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Design of an Online Optimisation Tool for Smart Home Heating Control

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DESIGN OF AN ONLINE OPTIMISATION TOOL FOR SMART HOME HEATING CONTROL

Research in Progress

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Abstract

The performance of model predictive smart home heating control (SHHC) heavily depends on the accuracy of the initial setup for individual building characteristics. Since owners or renters of residential buildings are predominantly not experts, users' acceptance of SHHC requires ease of use in the setup and minimal user intervention (e.g. only declaration of preferences), but at the same time high reliability of the initial parameter settings and flexibility to handle different preferences. In contrast, the training time of self-learning SHHC (e.g. based on artificial neural networks) to reach a reliable control status could conflict with the users' request for comfortable heating from the very beginning. Dealing with this trade-off, this paper follows the tradition of design science research and presents a prototype of an online optimisation tool (OOT) for SHHC. The OOT is multi objective (e.g. minimising lifecycle energy (cost) or carbon emissions) under constraints such as thermal comfort. While the OOT is based on a discrete dynamic model, its self-adaptation is accelerated by a database of physically simulated characteristic buildings, which allows parameter setting at the beginning by a similarity measurement. The OOT artefact provides a base for empirically testing advantages of different SHHC design alternatives.

Keywords: Smart Home Heating Control, Online Optimisation, Model Predictive Control, Information Systems Design.

1 Introduction

Growth of population, exhaustion of energy resources and global warming require increasing resource efficiency and decreasing carbon emissions all over the world. Buildings count for more than 40 % of total energy consumption in most developed countries (European Commission, 2016a), with heating causing up to 72 % of the energy consumption in the residential sector and larger carbon emissions than the manufacturing sector in 2016 (International Energy Agency, 2016). Hence, heating savings could significantly facilitate a reduction of greenhouse gas emissions (European Union, 2015). Since insulation of buildings and exchange of heating installations proceed slowly due to various, but esp. financial reasons (European Commission, 2016b), supervisory control (SC), which automatically monitors and controls heating devices based on an ongoing optimisation of heating plans, could be an affordable alternative to save heating energy compared to manual control by users.

The performance of SC heavily depends on the accuracy of the setup for the individual building characteristics. Aggravatingly, the outcome of control inputs has to be predicted under uncertain indoor (e.g. occupancy) and outdoor conditions (e.g. weather). However, users in the residential sector are not experts and analysing all required parameters of a building in detail (e.g. thermal conductivity of walls, ceiling or floor depending on construction materials) is too much effort anyway. Hence, transferring intelligent SC for heating systems into the residential sector requires appropriate solutions: Flexible handling of different user preferences, widely self-explaining ease of use in the setup and minimising user intervention, but at the same time high reliability of the initial parameter settings and mainly self-adaptation to changing conditions have to be considered. Furthermore, the parametrisation might be enhanced by ongoing system learning.

Based on the idea of the internet of things (IoT), which realises the connection between tangible things and the internet by interoperable information and communication technologies (Atzori et al., 2010; Gubbi et al., 2013; Rayes and Salam, 2017), smart home heating control (SHHC) aims at coping with these challenges. Smart home appliances, being connected through internet, enable functions such as alert, monitor, control or intelligence by efficiently managing home devices (Collotta and Pau, 2015; Li Jiang et al., 2004; Risteska Stojkoska and Trivodaliev, 2017). Hence, the objectives of SHHC – a combination of IoT and traditional heating devices in the residential sector that allows optimising heating plans based on advanced control methods including contextual information – are manifold: At least, it should increase users' comfort and save heating energy compared to manual control.

Although SHHC might be an emerging market (e.g. Meola, 2016; Perera et al., 2014), its use is not yet widespread: Not more than 3 % of people own smart thermostats and only 7 % intend to buy one within the next year (Deloitte, 2016). A possible troublesome setup is one substantial factor that hinders a widespread use of SHHC in the residential sector (Icontrol Networks, 2015). As a consequence, physically modelling of individual building characteristics to parametrise a model predictive SHHC could be omitted by system's self-learning from realised combinations of control input and outcome of this particular building or by interpreting big data and transferring the outcome-control-relationship to the particular building. While in the first case users' comfort might be restricted during the learning phase, in the latter the prediction quality of the transferred functional relationship might be insufficient.

Dealing with this dilemma, our paper follows design science research (Hevner et al., 2004; Peffers et al., 2007) and presents a prototype of an online optimisation tool (OOT) for SHHC in residential buildings. It allows parametrisation of a physical building model prediction by similarity measurement based on a database of characteristic, partially simulated buildings and specifications that can be given by non-expert users. Hence, it aims at achieving reliable predictions at setup despite an extensive ease of use. It is based on a model predictive control (MPC) with immediate parametrisation and ongoing self-adjustment. Our online tool design contributes to the development of smart home applications by integrating elements of IoT, SC and cloud computing. The OOT mainly aims at energy saving without user intervention under constraints such as thermal comfort and various indoor and outdoor conditions.

After a short literature review, key elements of the OOT design are presented and implementation milestones are discussed. Before the conclusions and the outline of further research are given, our evaluation strategy is summarised.

2 Literature Review

Research on advanced IT-based techniques for building climate control, aiming at improving energy efficiency while guaranteeing a certain climate comfort level, have gained much momentum. Approaches deal with different types of heating, ventilation and air conditioning (HVAC) systems (Afram et al., 2017; Afram and Janabi-Sharifi, 2014) as well as with only one particular function, such as heating (Drgona et al., 2015; Javed et al., 2014). The integration of SC into HVAC systems has been shown to reduce the energy consumption from 7 % to even more than 50 % (Afram et al., 2017; Kim et al., 2016). SC as a total system monitoring and control mechanism for all HVAC subsystems allows an overall consideration of the system level characteristics and interactions among all components and their respective variables (Levenhagen and Spethmann, 1993). A widespread SC method is MPC (Domahidi et al., 2014; Drgona et al., 2015; Hazyuk et al., 2014; Javed et al., 2014; Khanmirza et al., 2016; Lehmann et al., 2013), which allows taking uncertain indoor (e.g. occupancy) and outdoor conditions (e.g. weather) into account and automatically adjusting optimal control settings without need for ongoing user interventions (e.g. Wang and Ma, 2008).

If a physical model of an individual building, which is required for forward models like MPC, is unavailable or too effortful, inverse or data-driven models are an alternative (Javed et al., 2014): Inverse models can be developed using a rich data set that covers all possible working conditions in order to learn by training a near optimal control policy over time. Out of the range of inverse models, e.g. statistical models using regression (Jacob, 2008; Ma et al., 2011; Penya et al., 2011; Safa, 2012), data mining models such as artificial neural networks (ANN) (Kalogirou, 2000, 2001; Yang et al., 2003), stochastic models (Zlatanović et al., 2011) or fuzzy logic models (Chen et al., 2006; Lu et al., 2010; Soyguder and Alli, 2009), ANN is the most frequently applied one (for details Afram et al., 2017).

While developing inverse models is comparatively easy, there are disadvantages in accuracy and esp. in the time needed for training. Hence, first approaches combine supervisory MPC with ANN for HVAC systems control in the setting of university buildings (Ferreira et al., 2012; He et al., 2014; Ruano et al., 2016), airport buildings (Huang et al., 2014, 2015a, 2015b), office buildings (Garnier et al., 2015; Kim et al., 2016; Kusiak et al., 2010, 2014; Kusiak, Tang, et al., 2011; Kusiak, Xu, et al., 2011; Wei et al., 2015; Zeng et al., 2015) and school buildings (Asadi et al., 2014). However, all these applications are developed for expert users in the non-residential building sector; hence ease of use is not of high priority.

In contrast, the latter is facilitated by IoT, which has given rise to the emergence of smart services such as smart home (Wünderlich et al., 2013). IoT and the impact of IoT on everyday-life and industry has been part of research since 2009 (Díaz et al., 2016; Liu et al., 2016; Xu et al., 2014), e.g. IoT in healthcare (Domingo, 2012), food safety (Pang et al., 2015), transportation and logistics (Karakostas, 2013) or smart home (Collotta and Pau, 2015; Kleiminger et al., 2014; Risteska Stojkoska and Trivodaliev, 2017). While there are several approaches dealing with intelligent thermostats (for an overview Nacer et al., 2017) focussing on users' occupancy (Gao and Whitehouse, 2009; Kleiminger et al., 2014; Lu et al., 2010; Oldewurtel et al., 2013) and/or weather changes (Oldewurtel et al., 2012), only a few propose predictive SHHC for residential buildings, which predominantly use autonomous learning (e.g. Barrett and Linder, 2015; Makhlouf et al., 2016). However, since extensive training-data is required, users' comfort is initially not guaranteed during the long-lasting learning process to achieve high system performance. This problem could be avoided by using MPC-based SHHC. Its needed building-specific parametrisation is a severe obstacle by non-expert users. To the best of our knowledge, there is no approach that addresses this dilemma.

Hence, our artefact combines MPC and self-adaptation. Our OOT as part of SHHC is multi-objective (e.g. minimising lifecycle energy (cost) or carbon emissions) under constraints such as thermal comfort and based on a discrete dynamic model. Self-adaptation is accelerated by a database of physically simulated characteristic buildings, which allows parameter setting at the beginning by a similarity measurement. This provides estimates for the thermal characteristics of the building, which could be continuously adjusted by ongoing learning.

3 Online Tool Design

From a user perspective the OOT consists of a hardware and a cloud computing part (Figure 1). A SmartHub with internet connection is the central administration device. It communicates with smart thermostats on a common wireless technology (Z-wave) (Robles and Kim, 2010). For security, an encrypted communication protocol is implemented (Cuzzocrea, 2014; Díaz et al., 2016; Möllers and Sorge, 2016). A rich internet application (RIA) (Farrell and Nezlek, 2007) guides the user through the initial setup of the SmartHub and provides access to manual thermostat regulation, if required.

Different open source application programming interfaces (APIs) between the OOT and the particular SHHC system provide input parameters for SC. Since it is widespread, we use MPC. After converting into a suitable format, the OOT transfers the data to the MPC and retrieves control instructions. They are stored in the database for validation purposes and sent to the SmartHub. Being the central control device between each thermostat and the OOT, it sends the instruction to a determined thermostat and retrieves the room temperature for validation purposes in return.

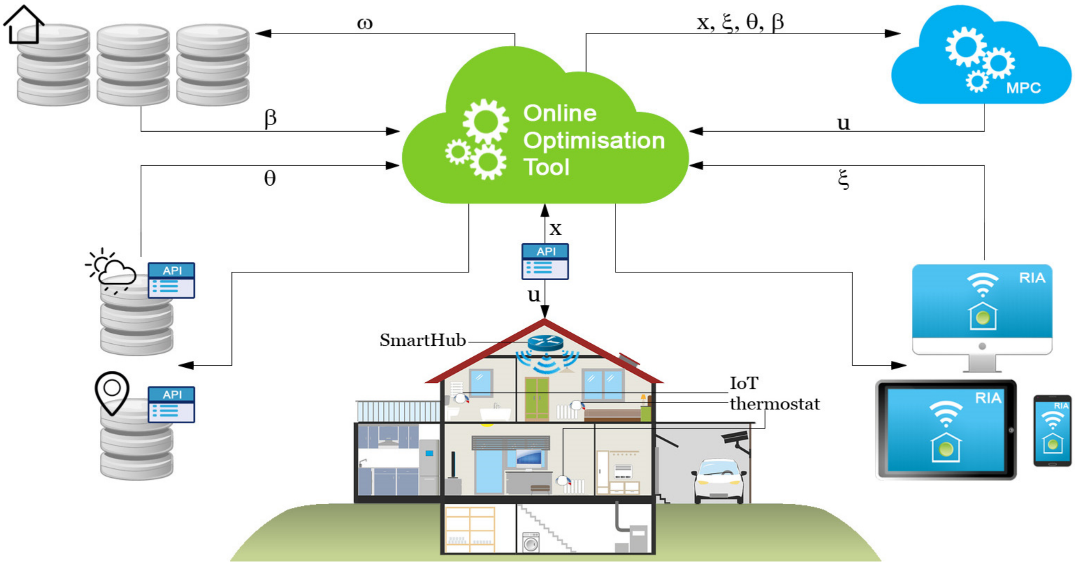

Figure 1: Scheme of the online optimisation tool (OOT)

3.1 MPC Design

To ensure low installation cost and remote user interventions, all optimisation and control systems are centralised in a cloud solution. Hence, MPC-based optimisation needs to be embedded in an online tool (Figure 2) and to follow a clear process. At setup the user has to provide characteristic data ω for every room of the building. A similarity measurement with data of already physically modelled buildings, which are stored in a database, provides required building parameters β for the MPC-based optimisation. External influences θ, esp. weather forecasts (e.g. duration of solar radiation and outdoor temperature), given constraints and the current state of the building x (e.g. room temperature) are included in the optimisation model. To retrieve all required weather data, the API of OpenWeatherMap, Inc. (Weather API, 2017), which uses the geolocation of the building to call current weather data, is connected to our OOT. Constraints, which have to be fulfilled on a certain confidence level, are built by considering user-specific preferences ξ like comfort temperature and absence schedule, which have to be entered in the RIA. Our OOT calculates the predicted mean vote index (PMV), which is a widely used index for assessing thermal comfort using Fanger's model (van Hoof, 2008). It predicts the expected comfort vote on the ASHRAE scale (Humphreys and Hancock, 2007) that ranges from -3 (cold) to 3 (hot), 0 admitting a neutral value. It is assumed that most people feel comfortable in a range of [-0.5; +0.5] around their target temperature. The outcome of the MPC optimisation process are control inputs u for every connected thermostat.

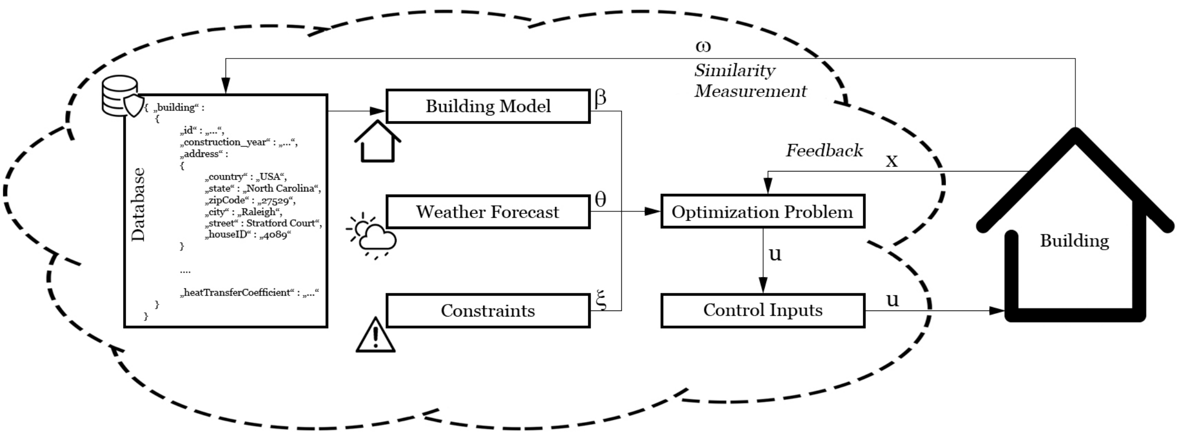

Figure 2: MPC design

3.2 MPC Optimisation Structure

MPC uses a physical building model to predict at time $t = \tau$ $\left(t \in [\tau, \tau+1, ..., T]\right)$ future state vectors $\chi_{t>\tau}$ $\left(\chi_t := \left((x_i)_{1\le i\le I} \in \Re^I\right)_t\right)$. Time-dependent state systems $X_t := \left[(\chi_t)_{\tau\le t\le T} \in \Re^{I\times T}\right]_t \in \Re^{I\times T\times T}$ contain actual states up to t and forecasts from $t+1$ to the planning horizon T. The control strategy consists of time-dependent vectors υ_t $\left(\left(\upsilon_j := (u_j)_{1\le j\le J} \in \Re^J\right)_t\right)$ of optimal heating control variables u_j, i.e. a heating plan $U_t := \left[(\upsilon_t)_{\tau\le t\le T} \in \Re^{J\times T}\right]_t \in \Re^{J\times T\times T}$ up to T. Hence over time, the heating plan contains a growing number of actual controls. A certain fixed objective function $g(X_t, U_t)$ with time-dependent state systems X_t, which models user preferences and is likely multi-criterial (e.g. lifecycle cost or carbon emissions), is minimised under some constraints such as thermal comfort ranges or technical control limits. Widespread control objectives are minimising the energy consumption (Liu et al., 2013; Moon et al., 2016), minimising operating cost (Tutkun, 2014) or satisfying thermal comfort (Ferreira et al., 2012; Hazyuk et al., 2014). Our OOT minimises energy cost and carbon emissions. Due to the dynamic optimisation problem, system dynamics might be modelled by recurring X_{t+1} on X_t and U_t. Our OOT captures dynamics linearly to ensure that the model will result in a convex and solvable problem. Hence, it can be solved using common optimisation software.

Disturbances like weather are likely to occur and may generate future states that do not fulfil all constraints of the model. We use a chance-constrained formulation, in which constraints have only to be fulfilled with a user-specific confidence level α_t, to cope with the uncertainty. X_t^l and X_t^u resp. U_t^l and U_t^u give lower and upper bounds. Simplified, the stochastic optimisation model is of the following general type:

(1) $\min_{U_t} g(X_t, U_t) \quad \forall t \in [\tau, \tau+1, ..., T]$ (objective function)

(2) $\mathbb{P}\begin{pmatrix} X_t^l \le X_t \le X_t^u \\ U_t^l \le U_t \le U_t^u \end{pmatrix} \ge \alpha_t$ (constraints)

(3) $X_{t+1} = f(X_t, U_t)$ (dynamics)

To incorporate a user-preference-driven multi-objective MPC problem (Bemporad and Muñoz de la Peña, 2009; Wojsznis et al., 2007), our approach uses weighting factor ε_t for minimising energy cost and $1 - \varepsilon_t$ for minimising carbon emissions with $\varepsilon_t \in [0; 1]$ for all t. By setting individual ε_t the user is able to calibrate the objective function of the optimisation problem.

3.3 MPC-OOT-Interplay

At every optimisation step t all gathered data is transferred from the OOT to the MPC, which calculates the optimal control strategy for every room. The outcomes of this process are then re-transferred to the OOT and applied to the system by setting all heating devices according to the heating plan U_t. For validation and system learning reasons, the OOT writes input and output data into the database. After a successful write operation, the control input U_t and the addressed thermostat ID is passed via the open source API to the building's SmartHub, which finally sends the control instruction to the thermostat. At $t+1$ (equidistant control strategy) forecasts can be adjusted according to (3) by measuring actual variables and analysing possible deviations. Hence, feedback on the efficacy of the heating plan can be introduced in a new optimisation. The heating plan will then stepwise be adjusted accordingly. Self-creation of feedback improves the system's learning, even if incorrect information was provided on the initial setup, and offers the user as few encroach as possible.

MPC needs lots of computer and memory resources (Wang and Ma, 2008), strongly depending on the number of optimisation cycles, intervals of query information and heating adjustments. To ensure neutral PMVs and save system resources, fixed timeout periods and event listeners are combined to determine the MPC optimisation cycle time. The latter continuously listen on the information and immediately fire an event handler if any condition (e.g. weather forecast) changes, while ignoring changes for a fixed timeout. Since learning is more volatile at the beginning, timeout periods can be continuously extended having reached a stable PMV within the comfort range.

3.4 Approximation of Physical Building Parameters

Figure 3: RIA user Interface

Since typical users are not experts, required physical data such as heating coefficients can't be gathered immediately. In fact, for ease of use a RIA has been developed as guided application for setting-up the SHHC. Users have to enter building- (e.g. year of construction or modernisation, roof type) and room-specific data (e.g. height, comfort temperature) as well as preferences like comfort temperature. Figure 3 shows the RIA running on a mobile device. Initial building data, which is not immediately appropriate as physical building parameters for the MPC, but sufficient for a similarity measurement, is transferred to the database of the OOT. Required parameters such as the efficacy of certain heating controls under certain user requirements and conditions can be determined by measuring actual states of the systems and learning to functionally interpret the deviations to the planned states. Thus, an effortful technical analysis of each building becomes obsolete. Identified functional relations can be transferred to similar buildings, for which the SHHC has to be set up.

To compare buildings, particularly such with special features (e.g. windows with special insulation, unusual roof type), a method of similarity measurement that covers the individual characteristics is required. A popular method of similarity measurement in data mining is cluster analysis (Han et al., 2011). A combination of different clustering methods may lead to more robustness, novelty and stability of the cluster process. Out of the large range of methods worth considering (for an overview Jain et al., 1999; Kaufman and Rousseeuw, 2008), our OOT uses a combination of partition-based and connectivity-based clustering (Fred and Jain, 2005). In partition-based clustering a central vector represents clusters. To configure these algorithms, a maximum number of clusters k has to be fixed. This isn't possible without knowing the number of data. An object is iterated over the clusters until the assignment to a cluster does not change anymore. Connectivity-based clustering, also known as hierarchical clustering, connects objects to form clusters by using appropriate metrics. All RIA-gathered information is numeric or can be transformed into numeric values. E.g., the attribute "room flooring" is transformed into a numeric value by use of the thermal resistance of the flooring (m^2K/W). Thus, the Euclidean distance metric can be used to compare attributes (e.g. year of construction). A complete linkage clustering (hierarchical) will perform the first clustering iteration.

To increase the robustness of the linkage, a second iteration is performed based on k-means clustering. The needed maximum number of clusters k can be fixed based on the absolute number of data after the first iteration. Furthermore, the complexity issue of connectivity-based algorithms (e.g. $O(n^3)$ for agglomerative clustering) is reduced by minimising the number of first level clusters on the hierarchy. The database design is based on common principles of data warehouse concepts (e.g. Aufaure, 2013;

Labio et al., 1997) and is implemented with NoSQL (Teorey et al., 2011) on MongoDB Atlas (Chodorow, 2013; MongoDB Atlas, 2017). This offers re-scalability for growing data and covers database infrastructure and security issues. Furthermore, it allows using different data marts for analysing purposes. If the amount of data reaches the dimensions of Big Data, the database construction could be migrated to other principles, such as Hadoop/MapReduce (Patel et al., 2012; White, 2012).

The database represents a core part of the OOT. For start-up, different buildings with a focus on German building standards were remodelled in the context of the research project EULE (design of an energy saving campus site at Saarland University, see e.g. Bauer et al., 2013; Bauer et al., 2014; Baumeister and Schäfer, 2014) with EnergyPlus (Crawley et al., 2001) and the simulation performed with Dymola® and Modelica® (Dymola, 2017). This approach guarantees self-producing data. While the simulation is time-consuming, our prototype is focused on the field programmable gate array (FPGA)-based MPC implementation according to *Jerez et al.* (2011). The OOT-Back-End as a control system, where all data flows through, follows the idea of cloud computing and is implemented as a RIA.

4 Evaluation Strategy

First steps have been undertaken for validation and evaluation. In addition to an ongoing system usability testing, Table 1 shows possible combinations of evaluation objects and methods, the latter according to *Hevner et al.* (2004), the most promising combinations for our artefact being marked with second-best alternatives in brackets. Since the portfolio of evaluation objects is heterogeneous, our evaluation strategy will be multi-pronged. For illustration, explanatory details for the first two evaluation objects are given: (i) The similarity measurement finally aims at identifying buildings with comparable reactions to heating control input. This heavily depends on their heat transfer coefficient, which can analytically be determined based on the thermal conductivity of all construction materials. Hence, the goodness of clustering and the corresponding implied heat transfer coefficient, which can be determined on a backwards execution of the MPC calculation, can be objectively evaluated for a subsample at least. Simulating the results of alternate clustering methods or sets of independent variables, which have to be provided by the user in the RIA, then will help to adjust this artefact's element if necessary. (ii) Since users have to enter their preferences guided by the RIA, evaluation can be focussed on the appropriateness of the therein lodged categories of preferences and provided preference functions, which were gathered in interviews with potential users. However, they could be biased if fictional pre-survey and real life implementation conditions differ. E.g., as a result of interviews and in order to handle the trade-off between complexity and RIA's practicability, a simple weighting of preferences is implemented rather than nonlinear trade-offs or complex threshold functions. Observations and user interviews have to prove if this is sufficient for real life use. If not, controlled experiments could be used to adjust RIA's data entry: Psychological experiments suggests that users often don't exhibit well-defined preferences (e.g. Bettman et al., 1998; Payne et al. 1992); instead, they might construct them on the spot when needed. So, a controlled experiment with an experimental group that is allowed to freely choose from a wide set of preference categories, while a second control group has limited preselected options to vote for could show if selected categories differ among the groups.

For simplification, Table 1 subsumes issues like usability (e.g. ease of use), system security, technical performance (e.g. runtime behaviour) and other nonfinancial measures under overall cost-benefit. The performance of our prototype has to be compared to alternatives such as pure manual heating control or SC based on autonomous learning. As overall performance measure P

$$P = \prod_{i=1}^{I} \wp_i^{\kappa_i} \quad \text{with} \quad \sum_{i=1}^{I} \kappa_i = 1$$

with $\wp_i \in [0;1]$ as unified scale-restricted performance measure, $\wp_i = 1$ (0) as perfect (no) fulfilment of the i-th evaluation category ($i = \{1, 2, ..., I\}$) and $0 < \kappa_i < 1$ as category weighting we use a Cobb-Douglas function to model a partial substitutability between categories. Unification of $\wp_i$ is required to compare different dimensional original measures $\mathscr{M}_i$, e.g. life-cycle cost and carbon emissions, the user's comfort perception or speed of self-adaptation, hence a mapping $\mathscr{M}_i \rightarrow \wp_i \ \forall \ i$ is necessary.

Evaluation Method \ Evaluation Object		Elements of Artefact							Overall Cost-Benefit
		Similarity Measurement	Parametrisation of Optimisation				Efficiency of Optimisation	Efficiency of Control Strategy	
			Preferences	Physical Data of Building	External Influences	Current State of Building			
Observation	Case Study	(✓)	(✓)	✓	✓	✓			(✓)
	Field Study	(✓)	✓	✓	✓	✓			(✓)
Analysis	Static Analysis						✓	✓	
	Architecture Analysis	(✓)						(✓)	
	Optimisation	✓					(✓)		
	Dynamic Analysis						✓	✓	
Experiment	Controlled Experiment		✓	(✓)	(✓)	(✓)		(✓)	
	Simulation	✓		✓			(✓)	(✓)	
Testing	Functional	(✓)		(✓)	(✓)	(✓)		✓	
	Structural			(✓)	(✓)	(✓)		✓	
Descriptive	Informed Argument	(✓)	(✓)						✓
	Scenarios		(✓)						✓

Table 1: Combinations of evaluation methods and objects

5 Conclusions and Further Research

Our presented smart service prototype aims at resolving the dilemma between restricted users' comfort during the training phase using autonomous learning for heating SC and the challenge of knowledge-extensive, accurate parametrisation of MPC (Afram and Janabi-Sharifi, 2014) for non-expert users. Since it only requires changing smart thermostats and a SmartHub with internet connection as a central administration device, it is a low cost and largely maintenance-free investment. The key idea is to use MPC; however, parametrisation is done based on a similarity measurement instead of physically modelling each individual building. The data entry in the RIA takes the knowledge and the effort of a typical user into account. As the number of buildings gathered in the database of the OOT is gradually growing over time, at first the database contains simulation results of the physical models of characteristic buildings. Alternately, the possibility of joining existing databases will be checked. E.g., the U.S. Department of Energy runs the Building Performance Database (BPD) (US Department of Energy, 2017), which can be filtered on building category, location, building system or Energy Star Rating.

Deviations between forecasts and actual data are successively incorporated in our OOT according to (3). Adaptive MPC might resolve the shortcomings of parametrising MPC only once based on collected local or simulated data (Lindelöf et al., 2015). Hence, further research could show, if it is advantageous to hand over the training data generated by the use of our OOT to an additionally running ANN with a high maturity level as described in *Afram et al.* (2017). If the ANN achieves an accuracy comparable to the MPC over a fixed period of time, the control of the individual SHHC could be handed over from the MPC to the ANN based control to integrate learning about i.a. users' behaviour. Even though the geolocation of a building is already used to retrieve weather forecasts, users' geolocation provided by the usage of a mobile application (e.g. for smartphones) could also help to improve heating optimisation by taking occupancy into account. Moreover, further automation could be used to facilitate users' data entry in the long run. E.g., Google Street View might be used to determine the portion of a front's glazing or Google Earth to determine a building's floor-space.

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