though the improvement potential of these advanced technics has been proven both by energy simulation platforms and in some real buildings, quantitative comparisons between the state-of-the-art controllers used by control companies and the more advanced strategies being studied in research are still missing. To the authors' knowledge, no benchmark exists for the climate control of complex buildings, which are both accessible and recognized by companies and academics.

The purpose of this work is to propose a freely available detailed Modelica© model of a representative office building to serve as benchmark for building climate control algorithms. Companies, as well as academics are invited to test and compare their algorithms for different scenarios and publish their results for comparison. The authors would also like to organize a competition including different universities and companies where the energy use or cost and the thermal discomfort of the building are compared for each control algorithm.

DESCRIPTION

The choice of the building model is crucial as it should represent a typical office building but without unnecessary complexity. The proposed model is based on an existing building. The following sections describe the building, the boundaries and constraints of the system, the cost function that should be minimized and some technical details.

Building description

The building under investigation is a recently built Belgian office building with a floor area of 5000 m^2. The building is well insulated (U-value of 0.25 W/m^2K). The window-to-wall ratio is 0.36. All windows are retreated from the façade and they are equipped with solar shading devices. The building is divided into meeting rooms, open working areas, technical rooms (e.g. server room) and an underground garage. Besides space heating, cooling and ventilation, domestic hot water (DHW) is also taken into account.

Three different configurations of emission and production systems are proposed. **Scenario 1** represents a conventional system using radiators, ventilo-convectors, a central air-handling unit with heat recovery and VAV devices for meeting rooms and for the server-room. A gas-boiler and a dry-cooler supply heat and cold and three storage tanks are available (for hot water, cold water and DHW). In **scenario 2**, a geothermal system is considered. The major part of the heat and cold demand is supplied by a ground-coupled heat pump with the possibility of passive cooling. A small gas-boiler and a dry-cooler are used for the DHW, to cool the server room and to cover peak demand. Thermally activated floors/ceilings replace the radiators but the ventilation stays the same. Finally, **scenario 3** represents a more cost-driven building where the geothermal part is sized to cover the base load only. A condensing gas-boiler and a dry-cooler produce the remaining heat/cold. The emission and ventilation systems are the same as for scenario 2.

Boundary conditions, cost function and constraints

It is important to define which information will be accessible to the participants, what are the boundary conditions and constraints and what is the basis for comparison.

The goal of the control algorithm is to minimize the primary energy use or cost (i.e. the electricity used by the heat pump, the circulation pumps, the fans and the dry-cooler and the gas used by the gas-boiler) and to minimize thermal discomfort (using Predicted Mean Vote or other methods). Day/night electricity tariffs will be taken into account. The constraints are the limited power of the heating and cooling devices, the nominal flow rate of the pumps and, only a limited thermal unbalance is allowed in the ground to ensure long-term sustainable operation of the heat pump system.

We will provide to all participants a detailed description of the building and its hydraulic circuit. The developed algorithms will be tested considering two different cases. In **case a**, perfect knowledge of weather forecast and internal gains is assumed. In **case b**, we will provide weather forecast with a realistic accuracy and the internal gains will be stochastic. Afterwards the cost functions are evaluated using real weather data.

Reduced order model

Advanced control algorithms such as MPC need reduced order models to compute their predictions. In order to get such a model, the participants can set up virtual experiments for the model to gather the necessary identification data. We will also provide an identification data set and a proposal for a reduced order model.

Technical details

The model will be implemented in Modelica© using the IDEAS library (Baetens et al. 2012) developed at KU Leuven. The participants will get an FMU of the model that they can run in the free open-source platform OpenModelica. The participant can then write the controller in this platform, or couple OpenModelica to other software such as Matlab or Python. To lower the learning curve, a basic rule-based-controller implemented in OpenModelica will also be provided as an example, as well as guidelines for coupling to other software.

Copyright policy

All participants of the competition will be asked to share their results and algorithm description with the organizers (not necessarily with the other participants), so that we will be able to write a report about the comparison. The presented results can be anonimized upon request or a detailed description of the algorithm can be omitted.

CONCLUSION

In this extended abstract, a realistic office-building model is proposed as a benchmark for building climate control algorithms. Different scenarios are proposed by changing the production and emission systems, as well as by changing the level of accuracy of the weather forecast and internal gains. The general framework of a competition has been described where companies and universities would be able to compare building climate control algorithms with each other and assess their saving potential in a convincing way.

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LESSONS LEARNED FROM MODELLING AND CONTROL OF HYBRID GCHP SYSTEMS FOR ENERGY USE MINIMIZATION

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ABSTRACT

In this extended abstract, we give a short overview of the lessons learned from reduced-order modelling and model-based control applications to minimize the total energy use of a hybrid ground-coupled heat pump (HyGCHP) system under operational constraints. The HyGCHP system investigated incorporates a ground-coupled heat pump, a gas-fired boiler, a passive cooler and an active chiller. The applied control methods are prediction-based dynamic programming, non-linear model predictive control and linear optimal control. Our first finding is that the borehole thermal prediction dynamics can be modelled very accurately either by a low-order nonlinear autoregressive exogenous (NARX) model or by a low-order state-space model obtained by application of proper orthogonal decomposition approach to a finite-volume based emulator model. Second, the solution of the global optimal control problem of total energy use minimization does not depend on future states, on inputs and on disturbances. Finally, the results from application of the linear optimal control show that the controlled system is not strongly sensitive to heat pump coefficient of performance.

INTRODUCTION

For ground-coupled heat pump (GCHP) systems with vertical borehole heat exchangers (BHEs), the large investment cost for the BHEs represents a major bottleneck. This explains the trend towards compact, hybrid GCHP systems (HyGCHPs), which combine smaller boreholes with supplementary heating, or cooling devices such as gas-fired boilers and active chillers (see Figure 1).

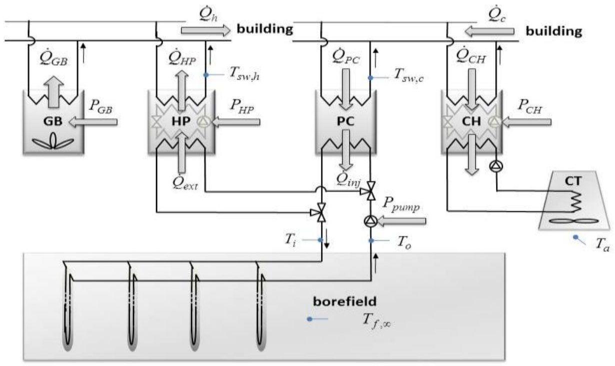

Figure 1: Hybrid system (gb=gas boiler, hp=heat pump, pc=passive cooler, ch=chiller, CT=cooling tower).

The first step towards developing a model-based intelligent control algorithm for HyGCHP systems is the reduced-order modelling of borehole/borefield thermal dynamics. To this end, first, a borefield is modelled as a single equivalent borehole, which is sized according to the specified building loads. Second, for the equivalent borehole an equivalent diameter approach (Chiasson, 2007) is used. In the equivalent diameter approach, the heat transfer from the U-tube is approximated by the heat transfer from a single pipe with a hypothetical diameter through which the heat exchanging fluid circulates. After these two steps, grout and ground regions are discretized and a finite-volume, large-scale model for the thermal dynamics is developed, for which the input is the net heat transfer rate to the ground and the output is the mean temperature of the heat carrier fluid in the U-tubes of the boreholes. The temperatures of nodal points in the grout and ground regions together with the mean temperature of the heat carrier fluid constitute the state variables. The model obtained in this way is called the ***emulator*** model of the system. The emulator model is used for two purposes, (a) to obtain reduced-order models and (b) to assess the performance of different control methods. Two reduced-order models are derived from the emulator model. The first one is a NARX model:

$$y(k) = f_{NARX}(y(k-1), y(k-2), u(k-1), u(k-2)), \tag{1}$$

where f_{NARX} is a wavelet network. This model is used as the control model for dynamic programming. The second control-oriented model is the following state-space model (SS) obtained from the emulator model via the proper orthogonal decomposition (POD) model-order reduction technique:

$$x(k+1) = Ax(k) + Bu(k), \quad y = Cx(k). \tag{2}$$

In both models, y is the heat carrier fluid mean temperature (T_f) and u is the neat heat transfer rate to the ground. Multi-sine inputs are applied to the emulator model with a sampling period of 4 h to create the data for the construction of the above two models. The normalized root mean-square error (NRMSE) performances of the two models against the emulator model are as follows:

$$NARX_{nrmse}^{id} = 98.72\,\%\,,\ NARX_{nrmse}^{val} = 98.63\,\%,\ SS_{nrmse}^{id} = 98.54\,\%\,, SS_{nrmse}^{val} = 98.55\,\%,$$

where the superscripts “id” and “val” are used to denote identification and validation cases. The NARX model is used in a dynamic programming control and the SS model is used in a non-linear model predictive control (NMPC) method. The control objective is the minimization of total energy used by all components while guaranteeing that T_f remains in the range [0.5, 19.5] °C. Interestingly, the results of dynamic programming and NMPC are ***indistinguishable*** implying that the instantaneous energy use minimization is the same as the energy use minimization over the whole period, which was one year. Figure 2a shows that the heat carrier fluid temperature bounds are hit (but not crossed), while Figure 3b suggests that the highest cost is associated with the heating regime.

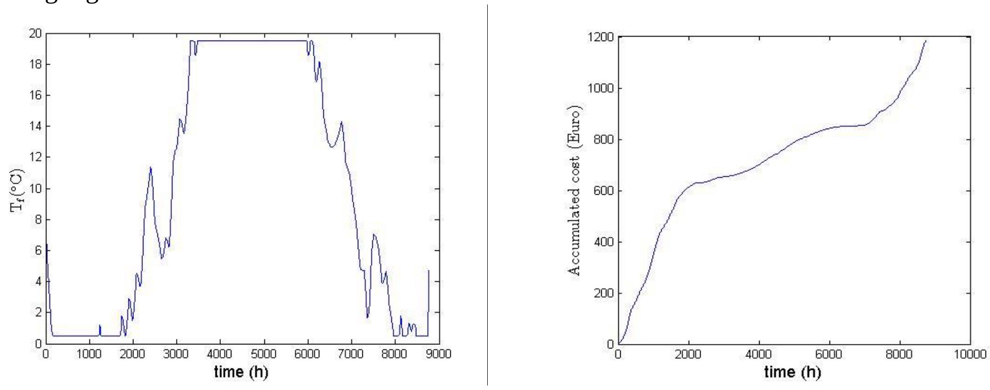

Figure 2: Evolution of T_f and accumulated cost.

Next, a series of linear optimal control (LOC) problems with constant heat pump COPs are tested. The results for total annual cost for LOC are very close to the result for dynamic programming or NMPC cases (Figure 3, left) but the heat carrier fluid temperature bounds are crossed to some extent for some COP values in LOC (Figure 3, right).

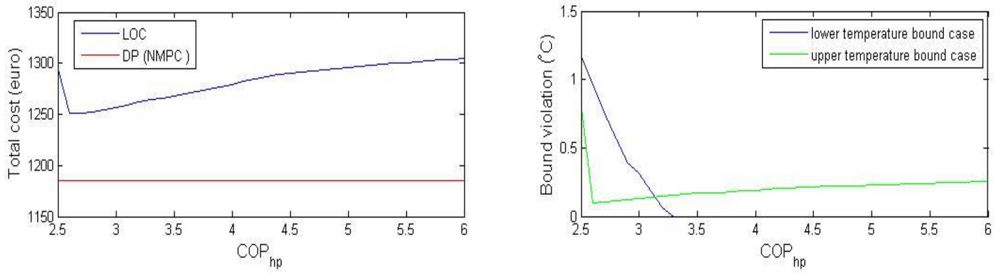

Figure 3: Total cost and temperature bound violation versus heat pump COP in linear optimal control (LOC).

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COMBINING SIMULATION AND OPTIMISATION FOR MAXIMUM BUILDING PERFORMANCE

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INTRODUCTION

The HVAC research group at Aalto University (former Helsinki University of Technology) has been developing combined use of building simulation and optimisation since the beginning of this millennium. The first trials were simple single-objective problems but soon the approach was changed into multi-objective. From the beginning, the goal has been to develop and use a true combination of a simulation software and an optimisation algorithm. Another goal has been the transfer of knowledge and skills to Finnish companies who would have huge benefit of using optimisation.

TOOLS

The main tool for building simulation has been IDA-ICE which is best known in the Nordic countries, but which nevertheless is among the most advanced building simulation programmes globally. In single-objective optimisation GenOpt package was first used. However, because there is no multi-objective algorithm included in GenOpt, an in house NSGA-II algorithm was coded and combined with IDA. The latest development is Multi-Objective Building Optimisation package (MOBO) which is a generic type algorithm selection and can be combined virtually with any software, which is producing values for the objective functions.

OPTIMISATION METHODOLOGY

Different optimisation methods have been used for building energy optimisation starting from Hooke-Jeeves and similar single-objective algorithms. However, GA-type algorithms in different variants have proven to be very useful for most building energy optimisation cases. GA has been used as such but also in stages with a preparation phase to have a good initial population or a refining phase to draw some solutions closer to the true pareto front. In addition, some variants of the original NSGA-II have been developed. One variant with a passive archive strategy and another with an active archive strategy. The results indicate that the active NSGA-II has a better repeatability in finding optimal solutions with a high convergence than the original or the passive type algorithm. Finally, some trials in dividing the optimisation process into several stages from the decision parameters point-of-view has been made. In the first stage the building's thermal performance is optimised, in the second stage the heating and cooling systems are optimised and in the third stage the renewable energy systems are attached and optimised.

IMPLEMENTED CASE STUDIES

The most common case has been a residential detached building or dwelling. The decision variables mainly used are some features of the building construction like insulation thicknesses, envelope tightness, window types or solar shading. The primary system variables have been the type of heating system, the type of ventilation heat recovery, the cooling options and the size of the renewable energy productions systems. Objectives are usually energy demand or CO2 emissions on one hand and investment or LCC cost on the other hand. In a Nordic climate, the heating system is dominating the solutions compared to the influence of the other variables. The summer time thermal conditions have been ensured by using an hour-degree constraint which rejects the solutions with not acceptable thermal conditions.

Also some office and shopping center cases have been optimised. An office case easily gets quite complicated as there are many energy related systems to consider and system features on different parts of the building might need to be treated as separate variables. The simulation model of a large building must also usually be streamlined by merging adjacent spaces to keep the simulation time in reasonable limits. An experience with a LEED certified shopping centre showed that with a detailed model and long simulation time the GA population has to be kept rather small. Because of that, the pareto-front remains sparse.

May be one of the most important lessons learned is that the largest potential for optimisation in the building process is in the very beginning of the planning. During the conceptual design stage, there are the best opportunities to influence the building performance. Every decision made before the optimisation reduces the number of freedoms and the possibilities for finding prominent improvements.

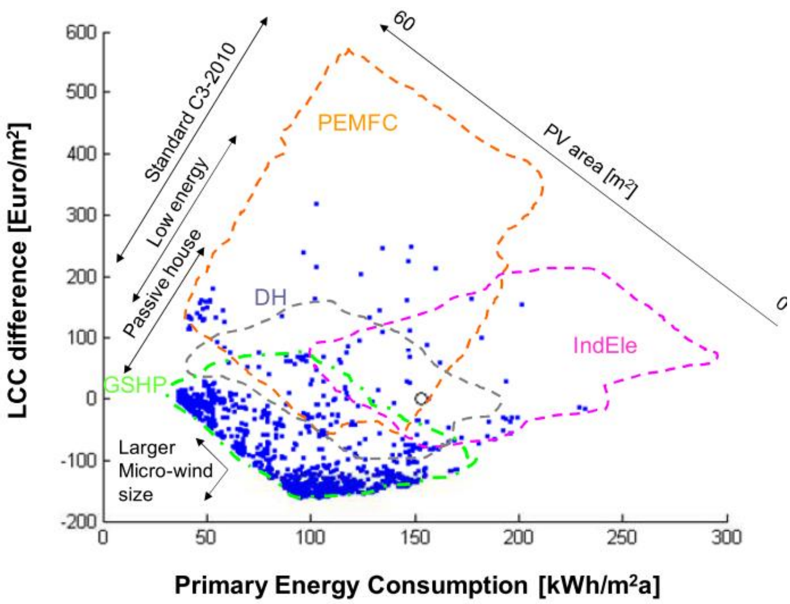

Fig. 4. Contribution of the various design variables in the optimisation results.

COOPERATION WITH COMPANIES

There have also been some projects with Finnish consulting companies dealing with optimisation. One major goal has been to push the knowledge of optimisation to be integrated in the building design work. This however has turned out to be a very difficult task. The majority of the companies have so established design routines that it has been practically impossible to change the old conventions. The best method for knowledge transfer seems to be to include building optimisation in the master thesis done in cooperation with a company. When the company then employs the new master, they directly get a person who has an understanding of the methodologies. Still this does not guarantee that optimisation will be taken into use, because there always is resistance against new conventions inside the company.

CONCLUSIONS

There is a potential for improving the performance of evolutionary algorithms (speed and results quality) by combining them with deterministic algorithms and/or suitable archiving strategies.

Performing the optimisation in several stages can remarkably save the total time for the optimisation task.

In a cold climate the type of the heating system is a dominating decision variable determining the location of the solution points on a macro-level.

The absolutely largest potential for optimisation in the building process is in the conceptual design stage. During later stages the possibility to influence important decisions is lost.

The potential of multi-objective simulation-based optimization approach is not sufficiently exploited in current building design practice. The deployment and integration of a new approach has been proven to be difficult.

PARETO OPTIMIZATION AND AGGREGATION: A NEW APPROACH TO INTEGRATE OPTIMIZATION WITH USER CRITERIA IN BPS

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ABSTRACT

Building performance simulation (BPS) is a complex domain, covering multiple objectives, comprising numerous parameters, and introducing many sources of uncertainty. Computational optimization using different algorithms has been introduced to building performance simulation in order to analyse the effect of often conflicting objectives. The implementation of optimization in practice however is often limited to assessing trade-offs between two objectives, e.g. energy consumption and thermal comfort. In this discussion paper, we present an idea to aggregate multiple objectives to a single objective problem, by grouping objectives into different categories. One of the advantages of this approach is to improve visualisation (as with a dimension of 3-4 or higher objectives it becomes very difficult to interpret the Pareto front. The second advantage is to reduce the memory space that is needed for high resolution approximation sets in Pareto optimization.

INTRODUCTION

This paper discusses a modelling and visualisation approach based on multi-objective optimization in standard building performance simulation (BPS). Major obstacles for integrating and using optimization in BPS have been identified by Attia et al. [2013] as follows:

(i)“requirement of high expertise”. Necessary input parameters such as number of design variables, number of objective function evaluations, population size, etc. can already be too complex to define for a standard BPS user. If there is high uncertainty in the input files for the optimization and the optimization process is often described as non-transparent or as a black box approach, consequently that leads to

(ii)“low trust in the results“. The user has no impact on the outcomes, and his/her preferences are not taken into account. Optimal solutions with respect to a limited number of objectives may be rejected, as they are not compromised solutions.

An environment is needed that integrates and links simulation and optimization, that is simple but still useful for the novice but can be complex for the more advanced user. It should provide a graphical user interface with which the user can interact and understand what giving preferences with respect to one objective may cause for changes in the design.

The approach presented here provides a means to address these obstacles by presenting a new methodology of aggregating multiple objectives. The concept of aggregating objectives is not new and has been shown, for instance, in [Kruisselbrink et al, 2009] but what will be new in the field of BPS is the use of a desirability index that allows a more controlled and user influenced approach of aggregating the objectives.

METHODOLOGY

Pareto optimization as shown in [Hopfe, 2009; Hopfe et al., 2012; Emmerich et al., 2008] is limited to a small number of objectives. With an increasing number of objectives, it becomes computational expensive as the number of solutions tends to grow exponentially; further, the visualisation of results becomes very difficult.
A desirability factor is introduced [Harrington, 1965; Kruisselbrink et al, 2009] in order to compare between different criteria. As such the designer can assign weighting values between 0 (poor quality) and 1 (high quality). For multi-objective optimization, this provides a means to easily aggregate a number of objectives to a single-objective (comparable to a weighted sum method, however, based on non-linear users preferences).

CASE STUDY

A Passivhaus has to comply to a large number of criteria related to energy consumption, thermal comfort and others. It will be used to demonstrate the methodology. The number of criteria defining our case study can be divided into fuzzy/ soft constraints (restricting to a number of overheating hours, compliance to building regulations) and a number of design objectives.

$\min f_i(x), i = 1, \ldots N$

$g_j(x) \leq b, j = 1, \ldots M$)

RESULTS

There is not just one "optimal" solution but rather a variety of solutions that are representing different trade offs in the objective space. As a consequence not all of these are optimal with respect to all objectives, and that means they do not optimally comply with all of the requirements. But decision makers may consider some constraints as soft constraints that he/she will be able to resolve at a later point. The boundary between constraint violation and satisfaction is therefore fluid for some criteria.

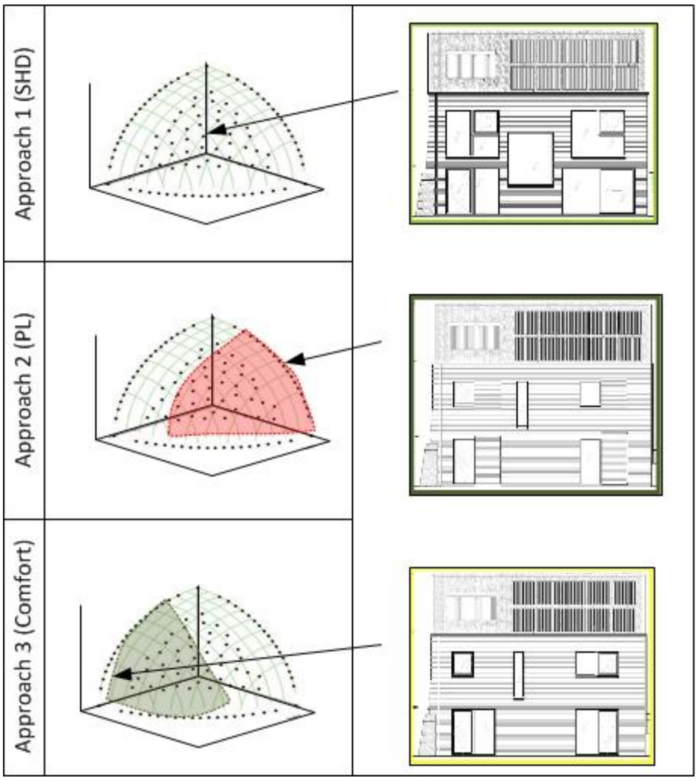

Figure 1 Resulting Pareto front with three objectives and subset of solutions depended on user's desirability.[1]

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[1] SHL=Specific Heating Demand, PL=Peak Load,

MULTI-OBJECTIVE OPTIMISATION TO SIMULTANEOUSLY ADDRESS ENERGY HUB SIZING AND SCHEDULING USING A LINEAR FORMULATION

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ABSTRACT

Multi-energy systems are expected to play an important role in future global energy mix. Effective design and operation of such systems is crucial for the realisation of the benefits they promise. This paper details an optimisation problem dealing with the simultaneous element selection, sizing and optimal operation of an energy hub using multiple objectives and a linear formulation. The approach is applied on a UK commercial building as a case study.

INTRODUCTION

The 'energy hub' concept, introduced by Geidl and Andersson (2007), is a framework to model the interactions between multiple energy carriers, energy converters and storage technologies. There are two types of problems where the energy hub is applicable: the first one is the optimal dispatch of energy between demand and supply or between different energy hubs. The second type is the design optimisation. The latter could be further subdivided into problems dealing with the optimal layout of elements inside an energy hub out of a series of options (Geidl and Andersson, 2007) and problems dealing with the optimal sizing of all the components that have been selected for an energy hub (Sheikhi et al, 2012). The aim of this study is to combine all the aforementioned approaches into a single methodology that will simultaneously consider which elements should be place in the energy hub, what their capacity should be and how they should be operated.

MAIN PART

Problem formulation

The methodology developed for the purposes of the optimal energy hub layout sizing and operation will be presented through an example. A series of potential energy systems and carriers for the energy hub of a small UK commercial building is presented in Fig. 1 and includes renewable as well as conventional energy units, connection to the national electricity grid and thermal storage.

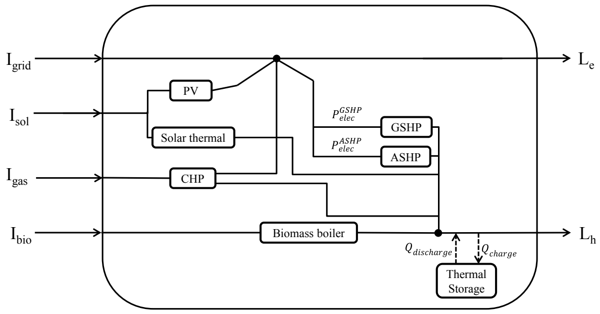

Figure 1 Energy hub layout illustrating all potential energy carriers and converters

The objective functions of the analysis involve the minimization of cost (both investment and operating) as well as carbon emissions. The two objective functions are presented below:

Cost objective function: $$f_1 = \sum_i (a_i y_i + b_i cap_i) + (\sum_{t,j} c_j I_j) \quad (1)$$

Carbon objective function: $$f_2 = \sum_{t,j} carbon_j I_j \quad (2)$$

$i \in$ {PV, solar thermal, ASHP, GSHP, biomass boiler, CHP, thermal storage}, $j \in$ {grid electricity, natural gas, biomass}

where the decision variables are y_i, a binary variable denoting the installation or not of technology i, cap_i that represents the rated capacity for the energy conversion technologies in kW and thermal storage in kWh or the area of PV and solar panels in m^2 and I_j representing the consumption of different carriers. In terms of parameters, a_i and b_i represent the fixed and the linear cost of the cost function for the potential technologies, c_j is the cost for the different energy carriers, and $carbon_j$ is the carbon factor for the different carrier. The energy balance of the energy hub and the thermal storage module are shown in Eq. (3-4):

$$\begin{bmatrix} L_h \\ L_e \end{bmatrix} = \begin{bmatrix} 0 & n_{sol}A_{sol} & n_{bio} & COP_{ASHP} & COP_{GSHP} \\ 1 & n_{PV}A_{PV} & 0 & -1 & -1 \end{bmatrix} \times [I_{grid} \quad I_{sol} \quad I_{bio} \quad P_{elec}^{ASHP} \quad P_{elec}^{GSHP}]^T + Q_{dis} - Q_{ch}, \forall t \quad (3)$$

$$Storage\ energy_{t+1} = Storage\ energy_t - 1/n_{discharge}Q_{discharge,t} + n_{charge}Q_{charge,t}, \forall t \quad (4)$$

where L_h and L_e represent the building's thermal and electrical energy requirements, n_{sol} and n_{PV} are the conversion efficiencies of the solar thermal and photovoltaic system, n_{bio} is the efficiency of the biomass boiler, COP_{ASHP} and COP_{GSHP} represent the conversion efficiency from electricity to heat in the ASHP and GSHP respectively, P_{elec}^{ASHP} and P_{elec}^{GSHP} are the electricity consumption by the heat pumps, and the variables Q represent the energy leaving or entering the thermal storage module.
Other problem constraints include non-violation of the maximum capacity, roof space availability for solar technologies, minimum part load during operation, maximum thermal storage charge and discharge rates, and non-concurrent charge and discharge of the thermal store.

Multi-objective optimization solution strategy

In this study, the ε-constraint method (Clark and Westerberg, 1983) is used to solve the multi-objective optimisation problem. Mathematically it can be expressed as follows:

$$\begin{aligned} &min \quad f_1 \\ &s.t. \quad f_2 \leq \varepsilon, \varepsilon \in \{\varepsilon^L, \varepsilon^1, \varepsilon^2, \cdots \varepsilon^{N-1}, \varepsilon^U\} \end{aligned} \quad (5)$$

where f_1 and f_2 are the two objective functions, ε^L and ε^U are the values of the objective function f_2 for the single-objective minimization problem of functions f_2 and f_1, respectively. The region between ε^L and ε^U into a set of N intervals.

RESULTS AND DISCUSSION

The results of the case study are presented in the Pareto front of Fig. 2. The cost optimal solution results in a configuration that includes a CHP engine and a thermal storage to cover the demand of the building, while the carbon optimal solution involves the installation of a biomass boiler with thermal storage as well photovoltaic panels on all of the available roof area. Intermediate solutions, moving from cost to carbon optimality, correspond to energy hub configurations with increasing PV area and biomass boiler capacity, while CHP capacity is reduced until it is eliminated from the energy hub configuration. Grid imported electricity is part of the operation in all different energy hub designs.

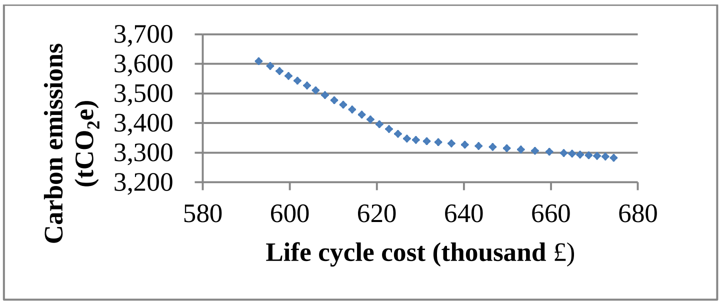

Figure 2 Pareto front showing cost and carbon emissions for different optimal energy hub layouts

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IMPLEMENTATIONS OF THE MULTI-OBJECTIVE BUILDING PERFORMANCE OPTIMIZATION SOFTWARE MOBO

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ABSTRACT

We think that there is a need for a new building optimization tool that should be a generic freeware and can fill the shortages recognised in available tools. MOBO (**M**ulti-**O**bjective **B**uilding **O**ptimization) is a generic freeware able to handle single and multi-objective optimization problems with continuous and discrete variables and constraint functions. It can be coupled to many simulation programs. It has a library of different types of algorithms and is able to handle multi-modal functions and have automatic constraint handling. This is a brief about the features and implementations of MOBO.

MAIN FEATURES OF MOBO

- MOBO is a generic freeware able to handle single and multi-objective optimization problems with continuous and discrete variables and constraint functions
- MOBO can be coupled to many external (simulation) programs
- It has a an extendable library of different types of algorithms (evolutionary, deterministic, hybrid, exhaustive and random)
- It is able to handle multi-modal functions and has automatic constraint handling
- The input is fed by a GUI for defining the optimization problem
- The user can write the input by algebraic formulas using standard symbols
- The output can be viewed by two graphs that show the progress of the optimization
- Allows parallel simulation
- Portability: MOBO can be used with different other platforms in addition to Windows.

The input (the optimization problem and simulation software parameters) is given through the Graphical User Interface (GUI), which checks that the input is correct interactively. For both the continuous and discrete variables, a pre-processing function can be added using standard algebraic symbols. The software supports approximately 50 functions that can be used in the formulas. Examples of these functions are *sin, cos, sqrt, exponent* etc. There is a library including different optimization algorithms. Currently there are 10 algorithms of different types: evolutionary with real and binary coding, deterministic, hybrid, exhaustive and random. Table 1 indicates the available algorithms and their features. MOBO can make parallel computations by running multiple simulations threads on parallel. All the algorithms can make use of the parallel computing feature except the algorithm of Hooke and Jeeves.

We have implemented MOBO in solving various optimization problems that we previously solved using other programs. Such problems include bi-objective and tri-objective problems with continuous, discrete or a mix of continuous and discrete variables, and with/without constraint functions. An example of the on-line results of MOBO is presented in Figure 1 for a bi-objective optimization problem for the minimization of the space heating energy and investment cost for a single-family house. The results in Figure 2 include the whole history of the brute force and random search method and the non-dominated solutions from two runs of a GA algorithms with a constraint (6000 additional investment cost) and without. The GA results are from running the algorithm once with 600 iterations. It can be noticed that the GA results capture the optimal solutions in the brute force with a good diversity of the points on the front. At this stage, MOBO implementations and testing are mainly targeting IDA-ICE, TRNSYS and E+ simulation programs.

The software is available for download from the following link http://www.ibpsa-nordic.org/tools.php. More information about MOBO can be found in this paper http://www.ibpsa.org/proceedings/BS2013/p_1489.pdf.

Table 1. Algorithms in MOBO

Algorithm	Single Obj.	Multi- Obj.	Constrained	Multi-modal	Automatic Constraint	Discrete variables	Continuous Variables	Parallel Computing
Binary NSGA-II	x	x	x		x	x	x	x
BINARY Pareto Archive NSGA-II	x	x	x		x	x	x	x
Binary OMNI-Optimizer	x	x	x	x	x	x	x	x
Real Coded NSGA-II	x	x	x		x		x	x
Real Coded Pareto Archive NSGA-II	x	x	x		x		x	x
Real Coded OMNI-Optimizer	x	x	x	x	x		x	x
Hooke-Jeeves	x		x		x		x	
Hybrid Algorithm	x		x		x	x	x	x
Brute-Force	x	x	x	x		x	x	x
Random Search	x	x	x	x		x	x	x

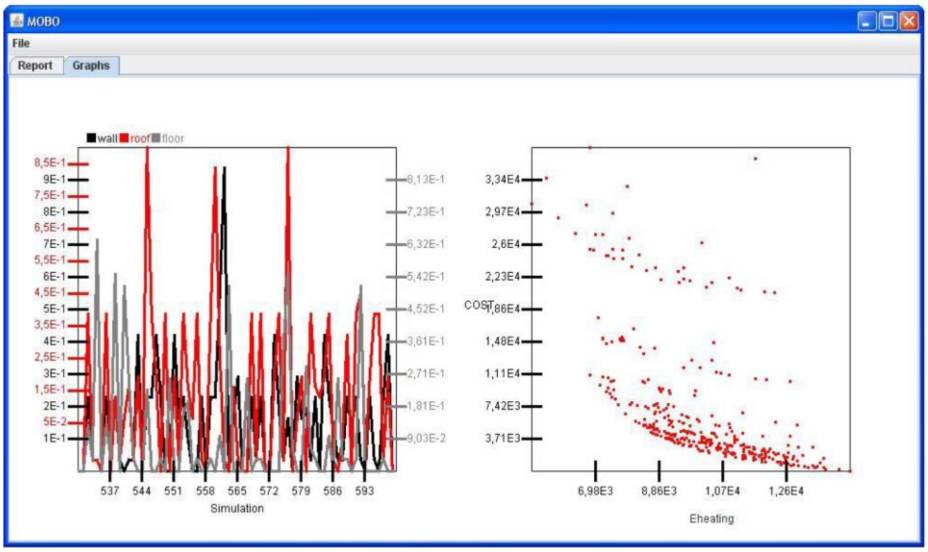

Figure 1. MOBO on-line results.

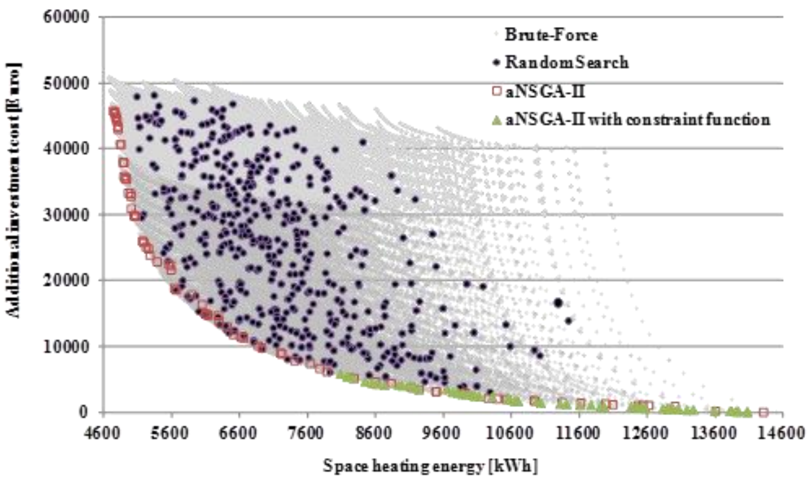

Figure 2. MOBO results of the four search/optimization runs.

OPTIMIZED RENEWABLE ENERGY INTEGRATION AT NEIGHBORHOOD SCALE

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ABSTRACT

The built environment represents a major share of global energy consumption. To effectively reduce the energy consumption of urban conglomerations, concepts to sufficiently integrate and manage energy from renewables are necessary. In this paper the energy-hub concept will be applied, which describes the relation between input and output energy flows and can be used to optimize the energy consumption during planning and operation. The concept will be used to evaluate a number of future energy scenarios for a village in Switzerland which has the goal of eliminating the consumption of fossil fuels.

INTRODUCTION

This paper applies the energy hub concept to evaluate a number of different future energy scenarios integrating renewable energy technologies for a village in Switzerland. The modeling concept of an energy hub, (developed by Geidl et al. 2007) describes the relation between input and output energy flows and can be used to optimize the energy consumption during planning and operation. It has the advantage to optimize the energy consumption, costs, emissions etc. due to regulating conversion, storage, and distribution of energy. The basic concept of an energy hub, which will be applied in this paper, consists of multiple input energy carriers which will be converted by the hub to multiple outputs. The energy hub concept will be applied to a village which has decided to increase renewable energy sources, and reduce the consumption of fossil fuels. As a starting point the existing situation concerning the energy demand of the village is analyzed. In a next step the potentials for different means of decentralized energy production is evaluated. In a third step, different future energy scenarios towards an energy sustainable community are defined. Finally an energy hub model of the village is developed and used to evaluate the different future energy scenarios for the village.

ASSESSMENT OF ENERGY SCENARIOS USING THE ENERGY HUB APPROACH

The current energy situation in the village

The village is located in Switzerland and consists of approximately 300 buildings, of which about 230 are residential and trade, and some additional buildings pertaining to agriculture, restaurants, industry, hotels, public buildings etc. As a starting point the existing situation concerning the energy demand of the village with respect to different uses, the different energy carriers, and their distribution and networks are analysed. To identify the energy consumption of the buildings, information pertaining to annual electricity, oil, and wood consumption and delivered energy from the district heating network was collected. Collected information was further analysed to identify the energy used for heating and for electricity. Based on this analysis the overall energy consumption of the village was 6 950 MWh electricity consumption for appliances and 13 888 MWh for net space heating.

Potential assessment of renewables

In the next step the potentials for decentralized energy production are evaluated. Decentralized energy production includes building integrated or local renewable energy production by photovoltaics. To evaluate the potential the simulation tool CitySim is applied (Robinson et al. 2009). In addition to photovoltaic, the potential to generate electricity by small hydro power turbines is explored. As an initial approach it is assumed that small water turbines could generate 680 MWh per year. An additional approach to increase renewables within the village is the extension of the current district heating network. First assumptions assume that the network is extended to cover also the city centre of the village.

Energy Scenarios

As a next step, five different future energy scenarios S1-5 are defined which will be explored with the application of the energy hub concept. As a starting point the focus lies on the integration of renewables in individual buildings, without integration into energy networks. It was assumed that the new village energy strategy is able to replace all existing energy carriers if required (connection to the electricity network, oil space heating, district heating network fired by wood chips, wood stoves). In the first scenario S1 the possibility of additional electricity from PVs is provided. It was assumed that electricity both from the electric grid and from PVs could be used directly to cover the electricity demand of appliances or it can be converted by the energy hub to heat. The other energy carriers (oil, wood chips, and wood) can be solely used to cover the space heating demand. The second scenario S2 takes the same energy carriers into account and additionally assumes the installation of a small hydro power plant. The third scenario S3 is similar to S2 but the feasible amount of photovoltaic is reduced to buildings outside the centre of the village. The fourth scenario S4 is also similar to S2 but assumes that the current heating district network will be closed. And finally the fifth scenario S5 assumes that the district heating network is further extended to the core centre of the village, assuming an increase in biomass potential.

Set-up of the energy hub model

The next step is the set-up of the energy hub model for the village: the multiple-energy carrier optimal dispatch model. This model evaluates the optimal dispatch of multiple input carriers to effectively cover the required heating and electricity load at the output of the hub. For optimizing the proposed energy systems a bi-objective function was assumed, aiming for minimal CO_2 emissions and minimal energy costs. These two objectives were combined using a weighting factor.

RESULTS AND DISCUSSION

Figure 1 shows energy hub model results for the proposed scenarios S1 to S5. The pareto curves show optimization results for different weighting factors $0 \leq \xi \leq 1$. Results indicate two to three times higher emissions for a weighting factor which prioritizes costs, whereas scenarios aiming for minimal emissions indicate a 40 to 60% increase in costs. Comparing the five different scenarios, S5 showed the lowest values for both CO_2 and costs. Scenarios which are optimized for costs consume mainly oil for space heating, whereas scenarios which are optimized for emissions do not take oil into account, but energy from renewables (photovoltaic and biomass), which clearly shows that emissions and costs are conflicting parameters. Pareto curves of scenarios S1, S2, S3, and S5 furthermore suggest that reducing the oil consumption is more effective in terms of reducing costs and emissions compared to other measures. The best-performing scenarios showed a reduction of 38% in CO_2 emissions compared to the current energy situation in the village.

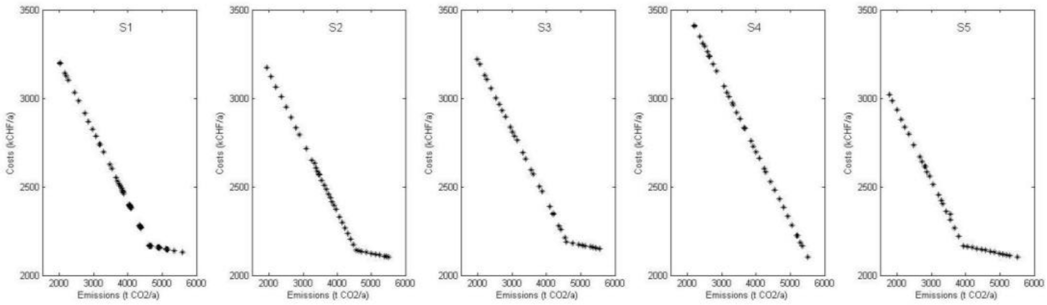

Figure 1 Pareto fronts (minimal costs ξ=1, minimal emissions ξ=0) of energy hub results for different scenarios S1-S5 (upper graphs).

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DISTRICT HEATING AND COOLING WITH LOW TEMPERATURE NETWORKS - SKETCH OF AN OPTIMIZATION PROBLEM

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ABSTRACT

In this paper the principle of low temperature district heating and cooling networks bases on uninsulated, water bearing pipes and large borehole fields is illustrated based on one example. Furthermore, the need of optimization work for future design and control strategies is highlighted and interesting challenges associated to this kind of heat and cold supply system are pointed out.

INTRODUCTION

Novel neighbourhood-based energy concepts can find synergies in the "heat" demand of residential buildings and the "cold" demand of buildings from the industry or the service sector. The concept of a low temperature district heating and cooling network, where water-bearing uninsulated pipes serve as an "intermediate temperature" source for heat pumps as well as for chillers, is aiming to take advantage of these synergies in urban areas. Large borehole fields can compensate seasonal mismatches between 'heat' and 'cold' demand by some extent. several of these networks are under construction or have been realized in Switzerland in recent times (Sulzer & Gautschi 2008), (Ruesch et al. 2013). The dynamic behaviour during operation strongly depends on the individual "users" and is not well known and difficult to predict. Nevertheless it strongly affects the flow levels and pressure drops in the network and accordingly the needed pumping power as well as the temperature distribution in the network and with it the efficiencies of the individual heat pumps. This paper discusses possible optimisation approaches for design and control of such networks.

AN EXAMPLE PROJECT

One example of such a network is being built by a housing cooperative (Familienheim Genossenschaft Zürich FGZ) with more than 2000 flats and a space heat and domestic hot water consumption of 35 GWh. The same network is used for datacentre cooling by two companies. The first phase (Figure 1) has a network length of 1.2 km, a borehole field of 153 boreholes with a length of 250m, a design energy demand of 9.5 GWh and an estimated cooling load of 15 GWh (more details in (Ruesch et al. 2013)). Three energy centers [E] constisting of circulation pumps, heat pump, conventional peak burners and local storages provide energy at the desired higher temperature levels for entire building blocks.

Figure 1. Sketch of the FGZ low temperature district heating network. The first construction phase (blue line) is starting operation in Sept. 2014 with three large heat pumps (E), cooling of a swisscom data centre and one large borehole field (3). Two further construction phases are planned for the future.

SIMULATION SOFTWARE

The software polysun provides a high level of hydraulic detail combined with fast simulation time and is there for well suited for optimization (Brönner et al. 2011). It is able to account for the highly variable flow distributions in such an undirected network guiding the interaction between energy sinks and sources as well as the pumping energy. Polysun can be called from external programs and was used for optimization studies by Bornatico et al. (Bornatico et al. 2012) who compared a particle swarm optimization and a genetic algorithm programmed in Matlab for the optimization of a solar combi system. The same autor also used detailed annual simulations with polysun in order to build a surrogated or meta-model, which is then used for optimization (Raffaele Bornatico u. a. 2013).

PHRASING OF AN OPTIMISATION PROBLEM

As there are no established design guidelines for low temperature networks optimization at the design level is of high interest. At the user level the size of the pumps, heat exchangers, local storage, heat pump or chiller and conventional peak burners can be optimized. At the level of the network, the topology and size of the piping and borehole fields have impacts on short and long term storage capacities and on the overall available peak power from the network. At the design stage, optimization consists of a bi-objective problem with a trade-off between a cost and an energy function and one major constraint; To provide the desired heating and cooling loads.

A further important field for optimizing low temperature networks is the control strategy. Most existing systems are controlled by the local demands with an overall control system able to block single consumers. Local short-circuits are avoided by one major control parameter, the globally fixed temperature difference between flow and return (for example 4K). Also other control parameters as target values for the flow or return temperature (with possible seasonal or even daily variations) are possible. An optimization of these control parameters and a comparison of the different reference temperatures is in progress. The local storage possibilities for DHW and the thermal capacities of the buildings allow a certain amount of flexibility in the timing of energy withdraw. For that reason, strategies aiming to correlate heating and cooling demands could be favourable for the energy efficiency, and control algorithms adapted to more flexible future electricity price models could result in a financial benefit.

It is evident that control and design optimization is interfering and control variables should be taken into account at the design level. However, an independent optimization of control issues for a fixed set of design parameters makes sense when existing networks are considered. For that case, the energy/cost trade-off is expected to be less pronounced and a single objective approach (energy) is supposed to be sufficient.

A major difference of low temperature networks to ‘classical’ HVAC systems is the existence of different stakeholders with sometimes differing interest and with a certain freedom to optimize their ‘part of the system’ according to local objectives. To give an example: Residential buildings are interested in running their heat pumps with high source temperatures, even though, operating heat pumps for DHW preparation in summer at lower source temperatures could be favourable for the global system efficiency in order to enable free cooling for other users. The comparison of a local ‘stakeholder wise’ optimization to a global optimization approach is envisaged.

Other peculiarities of such networks, as the strong long term effects of large borehole fields and the evolution of loads (connection of future construction phases, efficiency of future server technologies) extend the simulation times and complicate the formulation of a cost function. The large insecurities for future loads also amplify the need of a sensitivity analysis to justify optimization results.

CONCLUSION

As the principle of low temperature district heating and cooling is relatively new, there is a lack of knowledge about optimal design parameters and control strategies. Taking into account different stakeholders and their proper interest, the long-term effect of large borehole storage fields and insecurities in the evolution of heating and cooling demands are identified as the most challenging problems for this optimization work.

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OPTIMISATION METHODS FOR THE DESIGN OF URBAN ENERGY SYSTEMS

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INTRODUCTION

The design of urban energy systems involves the choice of the energy saving measures and of the energy conversion units to be considered in the energy system, their sizes and their corresponding operating conditions to be considered over the expected life time of the system's equipment. The decisions cover different aspects from the buildings structure and infrastructure, the heat distribution, the energy conversion system and the harvesting of renewable local resources to the control system. The optimization problem is therefore a large scale problem with integer and continuous variables. Considering the uncertainties of the stochastic environmental conditions, behaviours of the inhabitant and energy market prices, the optimisation under uncertainty has to be considered. In the proposed approach (Fig 1) superstructure modelling approach is used to represent in a single model the possible interactions between technological options. The thermo-economic and environmental impact performances of the system are then modeled. A multi-objective optimisation finds trade-offs between efficiency, costs and environmental impact. Results are analysed to assess the sensitivity to uncertain parameters and to verify optimality. New problems are often formulated by enriching the system superstructure, extending the system boundaries or integrating additional constraints.

SUPERSTRUCTURE MODELING

A system superstructure is a model that aim at representing the technological options in a single model and to model its performances. The superstructure modeling defines the list of options and their thermo-economic and environomic models and the different ways they can interact. The presence and the size of the different options are parametrized and associated with decision variables. The thermo-economic model aim at representing the efficiency of the technological options as a function of the environmental conditions and deduce their corresponding investment. The environomic model aim at modeling the environmental impact of the options considering the life cycle impact over the phases of its life. It therefore considers the contruction, operation and dismantling phases. One of the difficulty of the model development is the modeling of the interactions they reveals to be highly combinatorial in complex systems. A typical approach is to use predefined system configurations that are compared. Instead one can use an optimisation strategy to calculate the system configurations. The superstructure model uses process integration techniques and automatic superstructure programming that models all the possible interactions. It then uses integer variables to extract out of the list of the possible options that one that minimize the objective function [5].

A MASTER/SLAVE OPTIMISATION APPROACH

The problem is by essence a non linear non differentiable mixed integer non linear programming problem. A decomposition approach can be used to solve this problem ([6]). By partitioning the decisions variables into two sets, the optimisation problem is solved by solving a master optimisation problem that is using as an objective function the results of a slave optimisation problem. The decomposition strategy is such that the sub-problems (slave problems) can be solved using robust and efficient methods typically dealing with the combinatorial nature of the problem, while the master decision variables (the complicating ones) are calculated using heuristic optimisation methods like the evolutionary algorithms.

SLAVE OPTIMISATION USING A MULTI-TIME/MULTI-PERIOD APPROACH

A mixed integer linear programming model is used to calculate system performance and decide system configurations. Integer variables are used to decide if a connection exist and if an option is in use in the configuration. A multi-time/multiperiod approach is used to calculate the operating performances of the system. The model account for the system dynamics and the optimal predictive control aspects. The model account for storage capacities, the stochastic gains and renewable energy inputs in the system. Representing the performance over the life span of the buildings and equipments is a challenge since it represents up to 220000 hours of operation. Instead of using a typical year simulation, a probability approach can be used. A set of typical periods represented by a certain time sequence with a certain probability of occurrence represents the demand ([2]). To this set, we add the extreme conditions to be satisfied by the system. The definition of the typical days can be realised using clustering techniques and has proven to be more precise then the typical mean year approach while reducing the problem size by a factor 100. The time sequence (equivalent to one day of operation) is solved using a cyclic model, while the yearly operating cost is calculated by considering the yearly frequency of appearance of the period. Non linear equations (e.g temperature dependence) are modeled by discretising the operating conditions or by piecewise linearisation. The model is programed using AMPL and defines a mixed integer linear programing problem solved by robust branch and bound algorithm like CPLEX [3].

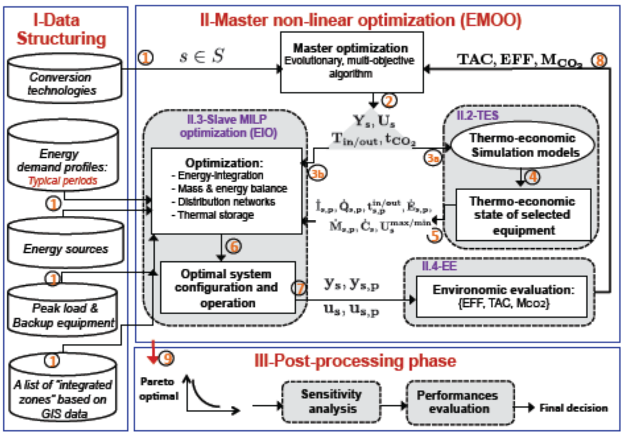

Figure 1: Problem-solving methodology [1]

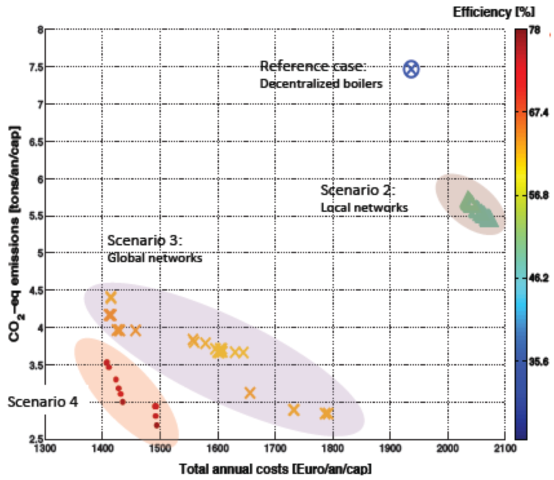

Figure 2: Pareto fronts for a urban energy system

MULTI-OBJECTIVE OPTIMIZATION AND UNCERTAINTIES

The master slave optimisation scheme uses the results of the slave optimisation to calculate the system performance, combining the estimation of the investment, the calculated yearly operating cost and the estimated environmental impact using the life cycle environmental assessment methods. For the later, a link with the ecoinvent life cycle inventory data base and the system model is created. An evolutionary algorithm is then used to generate thermo-economic and Environomic Pareto fronts. In urban energy systems, 3 objectives are used: the investment, the operating cost and the CO_2 emissions. Example of such resulting Pareto curve is given on figure 2. Multi-criteria and sensitivity analysis can then be applied to identify the more robust of the most preferred solutions. In addition, uncertainty analysis can be applied to deduce the most probable optimal solutions. This is done by applying Monte-Carlo simulation in the domain of uncertain parameters like energy and investment costs.

CONCLUSIONS

The optimisation strategy proposed for the design of urban energy system uses a decomposition based multiobjective optimisation approach. It allows to solve using a holistic approach the design of urban energy systems considering at the same time the energy efficiency measures, the energy conversion, the storage and the integration of renewable energy resources. The results of the optimisation leads to energy system design to be validated using more detailed dynamic simulation models that should integrate predictive control models. The method can be used to design the energy system of an geographical area considering not only the households application but the different energy services in a holistic approach as demonstrated by [4].

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PROPOSITION ON HOW TO INTEGRATE TECHNICAL UNCERTAINTIES INTO THE DESIGN OF DISTRICT ENERGY SYSTEMS

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In order to reach the goals of the mayor's convention, communities of all sizes undertake efforts in energy planning. The planning requires the knowledge of the current and future energy consumption. For the prediction of city or district wide energy demand, existing data is collected and building simulators are used. Ideally the planners get geo-localized heating or cooling loads to plan future installation or pathways. However, often the input data sets are incomplete and therefore completed with the help of assumptions.

Tracking the quality of the energy demands when they are aggregated at district level is difficult. In the case of a centralized heating system over or under sizing is very probable. Once the sizing is not correct, additional risks such as bad performance predictions appear as the system is used out of the original planned range.

Especially the prediction of the energy demand of each building is a difficult task as rarely precise information about the buildings physics are available. In addition, only few measurements such as annual energy, construction year and building usage consumptions exist. Therefore determining the real energy demand of building becomes a difficult task.

The annual energy bill depends on a mix of behavior, control and the technologies efficiency which often does not fit to the value that a physical building model estimates. Of course, both could be better calibrated, if individual visits were undertaken. On a city level, this represents a time (and money) consuming task rarely undertaken.

The more complex the building modeling software gets, the more data needs to be prepared that is generally not available such as shown in (Perez 2013, chap. 5.4). This leads to parametric studies that are difficult to verify and cannot separate behavior and performance.

The paper of (Rysanek, Choudhary 2013) shows a framework on the building level with the relevant elements calculating best and worst case scenarios. For the sake of simplification only the technical side will be discussed further. Each building has a three basic options:

- Business as usual do nothing, integrate building as it is,
- Refurbishment with impact on the energetic consumption (adding isolation, change windows,...),
- Exchange of technology (multiple energy systems, storage systems, load shifting,...).

These choices serve as input into the model. When these options are modeled as binary variables switching a certain option on or off, already millions of combinations are possible for a single building. They will grow exponentially on the district level with each building. Adding any sort of uncertainty into the technical parameters further increases calculation time (Rager, Dorsaz, Maréchal 2013).

Currently a framework has been used that separates the non linear and the linear parts of the energy system into a master-slave or decomposition approach. The slave part uses a MILP model solved with AMPL (Fourer 2003) and Gurobi (Gurobi Inc 2013) considering power and temperature levels. An evolutionary algorithm (Eddy, Lewis 2001) implemented in Dakota (Eldred, Adams, Ebeida, Jakeman, Swiler, Bohnhoff, Dalbey, Eddy, Hu, Vigil, Bauman, Hough 2013) tries to find the best solution for the master problem looking to maximizing the performance of the system while minimizing the CO2 life cycle emissions.

Therefore the question: How can such a framework be used to calculate realistic district energy systems while providing variances on the results in a promptly way?

On a district level two sub question are to be answered that can insure significantly the planning accuracy:

1. What is the energy and maximal power demand of a given building in a city?
2. What is the impact of technical uncertainty on a district energy plan or district energy system?

PROPOSITION

In a first approach the model could run without any uncertainty model what so ever. Based on the pareto frontier found, individual points can be tested on robustness to ensure that slight variations of key parameters do not significantly vary the result. Based on the conclusion of (Campolongo, Saltelli, Cariboni 2011) the following simplified approach is proposed:

1. Determination of the uncertain input values.
    a) Either big sample size if it can be evaluated quickly
    b) small sample size if calculation time is high
2. Quasi-random choice of uncertain input values, the rest of the values are chosen from optimal points
3. Study the propagation of uncertainty on the results.
4. If the variation of results is too big, new sample are made and added
5. Define a stopping rule, at the latest when all points of the pareto frontier are have been tested.

CONCLUSION

The variation of inputs allows to study the changes in system configuration and performance on uncertain inputs. It limits the search space to the best solutions found in an approach assuming perfect information and can considerably reduce calculation time. As a result, the original pareto frontier can be shown with an expected variance considering the uncertainties of certain input values.

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OPTIMAL DESIGN OF HVAC SYSTEMS AS PART OF THE FUTURE ENERGY SYSTEM

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ABSTRACT

Current methods of designing HVAC systems for residences do not take into account the potential energy cost savings of system components when optimal control is applied. This extended abstract presents a design approach that does consider this potential and discusses the additional advantages this implies, such as downscaling heat production systems or profiting from a fluctuating electricity price. Current implementations show promising calculation times, which should make the approach applicable to larger clusters of residences. It remains a challenge to quantify the performance of this design approach relative to other design procedures.

INTRODUCTION

Nowadays, design of HVAC systems in residences is still widely based on static methods, while researchers have clearly shown the benefit of employing dynamic simulations in the design process. Still, the latter design process typically focusses on one residence, neglecting the impact it might have on the global energy system, such as overloading the distribution grid feeder (Baetens et al., 2012) or peak electricity demand (Hasnain et al., 2000). This extended abstract introduces an approach towards HVAC systems design that is computationally efficient such that it allows upscaling and tackling the above mentioned global energy system impacts. Key in this approach is to combine simulation, control and design in one optimization problem.

METHODOLOGY

The starting point for the new approach stems from the field of model predictive control (MPC) for HVAC. This control method employs simple physical models that represent the most relevant dynamics in the controlled system and give a good estimate of the real system performance (Ma et al., 2012). According to Verhelst (2012), this control strategy not only reduces energy costs by anticipating fluctuating electricity prices, but also in some cases completely avoids the use of back-up systems. This implies reconsidering certain aspects, such as peak load and thermal energy storage sizing, when designing HVAC systems that employ MPC. This can be illustrated by considering the following optimal control problem (Eq. (1)-(4)) of an MPC for a residential building with a heat pump.

$$\min_{T_j,P_j} \sum_0^{ch} c_{el,j} \cdot P_j \tag{1}$$

$$subject\ to\ \ \forall j: f(T_j, T_{j+1}, P_j) = 0 \tag{2}$$

$$\forall j: g(T_j) \geq 0 \tag{3}$$

$$\forall j: 0 \leq P_j \leq P_{max} \tag{4}$$

In the optimal control problem, the dynamics of the system f along with the maximal power of the heat pump P_{max} are predetermined and depend upon the design of the system. In order to move from an optimal control to an optimal design problem as in Eq. (5)-(8), one can redefine P_{max} as a decision variable, without changing the complexity of the problem.

$$\min_{T_j,P_j,P_{max}} \sum_0^{dh} c_{el,j} \cdot P_j + w \cdot\ c_{inv}(P_{max}) \tag{5}$$

$$subject\ to\ \ \forall j: f(T_j, T_{j+1}, P_j) = 0 \tag{6}$$

$$\forall j: g(T_j) \geq 0 \tag{7}$$

$$\forall j: 0 \leq P_j \leq P_{max} \tag{8}$$

Another modification is the cost function, as on top of the operational cost, the investment cost $c_{inv}(P_{max})$ also plays an important role. The result of the optimal design problem is the size (power) of the heat pump, which not only depends on the investment cost, but also on the system dynamics and a fluctuating electricity price.

DISCUSSION

The optimal design problem combines both optimal control and design in one optimization problem, which allows exploiting certain dynamic aspects to obtain a better HVAC system design. One of these situations could be to activate the thermal mass of the residence to reduce peak heating and/or cooling demand, which could reduce the heat pump size. Another possibility is to include active thermal energy storage in the portfolio, which will automatically be selected and sized in case it becomes economically interesting. As the active thermal energy storage can contribute in covering peak demand, the heat pump can be downsized in its turn and contribute in the economic advantage.

Verhelst (2012) found that optimal control of a heat pump system could already reduce energy costs with 20 to 40%. This can make a heat pump a more appealing option compared to other technologies, however an honest comparison is only possible when the alternatives are also controlled in an optimal way. This problem does not arise in the proposed design scheme since it expands upon an optimal control formulation for each technology.

An important boundary condition for optimal design is the electricity price, which will probably be more dynamic in the future. Static design methods do not consider the potential cost reductions that certain technologies might possess and hence underestimate their potential. When performing simulation based design procedures, generally rule-based controllers are used. These controllers can exploit a fluctuating electricity price with a limited number of tariff periods, such as preheating a residence or thermal energy storage. Given an even more dynamic electricity price, this controller becomes increasingly hard to tune and might give suboptimal results. The optimal design approach presented in this extended abstract inherently takes the full dynamics of the electricity price profile into account and automatically decides between all possible control actions.

Current implementations of the presented optimal design approach show promising calculation times, which make it possible to consider multiple residences at once. On top of this, the model structure lends itself for a co-optimization with the electricity production park and electric vehicles, similar to the work of Hedegaard et al. (2013). This allows studying the optimal HVAC system in the future energy system, taking into account interactions with electric energy storage and electric power generation and transmission.

One of the major challenges of this optimal design approach is to quantify its performance. It is necessary to set up reference cases and compare the approach to other methodologies such as genetic optimization algorithms.

CONCLUSION

This extended abstract presents an alternative approach towards optimal design of HVAC systems for residences. The potential benefit compared to traditional approaches is discussed, however it remains a challenge to quantify and thus prove this.

ACKNOWLEDGEMENTS

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NOMENCLATURE

$c_{el,j}$	Electricity cost in time step j (EUR)	c_{inv}	Investment cost of a heat pump (EUR)
w	Weighting factor between costs (-)	T_j	Indoor air temperature at time step j (°C)
ch	Control horizon (h)	dh	Design horizon (h)
P_j	Heat pump electric power at time step j (W)	P_{max}	Maximal electrical power of the heat pump (W)

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EXPLORING THE POTENTIAL OF BUILDINGS IN THE SWISS ANCILLARY SERVICE MARKET

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ABSTRACT

The increasing penetration of fluctuating renewable energy sources (RES) in the power grid increases the need for ancillary services (AS), i.e. frequency reserves and voltage regulation. Traditionally, AS come from conventional power plants. If properly aggregated and controlled, however, loads can also offer AS. Possible advantages are lower cost and higher quality, sometimes even combined with a reduced environmental footprint. In this paper, we address AS provision with an aggregation of large office buildings. We investigate upper bounds on the amount of frequency reserves that can be extracted using a hierarchical control structure. Based on simulation results, we discuss the technical and economic potentials of office buildings when they participate in the Swiss frequency reserve market. Moreover, we point out challenges and open questions that are currently under investigation.

INTRODUCTION

Frequency reserves as an ancillary service

Maintaining the frequency close to a desired value, e.g. 50 Hz in Europe, is of paramount importance for the reliable and efficient operation of power systems. The transmission system operator (TSO) is responsible for this task, which is typically performed on three levels: primary, secondary and tertiary control. Primary control (PC) stabilizes the frequency after a disturbance. Secondary control (SC) restores the frequency to the desired value and maintains the scheduled exchanges between different control areas. Tertiary control (TC) releases secondary control in case of large disturbances. PC is fully distributed, SC is centralized and automatic, while TC is also centralized but can be activated either automatically or manually. Typically, the TSO procures the frequency reserves in a market setting where power plants bid both their reserve capacity and price in auctions.

The role of buildings and related work

Thermostatically controlled loads (TCLs) such as electric water heaters, refrigerators, and heating, ventilation and air-conditioning (HVAC) systems found in buildings can, in principle, provide frequency reserves. Due to their inherent thermal storage, the power consumption of such loads can be modified slightly without noticeable effect on the occupants' comfort. This practice is known as demand response (DR). To participate in AS, individual loads must be aggregated. In Oldewurtel et al. (2013), an overview of potential DR applications with aggregated loads is provided. It has been found that office buildings are promising candidates for AS for two main reasons. First, they can provide significant reserves even in small aggregations due to their high power consumption and large thermal mass. Second, building automation systems (BAS), which are usually integrated with the HVAC control systems, are installed in many office buildings and thus are, in principle, ready to react to signals sent from the TSO.

Goal of this paper

The aim of the *HeatReserves* project, funded by Nano-Tera.ch, is to investigate the potential for AS provision by DR resources in Switzerland[1]. This paper presents some recent results and current research directions related to the AS provision offered by a pool of office buildings, which is managed by an aggregator. Our goal is to describe and develop a method to reliably provide frequency control reserves with buildings, while satisfying occupants' comfort and respecting their privacy. In our analysis, we focus on SC and compare different reserve products for the Swiss AS market.

MODELING AND CONTROL

Building modeling

We consider buildings equipped with two types of HVAC systems typically found in Swiss office buildings. System A includes radiators for heating and cooled ceilings for cooling. In system B, heating and cooling are performed using a thermally activated building system (TABS)[2]. Blinds and lighting are controlled in both systems. The building thermal dynamics are described by a mathematical model that represents a single zone. The external

[1] The project partners are ETH Zurich (laboratories IfA and PSL), EMPA, University of St. Gallen (HSG), and Swissgrid.
[2] The building mass is incorporated as thermal storage for heating and cooling purposes and activated by a tube-system located in the slabs.

disturbances, i.e. weather conditions and occupancy, are assumed to be known (perfect prediction). To model the effect of reserve provision on building states, the requested reserve is modelled as an uncertainty. Moreover, we constrain the room temperature and illuminance to lie within prespecified regions to guarantee occupants' comfort, and also take actuator constraints into account. The remainder of this paper only considers heating/cooling actuators for reserve provision.

Scheduling and control

We propose a hierarchical control structure for the participation of buildings in the AS market (Figure 1). Level 1, the *Aggregator Scheduling*, is carried out centrally by the aggregator on a daily basis. Its goal is to determine the reserve amount and its allocation among the buildings that achieves the best tradeoff between reserve provision and electricity consumption. Reserve provision and comfort constraint satisfaction is guaranteed by techniques from robust optimization. In Level 2, the *Building HVAC controller* is obtained by using techniques from robust model predictive control. It calculates the HVAC set-points locally for each building every 15 minutes, preserving privacy and reducing real-time communication needs. Level 3, the *Signal tracking*, is equipped with a proportional controller to track the requested SC signal every 10 seconds. Details can be found in Vrettos et al. (2014).

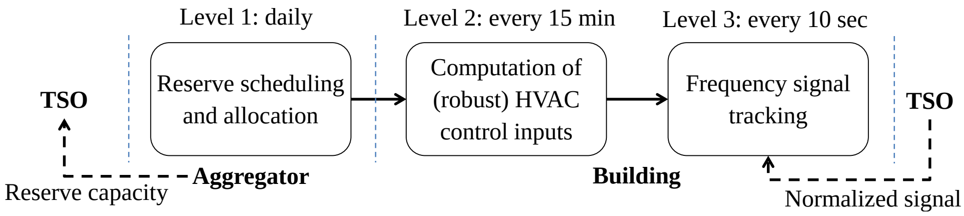

Figure 1: Hierarchical controller with task sequence and information flow.

DISCUSSION

Using an extract of the Swiss SC signal from 2012, we investigate in simulation an aggregation of 16 buildings for winter and summer. We consider (a) hourly and daily reserves, where the buildings provide the same reserve capacity over one hour and one day, respectively; (b) symmetric reserves, i.e. equal capacities for up and down reserves, and asymmetric reserves, i.e. different up and down reserves. Results show that 16 buildings can jointly provide a significant reserve capacity – up to 4 MW – both in winter and summer. However, this amount depends on occupancy patterns and ambient temperature. Moreover, the reserve provision increases the energy consumption, which can be significant in some cases. Aggregating the buildings increases the reserve capacity by up to 15%, compared to the case where each building participates in the AS market independently, due to the larger flexibility. Interestingly, hourly reserves result in a capacity that is up to 14% higher compared to daily reserves. In addition, asymmetric reserves are preferable from a building point of view because they result in a lower energy consumption. Note that these results are optimistic and must be interpreted as upper bounds on the reserve capacity due to the assumption of perfect prediction of external disturbances.

Current work concentrates on the following points: first, we are modeling the heating/cooling generators in more detail to better evaluate the tracking performance of the frequency signal. Second, we are in the process of generating a larger set of models for typical Swiss office buildings. Third, we are extending the scheduling algorithm to support reserves from multiple actuators within each building. Moreover, since loads are energy constrained resources, we are investigating potential benefits from considering frequency signals that are zero-mean over a certain time period, determined by the TSO. Additionally, we plan to investigate the effect of inexact prediction of external disturbances.

CONCLUSION

This paper presents a framework to access the potential of buildings for providing ancillary services (AS). Simulation results for different AS scenarios and products indicate that building aggregations are indeed able to provide frequency reserves to the grid, which can be sold to the transmission system operator (TSO).

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POPULATION OF THERMOSTATICALLY CONTROLLED LOADS FOR THE SWISS ANCILLARY SERVICE MARKET

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ABSTRACT

The power grid has been going through drastic changes due to the increase of renewable energy sources. Since in a power grid demand and supply must be balanced at all times, the uncertainty in renewable generation increases the need for the so-called ancillary services. In Switzerland, ancillary services are prominently provided by hydro or conventional power plants. Residential household appliances, such as electric water heaters and refrigerators, referred to as thermostatically controlled loads (TCLs), if properly aggregated and controlled can serve as additional means for ancillary services. The potential benefits of using TCLs for ancillary services include reduced reliance on power grid, less environmental footprint and better ancillary market liquidity. In this paper, we discuss challenges in modeling and control of TCLs to serve for ancillary services and our approaches to address them.

INTRODUCTION

TCL population for ancillary services

Thermostatically Controlled Loads (TCLs) are household appliances such as electric water heaters, refrigerators and air conditioners. They operate within a hysteretic temperature dead-band and as long as the TCLs are within their dead-band they provide the service requested by the electricity consumer. A population of TCLs can be manipulated by turning them on/off prematurely inside their temperature dead-band or by slightly adjusting their dead-band, in order to achieve some system-wide objective of their aggregate power consumption [1].

Requirements on aggregate power

In order for a TCL population to be an ancillary service option, certain requirements on their aggregate power needs to be guaranteed. If the population is to be used for the class of ancillary services referred to as secondary control, the aggregate power needs to track the so-called Load Frequency Control (LFC) signal. The LFC signal is provided from the system operator as a percentage of the total available power bounds of the population. The proposed architecture for an aggregator to control TCL population is shown in Figure 1(a). Research needs to address: 1. the total power bound that a TCL population can provide, 2. controlling the TCL population in order to track a given trajectory within this bound while ensuring users' comfort and devices' warranties.

Challenges in modeling and control

The main challenge in controlling aggregate power dynamics of a TCL population is developing a system model that is simple enough for optimization and control, while it is rich enough to capture the power dynamics and constraints of the aggregate loads. Due to limited communication between TCL aggregator and individual TCLs, model identification and control techniques needs to be achieved with partial measurements. Fig. 1(b) shows result of our analysis on tracking performance of population of electric water heaters given an LFC signal [3]. This work showed that including information of individual electric water heater parameters and measurements achieved significantly higher control performance (top panel) compared to cases with partial information (bottom panel).

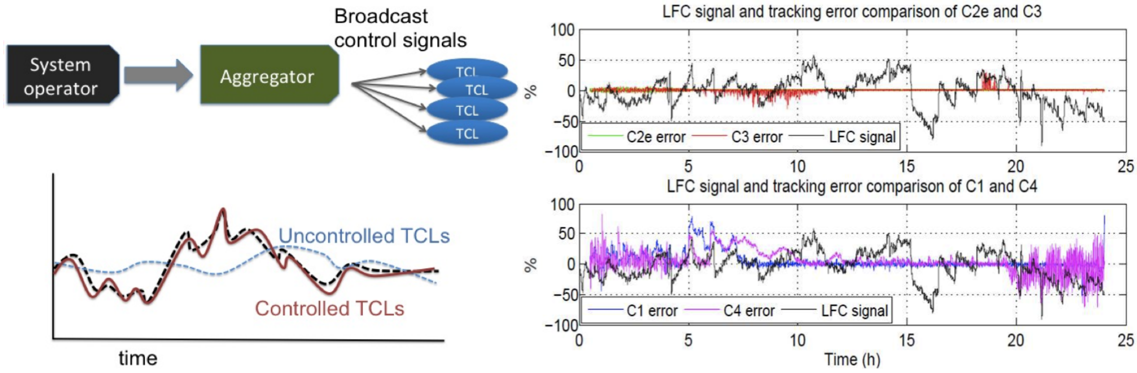

Figure 1: (a) Architecture for control of TCL population, (b) Population of water heaters tracking an LFC signal

CONTROL-BASED MODELING OF TCL POPULATION

In this paper, we presents several frameworks that we have been exploring on modeling dynamics of a population of TCLs subject to aggregate control signals.

Markov chain model

The temperature evolution of an individual TCL can be described by a stochastic hybrid differential equation, in which stochasticity captures uncertainties such as probabilistic water draws in an electric water heater. Instead of tracking the temperature evolution of each TCL in a population, we can track the fraction of population in each temperature interval and on/off mode with a set of coupled Partial Differential Equations (PDEs). The discretization of the PDE results in a Markov chain which well approximates the population power trajectories in case the parameters of all TCLs are the same, that is a homogeneous population [2]. For heterogeneous parameters, we are analyzing parameter sensitivity of the PDE to quantify the changes from nominal model. In addition, we are modeling and identifying the closed-loop PDEs resulting from implementing a population control strategy.

Energy storage model

We can think of a population of TCLs as an energy storage unit, that is, a battery, with energy and power capacities. For example, consider a population of air conditioners. If each device is operating at the lower edge of its dead-band, the battery is fully charged and it can provide power to the grid by turning all devices off, until devices reach their upper edge of dead-band. Conversely, if the population is operating at the upper edge of the dead-band, the battery is depleted, the TCLs need to cool off in order to be able to provide power. In recent work, we derived the time-varying power and energy capacity of such battery model analytically and through system identification [2]. We then used the model in an optimization framework to derive bounds on feasible power trajectories tractable by a population. Currently, we are working on quantifying achievable performance and uncertainty of this model.

Autoregressive model

In this modeling framework, we excite the population of TCLs with a given control signal, such as a slight adjustment of their dead-band set-points. We then measure the output power consumption of the population. The input/output mapping has been shown to follow approximately an Auto Regressive Moving Average with Exogenous input (ARMAX) model [1]. While parameters of such model may be derived analytically for a homogeneous population, we are using grey box system identification techniques for a heterogeneous population in order to optimally quantify and control the population power.

DISCUSSION

In all frameworks, we need to quantify modeling uncertainty in order to provide provable guarantees on LFC tracking performance of TCL population. We also need to develop parameter identifications and state estimation for the aggregate model under realistic communication networks. Based on the results and comparison of the analysis, we can recommend reasonable power capacities for TCL population to serve in the Swiss ancillary services.

CONCLUSION

While initial investigations have indicated potential of aggregate of TCLs to serve as ancillary services, full exploration and quantification of this potential is an open a problem that requires advancements in modeling, control and estimation for large scale stochastic systems. In this paper, we highlighted some of the challenges in achieving this objective and our current work in addressing the challenges.

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ADVANCED CONTROL FOR ENERGY EFFICIENT BUILDINGS: THEORY AND PRACTICE

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ABSTRACT

The building sector is the largest energy consumer in the world. Achieving substantial energy reduction in buildings may require rethinking the whole processes of design, construction, and operation of a building. Control design and tuning is one interesting piece of the whole process. It is an extremely important step, which is often not properly addressed, resulting into energy inefficiency and occupant discomfort. This short discussion paper highlights some of our efforts in introducing advanced control design to the building industry.

INTRODUCTION

Building controls design becomes challenging as practitioners move beyond standard heuristic controls approaches and seek to incorporate predictions of weather, occupancy, renewable energy availability, and energy price signals. Model predictive control (MPC) is a control methodology that can systematically use all the aforementioned predictions to improve building thermal comfort, decrease peak demand, and reduce total energy costs. In buildings, performance improvement using forecasted information is possible due to two basic mechanisms. The first mechanism is referred to as load shifting or active storage. Load shifting consists of shaping the energy profile delivered to a building, exploiting the possibility of storing energy for later use. Thermal storage is inherent to a building's structure and can be increased by including additional external energy storage devices. The optimal profile of delivered energy depends on various factors, which include time varying utility prices, availability of renewable energy, ambient temperature variation, and load shedding signals received from the utility grid. The second mechanism is component optimization. Buildings can be large systems with many control variables and degrees of freedom. Predictive models of building thermal dynamics and energy costs of control actuators allow computation of the optimal inputs to each actuator in order to deliver the desired energy profile.

Implementing advanced building control strategies such as MPC in today buildings is not straightforward for a long list of reasons. Next, we highlight some of the issues and the approach we are using to address them.

MODELING AND DATA

Building heating, ventilation, and air conditioning (HVAC) systems convert and transport energy through working fluids, primarily air and water. The flow dynamics of air and water through distribution networks are described by nonlinear partial differential equations. The computational fluid dynamics technique is computationally intensive and requires a complete geometry description at all length scales. This level of detail is rarely available for a real building. Our approach is to approximate the velocity, temperature, and pressure distributions with reduced order lumped nodal models. The nodes in a nodal HVAC system model are thermal zones and components. Each node behaviour is described by nonlinear static and differential equation whose parameters are learned from historical building data.

HVAC components are arranged into HVAC systems in a variety of different configurations because of evolving design practices. A handful of standard configuration types are more common than others, but virtually every building is unique. Therefore, the spatial locations, type of components, and methods used to implement a control action are highly dependent on the specific HVAC system. For instance, overhead air distribution systems use a different set of actuators from under-floor air distribution systems, and both differ from systems that use water-based radiators for conditioning. A tool which allows to easily configurea system into a nodal abstraction is a fundamental requirement for the scalability of any advance control approach.

CONTROL DESIGN

Most modern buildings employ some level of automated control. In the majority of cases, building systems are controlled by basic control logic that errs on the side of simplicity over subtlety. This simple control logic is implemented with distinct but interconnected proportional-integral-derivative (PID) control loops and switching logic. This logic responds to setpoints and schedules for building components such as chillers and cooling towers.

Advanced decision systems are available on the market to optimize the high-level system based on component modeling, feedback, and forecasts. A variety of proprietary control sequences for chillers, boilers, and cooling towers are available in the building industry. However, to the best of the authors' knowledge, their implementation is not widespread and often limited to specific configurations and components of the cooling and heating systems.

Once a nodal abstraction has been design and its parameters learned from data, a simple MPC problem can be easily formulated with the objective of minimizing total heating and cooling energy consumption, minimizing the peak power consumption, and maintaining zones within a desired temperature range despite predicted load changes. For medium size buildings the resulting optimization problem has thousands of variables and constraints. We developed the Berkeley Library for Optimization Modeling (BLOM), a tool for optimization-based modeling and control formulation implemented in Simulink (Kelman et al. 2012). The underlying structure for BLOM is a novel way of representing linear and nonlinear mathematical functions that allows for easy computation of closed form gradients, Jacobians and Hessians. This formulation provides an efficient problem representation for optimization-based modeling and is scalable to large optimization problems. With BLOM, an optimization-based controller for a dynamic system can be developed and exported from the same model that is used in forward simulation. BLOM is capable of solving several types of optimization problems, including static optimization problems and optimization problem with dynamics. Its intended use is for nonlinear model predictive control.

DISCUSSION

Prediction Uncertainty

There are clear benefits in using MPC for buildings under the assumption that MPC has perfect knowledge of predicted disturbances and system dynamics. In (Ma et al. 2012) the reader can find as simple building example where the MPC performance deteriorates as the uncertainty increase. In fact, MPC can fail to keep the zone temperature within the comfort constraints due to misleading predictions. MPC consumes more energy than a simple proportional controller because MPC is performing precooling even if occupants do not enter the space. Stochastic MPC is a better approach to address this issue when probability distribution functions of the loads are available. In this case, one would minimize expected costs and satisfy constraints with a given probability.

Computational Complexity of Model Predictive Control

As the complexity of the building model increases, centralized MPC might become computationally intractable due to the limited computational resources available on current building control platforms. This limitation is critical at the low level of the control architecture where distributed inexpensive computing platforms are common. The limitation might be overcome by efficient numerical solvers tailored to the specific hardware or with the use of distributed MPC. In distributed MPC, the centralized problem is decomposed into a set of smaller problems which can be associated with different subsystems such as VAV boxes and AHUs. Each subsystem solves local small MPC problems with information from local and neighboring subsystems. The local MPC modules communicate with each other to converge to an optimal solution.

Equipment Retrofitting

MPC requires sensor data from a building in order to initialize simulations and make predictions. Additionally, there must be some way to communicate the computed optimal control inputs either to lower level controllers (for setpoint tracking) or directly to the control actuators. Modern digital building automation systems satisfy these requirements, but are only present in new buildings. In order to apply MPC to the existing stock of older buildings, HVAC equipment must be retrofitted for digital control and additional sensors need to be added or existing sensors replaced with digital versions. This can be prohibitively expensive, and must be offset by the operational energy cost.

Thermal Comfort and Other Requirements

The control objective of an HVAC system is occupant thermal comfort. Often comfort is treated as being equivalent to a specific range of spatial air temperatures. A large body of ASHRAE and other literature have investigated more complicated representations of occupant comfort. These more detailed comfort models take into account metabolism and biological factors, air velocity, humidity, heat transfer through radiation, free convection, and other effects. In addition to maintaining comfort and temperature regulation, HVAC controllers can have additional requirements on humidity regulation, proportions of fresh versus recirculated air for indoor air quality, flow rates for ventilation, and pressurization of spaces.

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Part of the text of this note has been extracted from the article (Ma et al. 2012). We refer the interested reader to it for further reading, for a rigorous presentation of the MPC design and detailed references.

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