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Procedia Engineering 205 (2017) 1975–1982

Procedia Engineering

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10th International Symposium on Heating, Ventilation and Air Conditioning, ISHVAC2017, 19-22 October 2017, Jinan, China

Semantic Inference-Based Control Strategies for Building HVAC Systems Using Modelica-Based Physical Models

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Abstract

The focus of this paper is on an integrated approach for HVAC modeling (semantic and physical), optimization, and control. It utilizes the Building Control Virtual Test Bed (BCVTB) platform to integrate ontologies along with rule sets into Model Predictive Control (MPC) routines and Modelica-based simulations. The ontologies represent the data in the form of semantic models of the domain. They include concepts and the relationships between them, i.e., mechanical equipment, zones, and sensors. While the MPC ensures optimized physical control, the ontologies and rule sets are responsible for data-driven and inference-based semantic control. The Web Ontology Language (OWL) is used to describe the ontologies, and Jena API was used as the framework to create the ontologies and define the rule sets.

Peer-review under responsibility of the scientific committee of the 10th International Symposium on Heating, Ventilation and Air Conditioning.

Keywords: Building Virtual Control Test Bed (BCVTB); Model Predictive Control (MPC); Modelica; Ontology; Physical Modeling

1. Introduction

The main function of heating, ventilating, and air conditioning (HVAC) systems in buildings is to provide a thermally comfortable indoor space for the occupants and satisfy the minimum indoor air quality (IAQ) requirements. Commercial building energy end-use distributions in 2010 indicate that more than 42% of the total energy consumption in buildings is associated with the HVAC systems [1]. There has been an interest in the past decade to minimize HVAC energy consumption in commercial buildings without scarifying the IAQ requirements or the occupant's thermal comfort. For example, a recent study incorporated a dynamic thermal sensation (DTS)

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Peer-review under responsibility of the scientific committee of the 10th International Symposium on Heating, Ventilation and Air Conditioning.
10.1016/j.proeng.2017.10.060

model into a Model Predictive Control (MPC) scheme that then made control decisions to condition the air and improve the occupant's thermal comfort [2]. MPC algorithms utilize abstract dynamic models of the processes under control. To the knowledge of the authors, no studies have implemented MPC-based thermal comfort models in a real building or in an integrated simulation platform.

The use of predictive occupant-based thermal comfort models could have significant impact on energy consumption and cost when the model is implemented in a real building or an integrated simulation platform. Currently, implementation in a real building is not feasible because it is not possible to account for all variations of building types. One practical approach is to implement the simulation models in an integrated simulation platform, known as co-simulation, where different simulators exchange data [3].

This study uses the software modeling language Modelica to develop the physical model of a building. Modelica supports object-oriented programming and is an equation-based language that can be used to model a wide range of complex physical systems, such as buildings. The Modelica Buildings Library [4] contains dynamic simulation models of HVAC systems and has been fully implemented in the Dymola software program. Dymola is a high-performance simulation tool that incorporates powerful optimization solvers and is compatible with the selected co-simulation platform.

During the past two decades, many researchers and experts in the area of building simulation have devoted considerable effort to developing and applying improved and advanced control methods. MPC has received considerable attention [5] since it allows for input from sources such as weather forecasts, occupancy predictions, comfort ranges and actuation constraints. From a mathematical standpoint, MPC processes optimize control outputs based on a prediction of how those processes will evolve over a time horizon. The main purpose of MPC is to compute the control outputs that minimize an objective function (i.e., cost or energy), which is usually a function of the system states. The state space control model is used as a constraint in the optimization problem.

Another area that has gained a great deal of attention both in academia and industry has been developing intelligent, event-driven automated control units for HVAC systems. Our hypothesis is that HVAC control units can benefit from state-of-the-art semantic web technologies. Semantic modeling has been used in different areas including healthcare [6], biology [7], and transportation [8]. Semantic models can be utilized as placeholders for sensors or simulation data. Moreover, reasoning can be performed on the stored data.

The building community has started to utilize semantic web technologies both as data repositories and as reasoning tools. As a case, Corry et al. [9] proposed an ontology that receives data from building objects, sensors and simulation models and assesses that data in a structured way. That is, to use the ontology as a repository or data integration tool. Han et al. [10] used a rule-based semantic reasoning for context-aware building management to reduce energy waste. They used Jena Rules for reasoning purposes in context and policy.

This work presents a co-simulation platform where the physical and semantic models of HVAC systems are integrated into different control strategies, e.g., MPC or semantic rule-based approaches. The simulation results of the physical models are stored in the semantic models called ontologies. Per reception of new data, inference rules are triggered and new information is deduced. As an ultimate goal, real building sensors will provide data to the ontologies and the rules will take subsequent actions when their conditions are met.

2. Methods

Our methodology entails: a) developing Modelica models for HVAC system behavior, b) developing associated ontologies and rules to host Modelica-based simulation results, c) adapting MPC algorithms to optimize HVAC operation in terms of reducing energy consumption while meeting occupant comfort, and d) integrating these components in the BCVTB framework as depicted in Figure 1. In this setting, MPC (i.e., algorithms implemented in Matlab) will receive the values for the system state from Modelica simulation models (i.e., Dymola) and provide optimal setpoint values to Modelica models. Moreover, the system state values will be stored in the ontologies-based database and the rules will act upon them.

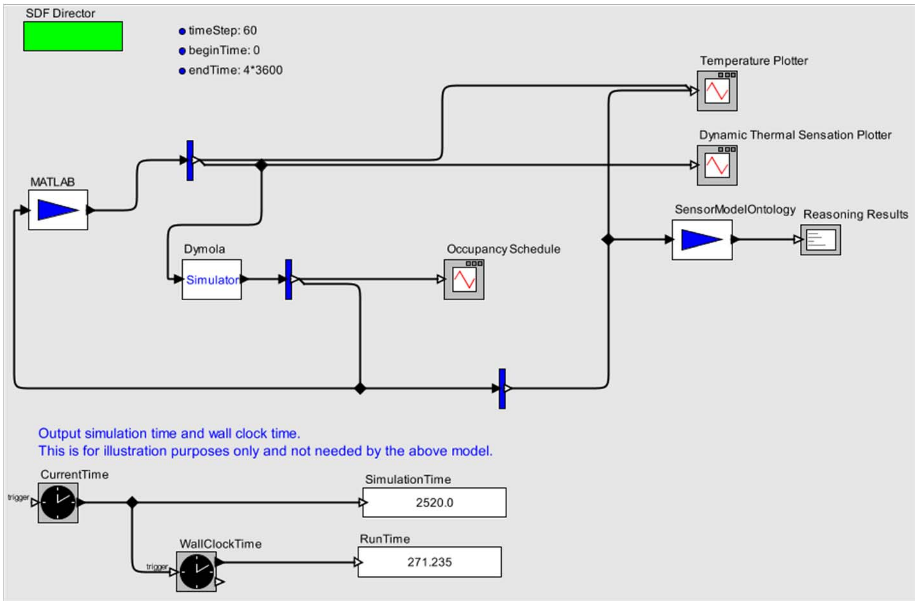

Fig 1. The integration of physical models in Dymola and control algorithms in Matlab in the BCVTB.

3. Physical Simulation Model

The physical model extends an example that was developed in the Modelica Building Library. The example includes models of the HVAC system, a building envelope and a model of air flow through the building. The HVAC system is variable air volume (VAV) with a reheat coil and an air damper in each inlet branch to one of five zones.

The supervisory control is based on ASHRAE [11] recommendations. In this rule-based control sequence, the supply fan speed is regulated based on the duct static pressure. The return fan controller tracks the supply fan air flow rate, reduced by a fixed offset. The duct static pressure setpoint is adjusted so that at least one VAV damper is 90% open. The economizer dampers are modulated to track the setpoint for the mixed air dry bulb temperature. In this control, priority is given to maintain a minimum outside air volume flow rate. In each zone, the VAV damper is adjusted to meet the room temperature setpoint for cooling, or is fully opened during heating. The room temperature setpoint is the optimal value derived from the MPC control while meeting the occupant demand. A finite state machine is used to capture the modes of operation and how the HVAC system transitions between the modes, which are occupied, unoccupied off, unoccupied night set back, unoccupied warm-up and unoccupied pre-cool. In the VAV model, air flow is computed based on the duct static pressure distribution and the performance curves of the fans. Local loop control is implemented using proportional and proportional-integral controllers, while the supervisory control is implemented using a finite state machine.

4. Semantic model

Due to the advancements in sensor technology and data acquisition techniques, automated control systems store a large amount of data from building operations. This allows decisions to be made based upon a wide range of heterogeneous information. To make decisions, it is necessary to know the identity of a sensor (an individual in Sensor semantics) and where it is placed in the system (Building, HVAC and Space semantics), what the time-step was at a specific time on a specific day (Time semantics), and that the measured value is, for example, a flow expressed in m^3 sec^{-1} (Unit semantics). Semantic web technologies such as Resource Description Framework (RDF) and Web Ontology Language (OWL) enable us to construct ontologies for different domains of HVAC systems and to store the semantic information as well as the numeric values from the various domains involved in the simulation.

Our proposed semantic info-structure is comprised of ontologies and rule-sets for supervisory control. As a case, the rules can identify if there is an occupied zone that is not thermally comfortable. Based on the reception of new data, the reasoning engine reasons over the rules, the knowledge and information, and reconfigures the next sets of control actions. The importance of this supervisory framework is that it is transparent via an English-like rule syntax, easy to change and scalable with respect to adding new rules or expanding the existing rules.

The semantic inference model, ontology, is a data model that combines data schema, entity dependency and semantic knowledge. An entity may have an "Object" or "Datatype" property that relates the entity to another entity or a literal data type, e.g., String or Boolean. To perform inference at the instance level, the semantic model will be instantiated with data (individuals) from different sources, i.e., simulation and optimization results. The instantiated model is a dynamic graph that may stretch or shrink based on the reception of new data and the reasoning over it. As a case in point, Figure 2 shows the schematic of a subset of the semantic model used in HVAC systems control. In this model, the semantics of different domains (e.g., HVAC, building, occupant) are represented by different ontologies and rule sets. The semantics of the domain independent areas (i.e., time, space, unit) are represented in the foundational ontologies. Through the "Object" properties, an entity in one domain may be related to an entity in another domain. Also, to describe the semantic knowledge via rules in between the domains, the inter-domain rules entail various entities from different domains. In the current stage of this work, the inference rules are not responsible for the supervisory control actions. Jena API is used in this work to develop semantic models.

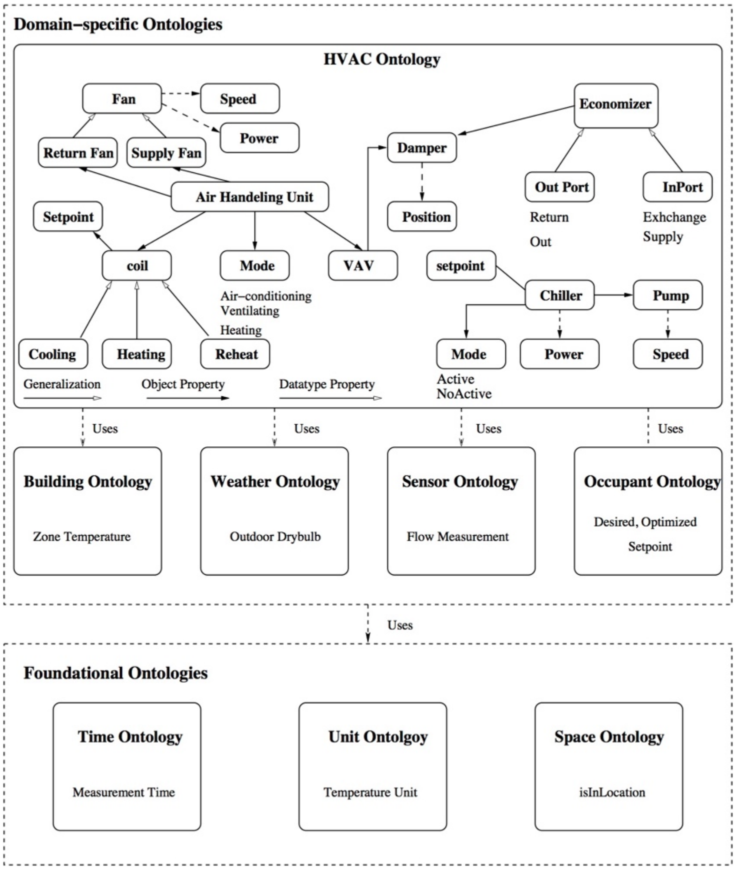

Fig 2. Domain specific ontologies.

Figure 3 illustrates sources of data that provide input to different ontologies in HVAC systems.

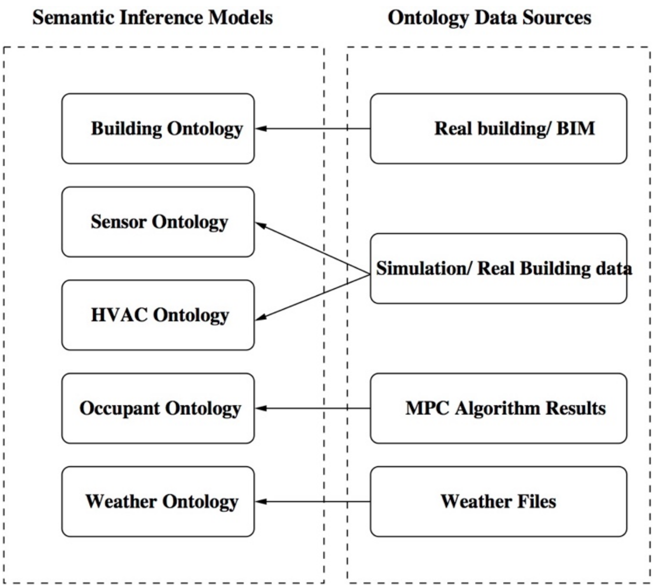

Fig 3. Sources of data implemented in the ontologies

Below is a Jena rule to identify if an occupied zone is outside of accepted thermal comfort ranges and the acceptable thermal condition has been violated. The built-in function "computeDTS" computes the thermal sensation index based on indoor and outdoor temperature. The rule uses different classes from different ontologies. As a case, sensor class from Sensor ontology and zone class from Building ontology are used in this rule.

```
[(?s rdf:type sensor:sensor) (?z rdf:type build:zone)(?s spatial:Inside ?z) ->
(?p :hasStudent ?s)(?o rdf:type occ:Occupant) (?o spatial:Inside ?z)(?s sensor:hasValue ?v) (?DTS
computeDTS(?v,?z,?out) (?DTS greaterThan 0.5)->
(?z build:thermalViolation true)]
```

5. MPC Formulation

The MPC algorithm utilizes a data-driven state-space dynamic thermal sensation (DTS) model with Wiener structure that was developed by Chen et al. [2]. The model captures the occupant's thermal sensation due to changes of indoor temperature through the following equations adapted from Chen et al. [2].

<u>*Cost:*</u>

$$\min \quad J_t = \sum_{k=1}^{n}\left[T_{sply}(t+k|t) - T_{chmbr}(t+k|t)\right]^2 + \lambda_1 \sum_{k=1}^{n}\left[T_{sply}(t+k|t) - T_{sply}(t+k-1|t)\right]^2 + \lambda_2 \sum_{k=1}^{n} q(t+k|t) \tag{1}$$

where λ_1 and λ_2 are large numbers that represent penalties for violation of thermal comfort. Here, q(k) is the optimization slack variable. The simulation time and horizon time step are represented by t and k, respectively. T_{sply} is the supply setpoint, which is considered equal to the supply temperature. J_t represents the energy consumption that is to be minimized. T_{chmbr} is the zone temperature.

The minimization is subject to the constraints defined in Eqs. 2 through 7.

Chamber dynamic model:

$$\begin{aligned} T_{sply}(t+k+1|t)+ \\ &= 0.965\,.\,T_{chmbr}(t+k|t) + 0.0286\,.\,T_{sply}(t+k|t) \\ &+ 0.0523\,.\,T_{sply}(t+k-1|t) - 0.0257\,.\,T_{sply}(t+k-2|t) \\ &- 0.0315\,.\,T_{sply}(t+k-3|t) + 0.0133\,.\,T_{out}(t+k|t) \\ &+ 0.0232\,.\,G_{in}(t+k|t) \end{aligned} \tag{2}$$

where G_{in} is the building gain and T_{out} is the outdoor temperature.

Thermal sensation model:

$$TS(t+k|t) = f(\,T_{chmbr}(t+k|t) + T_{chmbr}(t+k-1|t), \dots) \tag{3}$$

Thermal comfort model:

$$y_{min} - q(t+k|t) \ll TS(t+k|t) \ll y_{max} + q(t+k|t) \tag{4}$$

$$q(t+k|t) \gg 0 \tag{5}$$

where y is the thermal sensation bounds.

Supply air temperature:

$$T_{min} \ll T_{sply}(t+k|t) \ll T_{max} \tag{6}$$

$$-\triangle T_{sply} \ll T_{sply}(t+k+1|t) - T_{sply}(t+k|t) \ll \triangle T_{sply} \tag{7}$$

where T is the range for the supply temperature.

6. System Integration

The BCVTB is a Java-based software tool being developed by Lawrence Berkeley National Laboratory (LBNL). It is open-source, freely available software that can be used as a co-simulation platform. BCVTB has support for building performance simulation (BPS) programs (EnergyPlus, Radiance, TRNSYS, Dymola) and other simulation engines such as MATLAB/Simulink for co-simulation. BCVTB provides mechanisms to link to building automation systems (BAS) through the BACnet protocol. The model of data exchange in this environment is a software architecture where each simulator acts as a client. Moreover, Functional Mock-Up units (FMU), implementing Functional Mock-Up Interface (FMI), developed in any simulation environment, can be used for co-simulation in BCVTB.

In this work, BCVTB is utilized to integrate Matlab with Dymola and Jena API. Through co-simulation of these applications, the data is transferred from Dymola (Modelica)-based models and Matlab-based MPC routines to the ontologies depicted in Figure 1. In this setting, the time step for all the simulations is 60 seconds. The simulation uses the weather data in Chicago for four typical summer days in June. At each co-simulation time step, MPC sets the optimal value of the room setpoint temperature. Figure 4 shows the thermal sensation index for one zone during four hours simulated for the HVAC VAV system. As it indicates, after transitioning to a stable region, this index fluctuates between -0.5 to 0.6. The acceptable range is -0.5 to 0.5, where 0 is considered the most comfortable condition and 1 is considered slightly warm, according to ASHRAE [12]. Note that during the day the thermal sensation index is above 0 (warmer) and during the night it tends to be less than 0 due to night setbacks. Overall, as Figure 4 illustrates this co-simulation framework provides unique opportunities to quantify real-time thermal sensation of the occupants for the simulated model.

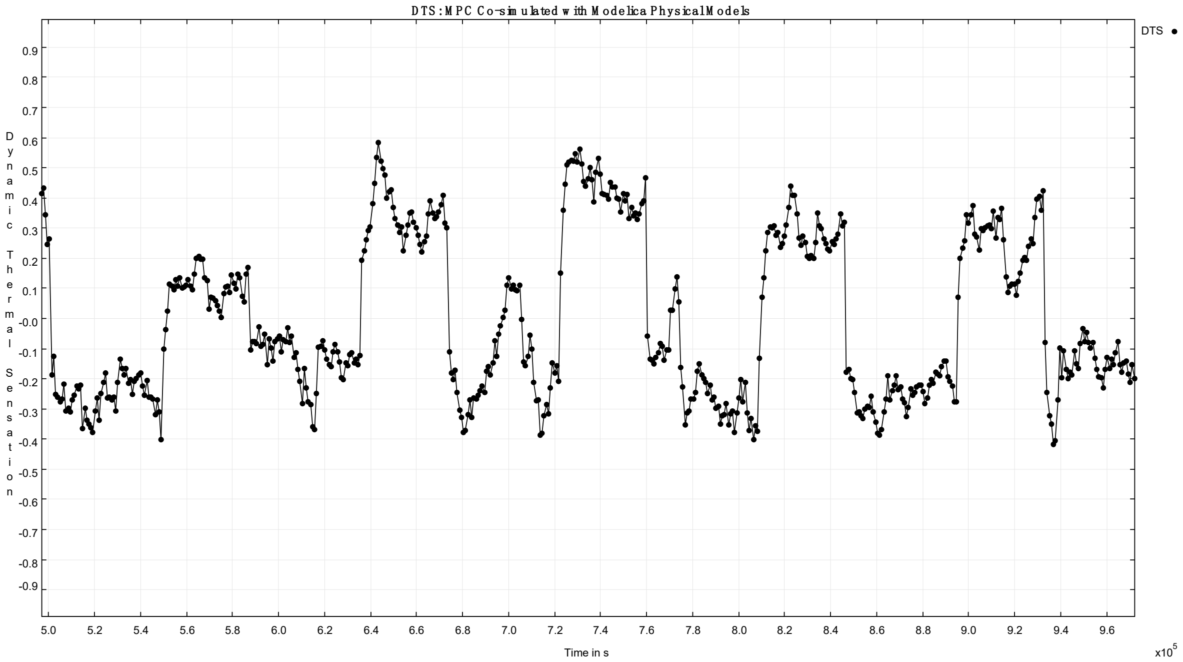

Fig 4.Temperature Profile co-simulation results

7. Discussion

Based on the outdoor temperature and metrics for occupant thermal comfort, the main outcome of the co-simulation is the optimal room temperature setpoint determined in the Modelica model. Based on the setpoint, the new room temperature is computed and fed-back to the MPC. Moreover, implementing the co-simulation strategy in the BCVTB, it is possible to achieve levels of comfort for the occupants (lower DTS value) that are superior to values obtained by the use of room dynamic models to derive the next temperature values [2]. The results indicate that MPC algorithms perform well (i.e., DTS not exceeding 0.5 for the most part) when MPC receives feedback from the Modelica simulation model regarding the dynamic state of the room conditions.

Developing an info-structure comprised of the ontologies and rule sets provides a framework for semantic data-driven supervisory control and detection of anomalies in the system. This work took the first step towards this goal by developing rules that reason over the simulation data stored in the ontologies and deducing new information from them. These inference processes, based on the data, are valuable tools for supervisory control. This framework is also a tool for HVAC designers and building operators to study the impacts of the occupant comfort levels, HVAC equipment and control strategies on the system performance.

8. Conclusion

The proposed framework defines a pathway toward the systematic evaluation of MPC control strategies in real building systems, with the scope of this study linking MPC control to Modelica models of HVAC system component behaviour and the occupant thermal sensation dynamic model. A semantic model, e.g., Sensor, Building, Occupant and Space ontology, and a set of associated semantic rules were defined to monitor the simulation data and identify whether all occupied room temperatures stay within a target range.

The BCVTB environment is utilized for the co-simulation of the MPC control algorithms and Modelica-based simulations for HVAC system behaviour. The simulation results were stored in ontologies where the reasoning engine reasons over the rules upon receiving new data.

Our future work will explore more in depth mechanisms for using the semantic knowledge and formal reasoning capabilities together with Modelica simulations for data driven supervisory control. We are particularly interested in the use of OWL to represent domain knowledge, and software environments such as Jena API for formal reasoning – that is, to specify relationships between the classes and to infer new knowledge and relationships among individuals from existing facts – and to find ways for integrating these capabilities into simulation and control environments involving BCVTB, Dymola and Matlab. Enhanced functionality could include, for example, support for spatio-temporal reasoning in an occupant- based control system.

Acknowledgement

The authors gratefully acknowledge the support from the NIST Graduate Student Measurement Science and Engineering (GMSE) program. This research was performed while Parastoo Delgoshaei held a NIST GMSE fellowship award.

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