IEA ANNEX 60 ACTIVITY 2.3: MODEL USE DURING OPERATION, APPROACH AND CASE STUDIES

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ABSTRACT

The IEA EBC Annex 60 is developing and demonstrating new generation computational tools for building and community energy systems based on the non-proprietary Modelica modelling language and Functional Mock-up Interface standards. The anticipated outcomes are open-source, freely available, documented, validated and verified computational tools that allow buildings, building systems and community energy grids to be designed and operated as integrated, robust, performance based systems with low energy use and low peak power demand. Activity 2.3 focuses on the use of models during building operations to augment monitoring, implement control algorithms and fault detection, and diagnostics methods. This paper presents an overview of the work carried out within Activity 2.3 including a description of three case studies.

INTRODUCTION

Modelica is an equation-based, object oriented modelling language for complex multi-physics systems. The use of Modelica for the built environment is promising as buildings involve multiple physical phenomena (e.g., heat transfer, fluid dynamics, electricity) and are complex in terms of their dynamics (e.g., coupling of continuous time physics with discrete time and discrete event control) and in terms of their sizes, ranging from equipment to buildings and communities with district heating, cooling and electrical distribution grids.

An advantage of Modelica is the modularity of the language that allows modification of the code according to the specific needs of the application. The object-orientation enables extension and reuse of components and the use of standardized interfaces enables collaboration across physical domains and disparate developer groups.

Modelica is a declarative modelling language. To simulate models expressed in Modelica, they are translated, typically to C code, and linked to numerical solvers. This translation process is done by a Modelica tool that provides symbolic processors, numerical solvers, code generators and utilities for run-time support. Using declarative models that are afterwards translated to executable code allows generating different code for conventional simulation, for simulation under real-time constraints, and for optimization. Therefore, there are many ways to use a Modelica model during buildings operation such as for Model Predictive Control (MPC), Fault Detection and Diagnosis (FDD) or Hardware in-the-Loop (HiL).

Model predictive control

The energy control of buildings has been widely studied and reported in the literature in the last fifteen years. A large body of literature has been published on applications of MPC to HVAC systems (Afram & Janabi-Sharifi, 2014). Compared with traditional control approaches, MPC eliminates many of standard control drawbacks in large-scale applications, including hard parameter tuning, weak prediction capability, difficult implementation of supervisory control and weak adaptability to varying operating conditions. From the operational point of view, four aspects are relevant in the engineering process of MPC energy efficiency applications (Ma, 2012):

- The index used in the cost function such as the predicted mean vote (Fanger, 1973; Braun et al., 2012; Hu & Karava, 2014). Also, other simpler yet descriptive comfort indices might be found used as a set of linear constraints on the zone temperatures, CO_2 concentrations, and relative humidity (ASHRAE, 2004; Freire et al., 2008; Kelman et al., 2011; Oldewurtel et al., 2010; Ma et al., 2011) .
- The modelling technology: including detailed modelling (Henze et al., 2005; Coffey et al., 2010); simplified modelling and grey-box models (Braun, 1990; Kelman et al., 2011; Oldewurtel et al., 2010; O'Neill et al., 2010; Andersen et al., 2000; Bacher & Madsen, 2011; Reynders et al., 2014), and black box models (Chen et al., 2006; Cigler et al., 2012; Liu & Henze, 2006a, 2006b).
- The implementation of the control actions: two major implementation methods can be found, either computing the control signals in real-time (Kelman et al., 2011; Oldewurtel et al., 2010), or using look-up tables for accessing solutions pre-computed off-

line (Alessio & Bemporad, 2009; Braun et al., 2012; Domahidi et al., 2011).

- The implementation technology and, consequently, the development and deployment framework of the MPC solution. TRNSYS, MATLAB and Modelica are at present time the most used tools for developing scalable and site-specific solutions for optimised control. The Modelica language has some key features that provides substantial advantages over the MATLAB and TRNSYS environments facing the complexity of large MPC application (Wetter & Haugstetter, 2006; Burhenne et al., 2013). A specific MPC library for linear problems provide integrated control system design in Modelica (Hölemann & Abel, 2009). Modelica models can be directly used in the main MPC loop (Imsland et al., 2008) unless the size of the model makes it computationally impractical. In those cases, they can be used as the data source for model reduction processes (Burhenne et al., 2013).

The design of building models for MPC is not a trivial task. On the one hand, MPC models have to provide accurate predictions of future states, and, on the other hand, they must be computationally efficient, so that they can be deployed on-site using cost-effective computational resources. At the same time, MPC models must provide results in a time frame compatible with the operational time constraints. Furthermore, MPC models must be embedded in systems that, for cost reasons, will not include all the sensing/actuating capabilities desired. Despite this reduced input set, the model accuracy of the MPC must be granted within precise and effective error boundaries. The fulfilment of such competing requirements compels the definition of a model-engineering framework, which establishes the methodological steps required to design accurate and robust MPC models.

Fault detection and diagnosis

FDD in building operation can be seen as part of the building optimization process. A large amount of energy is wasted because many HVAC&R systems are not operated in the way they were designed for (Katipamula & Brambley, 2005a, 2005b; Bruton et al., 2014). Malfunctioning or faults are often not detected or only detected when they manifest themselves at the system level and e.g. occupants complain (Bruton et al., 2014). In the Annex 60 (Wetter et al., 2013), the focus lies specifically in using Modelica models for FDD benefitting from the extensive existing model libraries for buildings and HVAC&R systems and the various interfaces and coupling mechanisms provided for those models.

Modelica models can be used for FDD in two different aspects: directly, by using simulation results as a reference for the monitored data and indirectly, by using simulation data as training data for black box models. In the latter case, the results of the black box model are then used as a reference for the monitored data. The direct use of Modelica models for FDD, based on fault models, has been reported in (Bunus et al., 2009; Lunde et al., 2006; Cui et al., 2011). However, in the building sector, Modelica models have been rarely used for FDD, partly due to the great effort that is typically involved in the establishment of a complex building and HVAC&R model and the long simulation times going along with detailed models. In the past few years a big step has been done with respect to the development of standardized building and HVAC&R libraries with the publication of the Modelica Buildings Library (Wetter et al., 2014), which facilitates the setup of simulation models for building performance analysis.

The indirect use of simulation models can be beneficial if, e.g., FDD is part of an online routine, but the respective simulation model is too slow. Typically, black box models are faster, but have high time and effort requirements in the (offline) training period. A drawback of all black box models is that they need large amounts of fault-free, and sometimes faulty, data for training. Therefore, monitoring data has to be classified by experts. This difficulty can partly be overcome by the use of simulation data from Modelica models.

A systematic and extensive generation of simulation data corresponding to standard HVAC&R systems and to common faults appearing in such systems can ease the configuration of black box models, which can then be applied for FDD in a wide range of different HVAC&R system. Common black box methods, which have been applied in the building sector are, for example, Bayesian classification, clustering, qualitative models and artificial neural networks (House et al., 1999; Müller et al., 2013; Du et al., 2014; Mann, 2011; Sterling et al., 2014). A comprehensive overview of several methods and their respective characteristics are given in (Bruton et al., 2014). In (House & Kelly, 1999), various methods are compared among each other and to rule-based methods and evaluated with respect to performance in FDD. However, there is still a need for systematic studies, which compare and evaluate different methods in order to obtain a clear picture of the scope of application and the specific difficulties of each method.

Finally, the possibility to import and export Modelica models as Functional Mock-up Units (FMUs) enables the integration of models using a standardized, tool-independent API into existing FDD routines or the development of integral solutions that couple tools for data analysis, simulation, FDD and optimization in one single environment. An integral solution can be realized, for example, using the Building Controls Virtual Test Bed (BCVTB) (Wetter, 2011) or JModelica with the python module PyFMI (Åkesson et al., 2010).

Hardware in-the-loop

HiL is a process that is widely used for product development and testing in industries such as automotive and aerospace. Example applications can be found in (Winkler & Gühmann, 2006; Ebner et al., 2007) where Modelica models were used for the development of hybrid electric vehicle, and the implementation of a HiL test platform for the simulations of drive cycles to test energy storage systems in electrified vehicles such as batteries or fuel cells respectively. In (Zhao et al., 2009), a HiL simulation system of civil aircraft thrust reverser with Modelica-based simulation platform was presented.

Although HiL in combination with Modelica is a common process in different industries, it has not yet found wide applicability in the buildings community. In (Kan et al., 2013), HiL simulation assisted design and validation approaches of Home Energy System with help of Modelica libraries are introduced. In (Nouidui et al., 2012), HiL was used for the development of a model-based controller of a blind. In this process, Modelica models of the Buildings library were used to construct a model of a physical test cell, which has a controllable blind. This model was used in real-time together with Radiance, and the Building Controls Virtual Test Bed to determine the blind position that minimized the energy consumption of the test cell. This blind position was then converted into an actuation signal that was used to control the blind of the physical test cell

CASE STUDIES

MPC development for energy control of underground public spaces

This case study concerns the SEAM4US EU FP7 project (SEAM4US, 2014) pilot that has been deployed, since August 2014, in the *Passeig de Gracia* (PdG) Line 3 metro Station in Barcelona, Spain. The pilot is currently operating, and it is aimed at demonstrating the effectiveness of MPC applied to the ventilation, lighting and passenger movement systems in underground subway stations. The development of the MPC component required a considerable modelling effort since the energy dynamics of the underground stations was narrowly reported in literature. The modelling of the environment dynamics included the passenger flow, the ventilation and the lighting systems, the outdoor and the indoor thermal, fluid and pollutants dynamics. In order to gain the necessary insights about the complex energy behaviours of the underground station, a model-engineering framework, combining different modelling and survey techniques at different scale of details, was established. A peculiar requirement of this process was the co-development of the analytic models and of the related sensor network, in which the modelling process supports the specifications of the sensor network (i.e. type, location, range and sensitivity of each sensor), and, the data gathered by means of the deployed sensor network support the model calibration phase. Three development stages were employed.

- A preliminary phase, based on finite element modelling of the urban canyon and of the indoor environment, was aimed at acquiring a qualitative understanding of the outdoor and indoor fluid and thermal dynamics. This phase drove the initial surveys, the design and the deployment of a preliminary sensor network.
- A development phase, based on Modelica, aimed at developing a whole building lumped parameter model of the station including the forced ventilation, and the lighting systems, the heat exchange and mass flow dynamics. The model is based on the Modelica Buildings library and has been calibrated according to ASHRAE guidelines (ASHRAE, 2002), using the data gathered by the deployed sensor network.
- An optimisation phase, in which the Modelica model was reduced into an embeddable statistical model that was deployed into the on-site MPC system. The sensor network was optimised, so that a one-to-one matching with the reduced model input and output variables was established.

The Modelica model was the enabling factor of the overall model engineering. Modelica offered all the key features that allowed the successful management of such a complex case. The Modelica equation based language provides natively a-causal modelling and, consequently, object orientation. Therefore, libraries are arranged in components – subcomponents hierarchies that match one to one the real world objects. This allows the effective implementation and the calibration of extremely large models. The final station model amounts at about 77,000 unknowns. Furthermore, components are open and easily customisable. Custom models of the station fans, escalators, lighting appliances, as well as of the built environment (i.e. horizontal openings) were developed on top of existing Modelica libraries, as a standard model development process. In addition, Modelica offers an unprecedented flexibility in the representation of complex environments. In fact, the well-structured representation of the domain was the enabling factor for the conduction of the complex evidence based calibration processes to match the model with the measured data. Nevertheless, the direct adoption of the Modelica model in the MPC loop was impractical for three main reasons. First of all the size of the model demanded relatively large computational resources. Second, coupling such a large model with the sensor network required an impractical state estimation process. Finally, the Modelica model did not provide support for the management of the uncertainty associated with the measured data in real-time monitored environments. A model optimisation phase was therefore required, in which the Modelica station model was reduced to a significantly smaller

Bayesian Network model. The model reduction was conducted through statistical clustering methodologies. Hence, a comprehensive data set including all the possible operating condition under MPC was necessary. The generation of this data set was a second modelling issue of the SEAM4US project. A custom co-simulation environment, called Model-In-the-Loop (MIL) Figure 1 was developed. MIL has been implemented in Simulink, and uses the FMU technology to combine many Modelica models under the same Simulink control loop. Simulink acts as the master element of the co-simulation arrangement providing the control clock and a fixed simulation step to all the other subsystems.

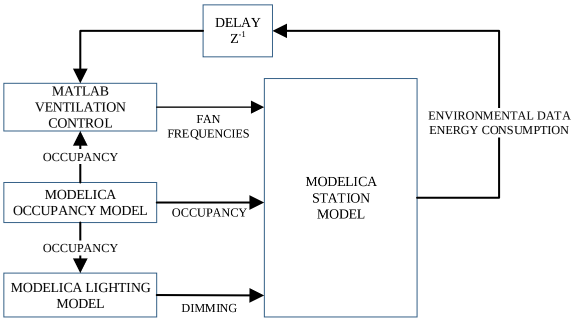

Figure 1. The Modelica Model-in-the-loop simulator

The Modelica Station model, the Occupancy model and the Lighting model are included in Simulink as FMU co-simulation components. The Modelica station model is interfaced with a weather file of Barcelona that provides external weather parameters. The model receives as inputs the occupancy levels of each space of the station, the lighting level of the appliances in each space, and the fan control frequencies. It then outputs all the indoor environmental parameters and the fan energy consumption. These parameters are then fed-back to the controller as the input for the next control step. The Modelica Occupancy model, based on the Modelica bond graph library, simulates passenger flows and the occupancy distribution in the spaces inside the station. The passenger flow is simulated as a mass flow occurring among the station spaces. The mass sources are modulated by train arrivals and scheduled flow rates observed from the outside. Model calibration has been carried out through observations of the flow rates of passenger entering and exiting the trains and the station entrances at different hours of the days. The internal flow is then regulated through mass flow delays calculated based on typical transit speeds. The Modelica Lighting model regulates the lighting level adaptively in relation to the occupancy level of each station space. Hence, it receives occupancy levels and implements a reactive form of control that is driven by the illumination needs defined for each specific situation that may occur in the station environment. Since the outputs of the lighting control influence environmental and comfort conditions, these outputs are provided as inputs to the Modelica station model.

The Ventilation controller is written in Matlab implementing different control logics. A random logic is used to generate the dataset for the model reduction phase. For the MPC implementation, a particle filtering policy was implemented. The controller randomly generates a number of different control options that are sent to the Bayesian Predictor, which estimates the environmental and energy consumption parameters. Then the controller ranks the predictor outcomes according to a cost function. The best performer is selected and used in the next control step. This brief description of the SEAM4US cease study showed how the Modelica modelling environment contributes to a large-scale model engineering application. The Modelica modelling technology provides key features and enabling factors at different levels. As a modelling language, it has the expressiveness and the efficiency to represent and simulate consistently end effectively large and complex domains. At system level, through the FMU technology, it can be effectively embedded into multi-domain multi-platform co-simulation environments.

Model-based FDD for District Cooling Systems

The project aims to improve the way current Energy Management Systems (EMS) operate by extending their capabilities with optimization and fault detection techniques that are based on physics-based models that represent district cooling systems (DCS) and their components (e.g., chillers, pumps and cooling towers).

The DCS object of this study is located at the US Naval Academy in Annapolis (MD). The system is characterized by a central loop where more than 20 buildings utilize the chilled water (CHW) for air conditioning. The buildings are all different ranging from data centres, gyms, swimming pools and other facilities. The CHW is provided to the central loop by two separate plants located in different zones of the campus. Each plant has three centrifugal liquid chillers (with both single and double stage compressors) and four cooling towers. The project is still in progress and it will end in January 2016.

This case study exemplifies of how simulation models that can be used during the design are reused during the operation thanks to the Functional Mock-Up Interface standard.

Within the scope of this project (add citation) has been demonstrated that model-based state and parameter estimation techniques can be a viable solution to integrate FDD in system operations. However, in order to fully exploit the capabilities provided by the state estimation approaches the models used should be provided in a more standardized and suitable way, reducing the cost and effort for future implementations. In (Bonvini et al., 2014c) and (Bonvini et al., 2014b) it has been developed a methodology that allows state and parameter estimation techniques to work with models represented using the FMI standard. Figure 2 shows the framework for model based fault detection that has been developed as part of this project.

In the upper part of Figure 2, the designers can use Modelica based tools (or any simulation tool that can export models using the FMI standard, e.g. Matlab) to describe the design the system and evaluate its performances via simulation. Once the system has been designed and the system is operated it is possible to reuse the same models, or part of them, in conjunction with FDD algorithms. Thus, models are not simply used to design a better system but also to make sure it operates as expected minimizing its energy footprint.

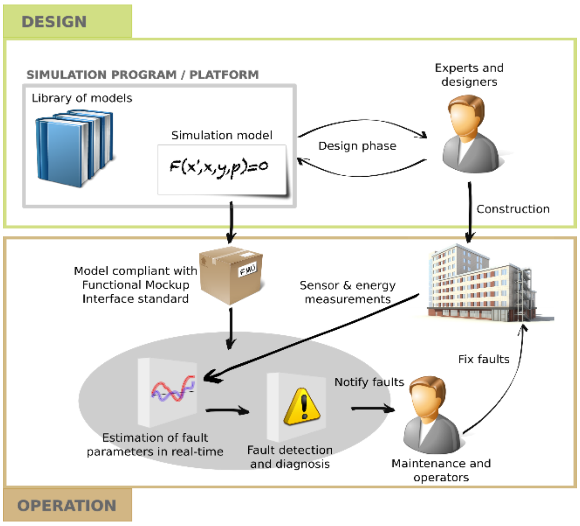

Figure 2. Model-based fault detection using state estimation techniques compliant with the FMI standard

The cooling plant and its components have been modelled in Modelica using the Modelica Buildings library (Wetter et al., 2014). Since this is a demonstration project, the model was created after the system was built. The plant model incorporates the chillers, cooling towers, pumps, pipes and valves as well the control systems coordinating their operation. The component models have been calibrated using measurements gathered from the plant. The calibration has been performed using GenOpt (Wetter, 2004). In the case of the chillers, the measurements used to calibrate the models were the inlet and outlet temperature of the condenser and chilled water, the chilled and condenser mass flow rates, and the power consumption of the compressor. The parameters of the models have been calibrated in order to minimize the difference between the power consumption and the outlet water temperatures computed by the model with respect to the measured values. After the calibration process, the model has been exported as FMU and used by the FDD algorithm.

The FDD algorithm uses the FMU model in the following way. The algorithm collects all the relevant data from the EMS. Then, the algorithm predicts the power consumption of the chiller and its coefficient of performance (COP) using the calibrated FMU model. In parallel, the FDD algorithm uses the same FMU model and estimates the COP and outlet temperatures using the observed measurements. This state and parameter estimation step computes a statistical description of the observed performance of the chiller based on its model. More details about the state and parameter estimation can be found in (Bonvini et al., 2014a). The results of the state estimation algorithm are then compared to the results of the calibrated model. One of the advantages of this approach is that it provides a statistical description of the efficiency, thus allowing the selection fault thresholds based on probability (e.g., when the probability that the estimated COP exceeds the expected one is higher than 95% a fault is identified). The FDD algorithm is based on a python package called EstimationPy developed by the LBNL team. This package further extends PyFMI (Modelon AB, n.d.) to provide state and parameter estimation capabilities using models compliant with the FMI standard. The algorithm is part of a more comprehensive framework hosted on a web services infrastructure. The infrastructure is in charge of collecting the data from the EMS, pre-process the data (e.g., fill possible gaps, remove inconsistencies, etc.), periodically execute the algorithm, store its results on a database and provide them to the users through a web-based dashboard.

Hardware in-the-loop

The study is being performed at the integrated building energy and control laboratory at The University of Alabama, Tuscaloosa, AL. A room served by a VAV terminal unit is the study object, where the room and VAV terminal unit are modelled in Modelica and downloaded to the HiL machine that is connected to a real VAV box controller. The objective of this case study is to research different control algorithms including fault tolerant controls for VAV boxes. This case study is still ongoing.

Figure 3 shows a schematic of the connectivity of the controllers to the dSpace processor running a Modelica model. Control logic downloaded to the controllers communicates via A/D and D/A boards with the room and VAV box models constructed in Dymola.

The VAV box with a reheat functionality is being modelled in Modelica using s heat exchanger and several dampers from the LBNL building library. This case study is using Dymola for Modelica and dSpace for HiL simulation.

Sometimes compatibility issues have encountered between the building code for dSpace and the Dymola-to-Simulink interface. This only occurs with certain models, such as MixedAir from the LBNL building library, and we have not yet located the root cause of these issues. These models work fine in Simulink but return a Simstruct Mex error during code

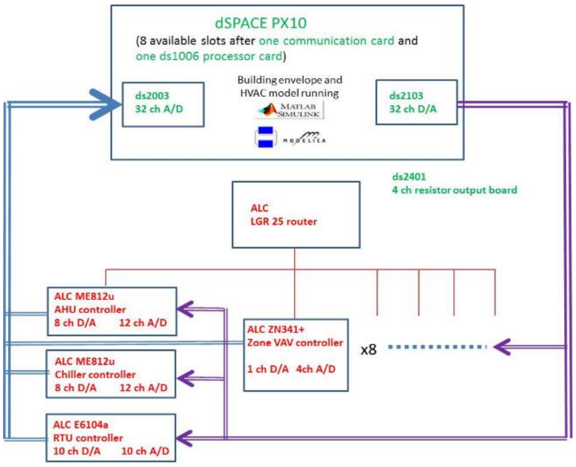

Figure 3. Schematic of HiL setup.

generation.

CONCLUSIONS

A number of relevant modelling advantages and shortcomings concerning the application of Modelica to the model use during operations emerged in the development of these case studies.

The Modelica component oriented language integrates in hybrid modelling processes. Several libraries are freely available for use in Modelica (e.g .(Baetens et al., 2012; Lauster et al., 2014; Nytsch-Geusen et al., 2013; Wetter et al., 2014)). These can be modified and/or extended and be integrated with other libraries.

The Modelica object-oriented approach allows for the development and the management of large and complex models. In such large-scale applications, the translators, the modelling language and environment are significantly stressed, and their robustness proved an enabling factor of the overall modelling process. This makes the Modelica toolchain well suited for handling highly complex models from the end user and the engineering perspective.

Modelica allows for a seamless use of the models developed in the design phase during the operational phase, for example, by exporting models as FMUs.

Finally, it is important to note that the advantages of Modelica can turn against the unexperienced developer. For example, because of the object-orientation employed in many libraries, it can be difficult to predict the depth to which a change in one component can have an effect in other components in the library. However, regression tests as are setup for the Annex60 library can detect such unintended side effects. In addition, the current capabilities of Modelica IDEs are still developing means to provide better debugging information. Also, training is highly recommended for novice users as the type of model verification and debugging done in equation-based languages differs from what users may be accustomed to when writing procedural code.

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