

## Towards a Semantically-enabled Control Strategy for Building Simulations: Integration of Semantic Technologies and Model Predictive Control

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### Abstract

State-of-the-art building simulation control methods incorporate physical constraints into their mathematical models, but omit implicit constraints associated with policies of operation and dependency relationships among rules representing those constraints. To overcome these shortcomings, there is a recent trend in enabling the control strategies with semantically-enabled rule checking capabilities. One solution is to exploit Semantic Web technologies in building simulation control. Such approaches provide the tools for semantic modeling of domains, and the ability to deduce new information based on the models through use of Description Logic (DL) implemented by inference-based rules. In a step toward enabling this capability, this paper presents a semantically-enabled control strategy for building energy management simulations that integrate semantic modeling and formal rule checking mechanisms into a Model Predictive Control (MPC) formulation. The approach addresses the high sensitivity of MPC to the selection of initial conditions by deriving the initial conditions from inference-based rules.

### Introduction

**Problem Statement.** According to a 2003 survey on commercial building energy consumption, heating, ventilation and air-conditioning (HVAC) systems are responsible for half of the energy consumed in commercial buildings (Energy Information Administration, 2006). Requirements for HVAC simulation and control are driven by a near-term trend toward performance-based design of buildings, and in a longer view, performance of buildings connected to the energy grid (Wetter et al., 2013). The importance of the control strategy in HVAC systems operation is due to several factors. First, as people experience and become more aware of the benefits of increased comfort in a (indoor) controlled environment, those experiences lead to higher expectations (Windham, 2014; Purdon et al., 2013). Second, there is a growing need

to reduce energy consumption, particularly of fossil fuels (Windham, 2014; Guo and Zhou, 2009). Advanced control algorithms are required to achieve low levels of energy consumption in commercial buildings. Unfortunately, state-of-the-art software tools are limited in their ability to simulate advanced controllers (Trka and Hensen, 2010). Some tools offer limited support for control, and others none at all. Domain-independent tools, such as Matlab, provide a computational framework for evaluating the mathematical aspects of model-based control, but are poorly suited for capturing the semantic knowledge of a domain and inference-based decision making for control. To address these challenges there is a need for new approaches to building simulation control that employ mixtures of formal and mathematical model-based control algorithms. One solution is to exploit Semantic Web technologies in the area of HVAC control. The Semantic Web provides an ontology-based, inference-based extensible framework to store and reuse data across different applications and domains. This approach has been adapted in the area of health care (Dung, T.Q. and Kameyama, W., 2007), biology (Taswell C., 2008), and transportation (Corsar et al., 2015).

During the past two decades, many researchers and experts in the area of building simulation have devoted considerable effort to the development and application of improved control methods. One area of interest is Model Predictive Control (MPC). MPC has received considerable attention (Faruque and Hourai, 2014; Privara et al., 2011) because it allows for input from sources such as weather forecasts, occupancy predictions, comfort ranges and actuation constraints. From a mathematical standpoint, MPC deals with modeling processes to optimize control outputs based on predicting how they will evolve in the future. The main purpose of MPC is to compute the control outputs to minimize an objective function, which is usually a function of the system states. The state space control model is used as

a constraint in the optimization problem. The MPC algorithm solves an incremental optimization problem over a time interval (prediction horizon), where the computed control output at the first time step is applied before the optimization is resolved and a new control signal is generated for the next time step in the prediction horizon. A second promising approach centers on use of Semantic Web technologies for the shared conceptualization of domains in the building environment, and tools for data-driven control. Together, these technologies offer solutions for semantically-rich inference-based control, and can deduce new implicit information for decision making through expressive features of Descriptive Logic (DL) based on the existing data.

**Objectives and Scope.** This paper presents a first step toward the integration of semantically-enabled control strategies with MPC optimization. Our prototype implementation creates ontologies, graphs of semantic concepts, and rules for capturing domain specific inference-based constraints.

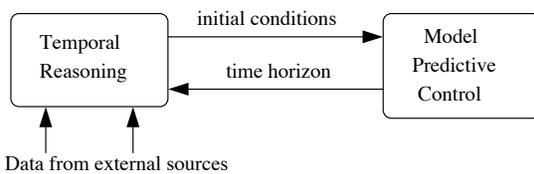


Figure 1: Architecture for coupled semantic/MPC HVAC system control.

A simplified architecture for simulation and control is shown in Figure 1. Initial conditions for the MPC stem from the semantic model and associated reasoning processes. The MPC provides time horizon information to the semantic model, which is combined with data from external sources. We will demonstrate the proposed approach on case study problem involving operation of a cooling, heating and power plant equipped with a thermal energy storage (TES) unit that is optimized for cost.

The remainder of this paper proceeds as follows: Section 2 contains a brief introduction to the uses of the Semantic Web and its enabling technologies. Section 3 explains the computational methods used in the case study. Results of the case study are presented in Section 4 and Section 5 discusses the next steps.

## Semantic Web Technologies in the Building Energy Domain

One goal in building automation and control is to emulate human thinking and inferencing processes. For our purposes, this can be interpreted as event-driven decision making and control with a semantic description of domains and associated rules. To achieve this goal, it is necessary to have network/Web access and awareness of the environmental and building system

state and formal systems for inferencing processes. The hypothesis of this work is that Semantic Web technologies can play a pivotal role in this approach.

The Semantic Web aims to give information a well-defined meaning, thereby creating a pathway for machine-to-machine communication and automated services based on descriptions of semantics (Berners-Lee et al., 2001). The realization of this goal will require mechanisms that can work and reason with data and semantic descriptions of data.

**Semantic Web Technologies.** Feigenbaum (2006) proposed the technical infrastructure that supports the Semantic Web vision known as Semantic Web Stack. In this architecture, each new layer extends, and provides compatibility with, the layers of technology below it. The lower layers provide capability for addressing resources on the Web, linking documents, and representing multiple languages. The extended markup language (XML) enables the construction and management of documents composed of structured portable data. The resource description framework (RDF) allows for the modeling of graphs of resources on the Web. An RDF Schema (RDFS) provides the basic vocabulary for RDF statements, and the machinery to create hierarchies of classes and properties. The Web Ontology Language (OWL) extends RDFS functionality. Together, these features and language capabilities provide the foundations for reasoning – deriving implicit additional facts that are not explicitly expressed by the ontology – with first order and descriptive logic. In the Semantic Web, a reasoner is software that can perform reasoning tasks typically for ontologies defined in OWL or RDFS.

It is argued that axiomatic systems are better candidates than non-axiomatic systems for representing the formal models to be used in the inferencing process (Krachina and Raskin, 2006). Axiomatic systems are systems composed of axioms. Many logic systems fall into the axiomatic category, e.g., first-order and descriptive logic. As a case, DL is the logical formalism for ontologies defined in OWL. Inference-based rules are the rules that define an inference of a new statement based on existing statements. An ontology-based approach relies heavily on expressive features of DL languages.

**Semantic Modeling.** Semantic models consist of ontologies, descriptions of individuals, and rules derived from engineering models. The ontology represents the concepts of the domain as classes and the relations between those classes as “Object Properties” (the connection between two objects of classes). As a case, they can represent the domain of mechanical equipment, weather, building, or occupant. Moreover, the classes may have attributes that are stored as a simple data type “Datatype Properties”. RDFS and OWL as ontology description languages can be

used to describe the semantic relationships between the concepts of the domain by the use of DL. Their purpose is to define ontologies that include classes, properties and their relationships to encode the semantics of the domain to be machine readable. Moreover, these languages provide means for the machine to effectively understand and reason about the contextual information. A context may refer to people, building, time, weather and so on.

Utilizing Semantic Web technologies for rule checking has several advantages: (1) Rules that represent policies are easily communicated and understood, (2) Rules retain a higher level of independence than logic embedded in systems, (3) Rules separate knowledge from its implementation logic, and (4) Rules can be changed without changing source code or the underlying model. A rule-based approach to problem solving is particularly beneficial when the application logic is dynamic (i.e., where a change in a policy needs to be immediately reflected throughout the application) and rules are imposed on the system by external entities. Both of these conditions apply to the simulation and control of energy systems in buildings

**A Trivial Example of Semantic Modeling.** Figure 2 shows an example of capturing domain specific constraints with inference-based rules.

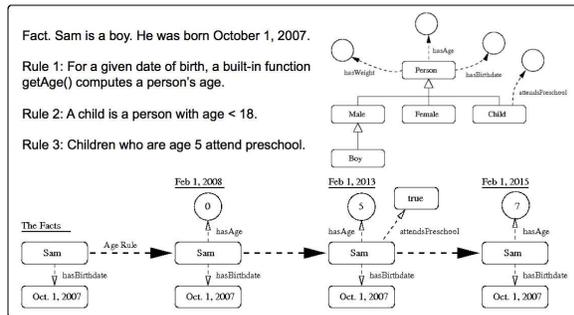


Figure 2: a simplified semantic models and rules Austin et al. (2015).

In the upper right of the Figure 2 is the relationship among classes and properties in a simplified family ontology. In this semantic model, a person has properties: `hasAge`, `hasWeight`, and `hasBirthDate`. A Child may (or may not) attend Preschool. The upper left of Figure 2 shows one axiom (fact) and three domain-specific rules. Sam is a boy born October 1, 2007. Given a birth date and a current time, a built-in function, `getAge()`, compute Sam's age. Further rules can be defined for when a person is also a child and when children attend Preschool. The schematic along the bottom of the Figure shows the evolution of a graph defining the properties of Sam, as a function of time. Some of the data (e.g., Sam's birth-date) remains constant over time. Other data (e.g., such as whether or not Sam attends preschool) is dynamic and is controlled by the domain-specific (fam-

ily) rules.

### Semantic Modeling in the Building Energy Domain

Figure 3 presents a framework for the generation and implementation of semantic models, reasoning, and design assessment in the building energy domain.

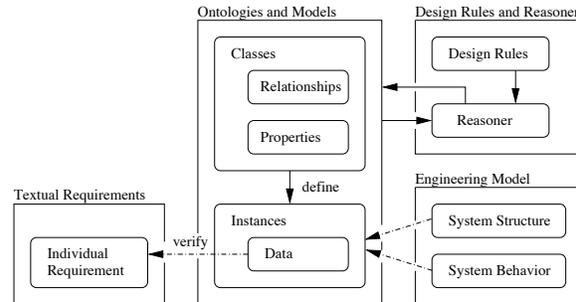


Figure 3: Framework for implementation of ontology-enabled design assessment (Delgoshaei, 2012).

In the building energy domain, the simulation results of physical models, e.g., Modelica, and Building Information Models (BIM), will determine the data in the ontologies. The fragment of code:

```
[Rule:(?t rdf:type TemperatureSensor)greaterThan(?r,23C)
(?t isLocated ?s)(?s rdf:type interiorSpace)
(?currentTime isSummerPeak true)->
resetSetPoint(?setPoint,20)]
```

shows, for example, how semantic concepts like “interiorSpace”, “isSummerPeak” can be used to capture a domain specific constraint for an inference-based rule to reset a temperature setpoint. The value of this approach is that these semantic definitions are adaptive and flexible to change. For example, the concept of “summer peak” may be defined differently in different HVAC controllers. Moreover, the concept of “interior space” will be defined once i.e., based on the number of exposed walls, and the inference-based rules will determine the category of each space based on that definition. This semantically-enabled approach will empower control techniques when used with physical-based control strategies i.e., MPC.

**Related Work.** Corry et al. (2015) 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. (2015) used a rule-based ontology reasoning for context-aware building management to reduce energy waste. They use Jena Rules for reasoning purposes in context and policy. Moreover, the framework has been tested for a real office to estimate the effect of energy saving measures. Furthermore, energy simulation was performed with and without the rule-based ontology system. The results were more promising in terms of lower energy waste when a rule-based ontology approach was used. Han et al. (2016)

utilizes ontology and inference rule sets for smart home control of appliances. Jena API was used to develop the ontology framework and the inference rule sets. Terkaj and Sojic (2015) explain the conversion of an EXPRESS schema representing Industry Foundation Classes (IFC) into an OWL ontology. IFC is the standard used for BIM. Beetz et al. (2009) developed a converter to transform any format using an EXPRESS schema, like IFC to RDF. Baumgrtel and Scherer (2016) study an optimization framework on green building design. They used the converted RDF from BIM models and provided input to the simulation model based on the values from the ontology.

## Methods

The proposed control employs a semantic model (consisting of an ontology and rule set) integrated into an MPC model. The predictive control approach will exploit dynamic models and predictions of zone loads, utility rates, and mechanical system models to minimize energy cost while meeting equipment and thermal comfort constraints. At each time step of the prediction horizon, the semantically-enabled control is called by the MPC unit to determine (via temporal reasoning) the applicable electricity rate tariff. The latter is based on time-variant electricity pricing (TOU) and set the inputs (i.e., electricity cost), or initial conditions (i.e., chiller mass flow rate), based on the inferred electricity rates (see Figure 4). Our prototype employs the Jena API (Apache Jena, 2016) to create an OWL model of ontologies for time and utility tariffs. Jena Rules are utilized to infer an applicable rate tariff during the MPC simulation.

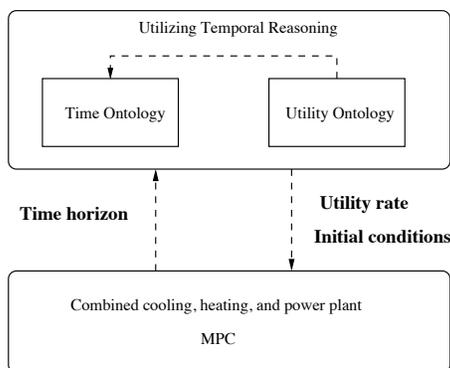


Figure 4: Multi-level control structure for HVAC systems.

In state-of-the-art HVAC control strategies, the operational schedule is fixed and based on the rate schedule. Our method, in contrast, utilizes the rate schedule defined in inference-based rules with MPC to find the optimal operating schedule, which has the advantage of providing a formal framework for choosing the right control strategy. As a case in point, it

has been shown by Braun (1992) that in chilled water plants, storage-priority control provided near-optimal performance when there were significant differentials between on-peak and off-peak energy charges. However, without TOU energy charges, chiller-priority performed better.

## Case Study Problem

The case study is based on the system and an MPC algorithm developed by Chandan et al. (2012) for modeling and cost optimization of a combined cooling, heating and power (CCHP) plant. The plant consists of seven electric chillers that can provide chilled water to a campus for cooling, a stratified thermal energy storage unit (TES), two generators, a gas turbine, a steam turbine, and a heat recovery unit. The plant supports co-generation, where the heat recovered from generators is utilized for production of thermal energy and electricity. TES is used to reshape the cooling demand during the course of a day by reducing the cooling load met by the chiller banks. The inputs to MPC are the cost of electricity and the building cooling load. The decision variables are the chiller mass flow rates, mass flow rate supplied to the building, the chiller supply temperature, the return temperature from the building, power supplied by the gas turbine, and power purchased from the grid.

**MPC Formulation.** Equation 1 is the objective function to be minimized by MPC with the prediction horizon of 24 hours. The first term represents the cost of electricity and the second term is the cost of fuel. Equation 2 captures the constraint on meeting the campus cooling demand with the chillers. Equation 3 shows the balance between the electricity purchased and consumed. The left hand side represents the total electricity purchased from the grid and generated on campus. The right hand side shows the campus electricity demand, pumps, chilled water plant, cooling tower fan, and chiller electricity consumption. Equations 2 and 3 are the system constraints for the objective function.

Objective function

$$J = \sum_{k=1}^{24} (1000c_{grid}(k)W_{grid}(k) + c_f(k)m_f(k)) \quad (1)$$

Cooling demand constraint: For all  $k = 1, 2, \dots, 24$

$$\sum_{i=1}^{n_{Chiller}} Q_{CHW,i}(k) = 1000Q_{Cooling}(k) \quad (2)$$

Electricity Demand Constraint: For all  $k = 1, 2, \dots, 24$

$$\begin{aligned}
 &W_{grid}(k) + W_{GT}(k) + W_{ST}(k) \\
 &= W_{Elec}(k) + \frac{1}{1000}(W_{P1}(k) + W_{P2}(k)) + \\
 &\frac{1}{1000}(W_{CHWP}(k) + W_{CWP}(k) + W_{CTF}(k)) + \quad (3) \\
 &\sum_{i=1} n_{Chiller} W_{COMP,i}(k)
 \end{aligned}$$

**Thermal Energy Storage Dynamics (TES).** The model employs a stratified two layer TES shown in Figure 5, where  $T_a$  and  $T_b$  denote the top and bottom layer water temperatures, respectively. The TES is operated in two modes. In charging mode the chiller bank will provide chilled water to the load and the TES. In discharging mode, chilled water from the TES and chiller bank are supplied to the load.

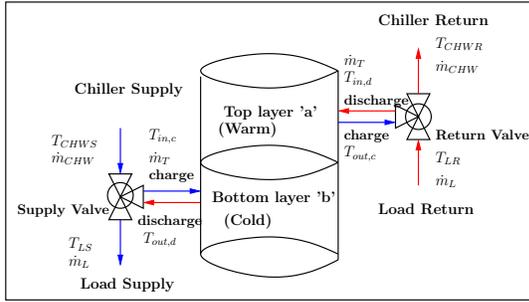


Figure 5: Schematic of the thermal energy storage.

Below are the equations to describe how the TES temperatures evolve over time in both charging and discharging modes. These equations also serve as constraints in the MPC formulation.

(a) Charging Mode Equations:

Overall Mass Flow Balance

$$\dot{m}_T = \dot{m}_{CHW} - \dot{m}_L \quad (4)$$

Top Layer Energy Balance

$$\rho c_{pw} \frac{dT_a}{dt} = f_{a,c} \dot{m}_T c_{pw} (T_b - T_a) + U_c A (T_b - T_a) \quad (5)$$

Bottom Layer Energy Balance

$$\rho c_{pw} \frac{dT_b}{dt} = f_{b,c} \dot{m}_T c_{pw} (T_{in,c} - T_b) + U_c A (T_a - T_b) \quad (6)$$

Supply Valve Temperatures

$$T_{in,c} = T_{LS} = T_{CHWS} \quad (7)$$

Return Valve Temperatures

$$\dot{m}_T T_{out,c} + \dot{m}_L T_{LR} = \dot{m}_{CHW} T_{CHWR} \quad (8)$$

(b) Discharging Mode Equations:

Overall Mass Flow Balance

$$\dot{m}_T = \dot{m}_L - \dot{m}_{CHW} \quad (9)$$

Top Layer Energy Balance

$$\rho c_{pw} \frac{dT_a}{dt} = f_{a,d} \dot{m}_T c_{pw} (T_{in,d} - T_a) + U_d A (T_b - T_a) \quad (10)$$

Bottom Layer Energy Balance

$$\rho c_{pw} \frac{dT_b}{dt} = f_{b,d} \dot{m}_T c_{pw} (T_a - T_b) + U_d A (T_a - T_b) \quad (11)$$

Supply Valve Energy Balance

$$\dot{m}_T T_{out,d} + \dot{m}_{CHW} T_{CHWS} = \dot{m}_L T_{LS} \quad (12)$$

Return Valve Temperatures

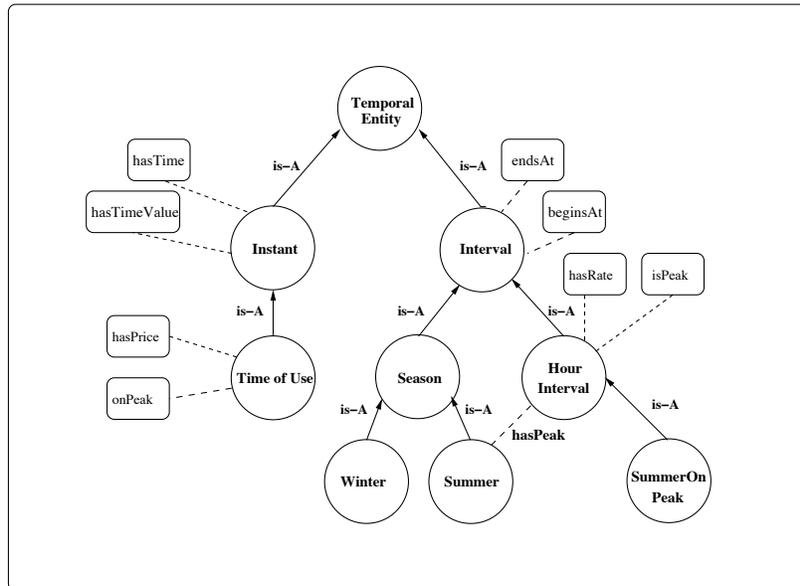
$$T_{in,d} = T_{CHWR} = T_{LR} \quad (13)$$

Equation 14 illustrates the heat transfer rates in charging and discharging modes. Here,  $Q_{CHW}$ ,  $Q_L$ ,  $Q_T$ , and  $\delta$  are chilled water heat transfer, campus demand, thermal storage heat transfer, and the thermal storage control signal, respectively.

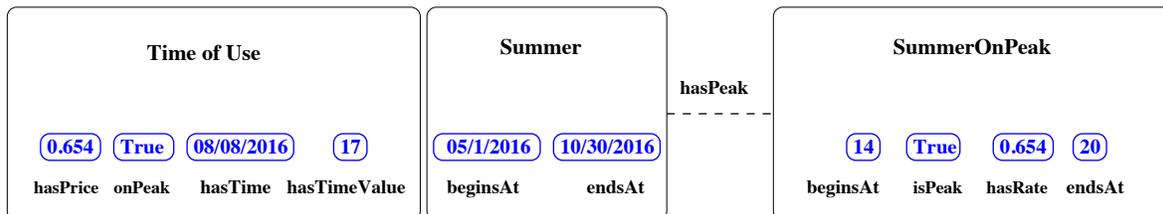
$$Q_{CHW} = \delta(Q_L + Q_T) + (1 - \delta)(Q_L - Q_T) \quad (14)$$

**Time and Utility Ontology and Rule Sets.**

The semantic modeling expands the temporal framework developed by Petnga and Austin (2013). It uses Jena API (Apache Jena, 2016) to create an ontology for defining electricity tariffs by extending the concepts from the Time ontology. Temporal reasoning is achieved by defining rules that reason about time. For example, temporal reasoning is used to determine if a specific point in time is in an interval, or if an interval of time happens before another interval. The classes of the Utility ontology are extensions from the Time ontology. Figure 6a depicts the concepts and the relationships between them in the Utility ontology. In this model, a time concept belongs to the categories of "Interval" or "Instant". The concept of "Interval" represents any duration, i.e., season, on/off/mid peak hour intervals. A concept may have datatype properties that are shown as rectangles attached to the concept. For example, the "hasTime" property stores the date and time values of an "Instant" in time. This general ontology will be used for different cities to represent their electricity tariff structures.



(a) Utility Ontology



(b) Section of the Utility ontology for city of Austin, Texas

Figure 6: Utility tariff ontology.

**Jena Rules**

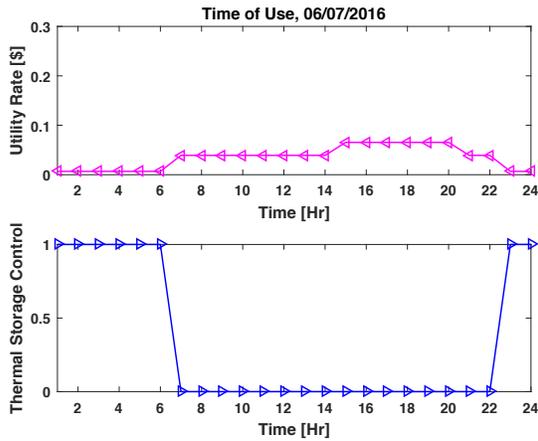
```
[Rule1: (?x rdf:type te:TemporalEntity) (?y rdf:type te:Instant) (?x te:beginsAt ?t1) (?x te:endsAt ?t2)
lessThan (?t1, ?t2) (?y te:hasTime ?t3) lessThan(?t1,?t3) greaterThan(?t2,?t3)
-> (?y te:isInInterval ?x) ]

[Rule2: (?season rdf:type te:Season) (?interval rdf:type te:TemporalEntity) (?season te:hasOnPeak ?hourInterval)
-> (?hourInterval te:isPeak "true"^^xs:boolean) ]

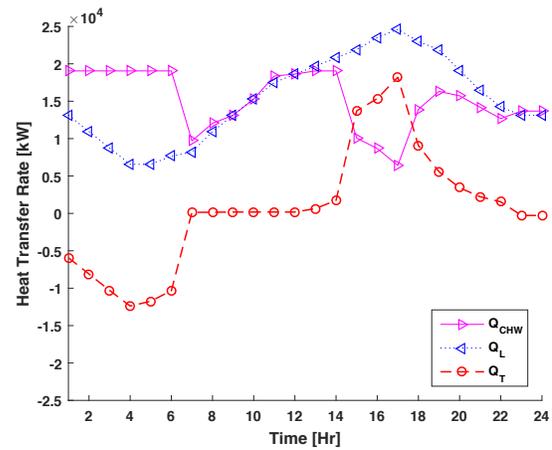
[Rule3: (?t te:isInHourInterval ?interval) (?interval te:isPeak ?peak)
-> (?t te:onPeak ?peak)]

[Rule4: (?tou rdf:type te:TimeOfUse) (?tou te:isInInterval ?season) (?tou te:hasTimeValue ?time)
(?tou te:isInHourInterval ?hourInterval) (?interval rdf:type te:Season)
(?interval te:hasPeak ?hourInterval) (?hourInterval te:hasRate ?rate) (?tou te:isInInterval ?interval)
-> (?tou te:hasPrice ?rate) ]
```

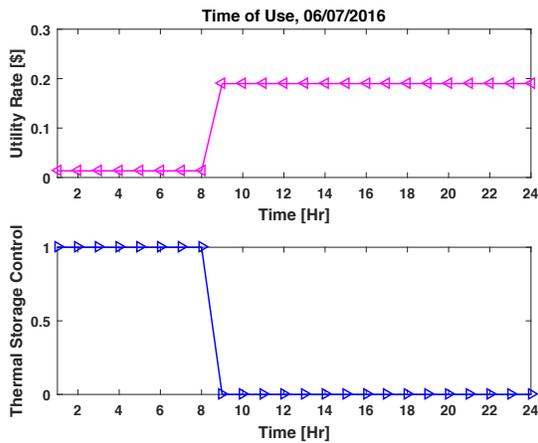
Figure 7: Sample OWL rules for Utility ontology.



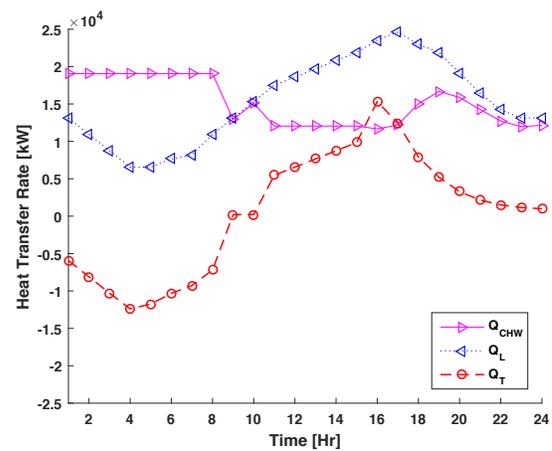
(a) Austin summer TES control



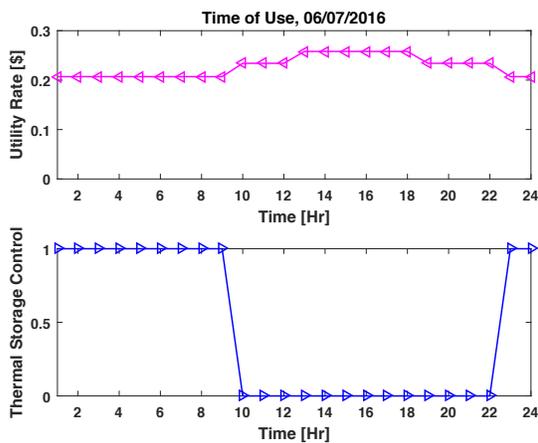
(b) Austin summer Q



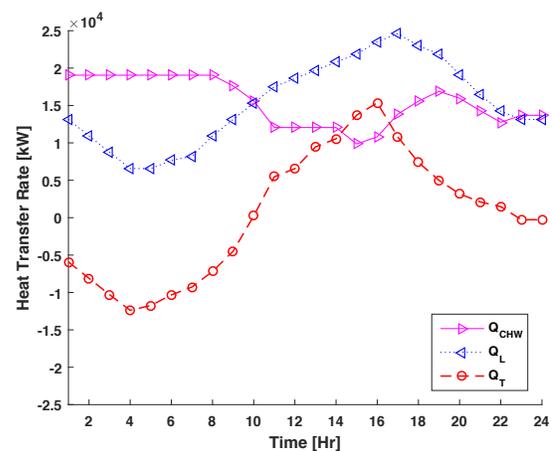
(c) New York City summer TES control



(d) New York City summer Q



(e) San Francisco summer TES control



(f) San Francisco summer Q

Figure 8: Simulation results for Austin, New York City and San Francisco; For TES 1=charge and 0=discharge

Figure 6b shows parts of Utility ontology for the city of Austin. As shown, the summer season in this city begins on 05/01 and ends on 10/30. During this season from 2 p.m. to 8 p.m. are on-peak hours. The electricity rate tariff is based on Time of Use (TOU) which breaks up the day into two or three time intervals, i.e., off-peak, on-peak, mid-peak. In addition, months are categorized as either the heating or cooling season. This approach encourages customers to shift the load away from the times of the day that demand and rates are higher. However, it does not necessarily lead to less energy consumption during critical peak periods, such as heat waves. As depicted in Figure 4, at the beginning of the time horizon, the MPC optimization routine acquires the predicted utility rate and initial conditions for the decision variables from the ontology. Figure 7 displays some sample Jena rules used in the case study. The Utility ontology receives the “Time Of Use” from the MPC routine and determines the season of operation through Rule1. Following that, Rule2 decides which rate category (on/off/mid) the time of use is in. Rule3 sets the flag of “onPeak” equal to the value of “isPeak” in that time interval, i.e., if time of use is in the on-peak category, the flag is set to “true”. Finally, Rule4 extracts and deduces the cost of electricity based on the hour and date of use.

## Results

The integrated approach provides a pathway toward robust strategies of control that take into account not only the physical constraints, but also the domain specific constraints and regulations of the operating environment. The numerical experiments indicate that MPC converges faster if inputs and initial conditions for the decision variables are obtained based on inferred results of the semantic rules. In this study the initial conditions for chiller mass flow rates are computed from Equation 4 if the semantic model determines the time is off-peak and TES should be charged.

Figure 8 shows the results of the simulation with integrated control. The MPC control method was tested under three different rate tariffs structures associated with Austin, New York City, and San Francisco. The benefit of defining the rate tariff in a semantic model and inference-based rules is that the MPC method is unchanged even as the electricity tariff structure is changed. It is important to note that all three case studies use the same temporal logic (rule sets), however, different ontologies are created for each city to represent the semantics of the electricity tariff for that specific city.

Figure 8a, bottom, shows the thermal storage control signal (i.e., 1 charge and 0 discharge) based on the inferred electricity rate for the city of Austin. Note that the discharging process begins when the elec-

tricity rate increases (depicted on the top), during the on-peak and mid-peak periods. Figures 8c and e depict the rate structure and the TES control signal during a specific TOU in NYC and San Francisco, respectively. The impact of the TES control strategy on chiller cooling loads for the city of Austin is shown in Figure 8b. Figures 8d and f illustrate the chiller, TES and campus heat transfer rates for New York City and San Francisco, respectively. Note the difference between TES heat transfer rates between these three cities. NYC and Austin benefit more from TES during peak periods as compared to San Francisco due to the small deviations between on- and off-peak rates (a flat rate structure). The operational cost of the plant on the simulated day is \$26,654, \$32,900, \$20,700 for NYC, San Francisco, and Austin, respectively. In terms of the simulation time, NYC, with three utility rate variations during a day, requires less computational time than Austin and San Francisco which each have five utility rate variations. The elapsed time using a personal desktop with Core i7-4470 3.4GHz CPU and 32 GB RAM was 263.3, 437.5, and 314.2 seconds for NYC, San Francisco, and Austin, respectively.

## Discussion

This work is an attempt to integrate the semantic constraints of a certain domain (regulations) with physical constraints described as mathematical equations. In our example, different utility tariff regulations were represented as inference-based rules. The next logical step is to expand the framework to include multiple domains along with their semantic constraints, i.e., building, mechanical equipment, occupants. The physical models and MPC will interact with these semantic models as shown in Figure 9. And the results of physical simulations will provide inputs to MPC and the ontologies. Consequently, they will receive inputs for system properties and setpoints from MPC or inference-based rules. Future work will include improvement of the MPC formulation to better represent the underlying physical model. For example, the present case study problem formulation does not include level-of-charge in the storage. As a result, full storage discharge strategies can not be considered. Moreover, the current MPC formulation solution method (Newton’s method) is very sensitive to the initial conditions. Therefore, a more robust solution method is required.

## Conclusion

This paper introduces a cross-disciplinary (i.e., computer science and engineering) approach for building simulation control. This control strategy uses semantic-based control integrated with MPC control. To demonstrate the concept, this control strategy is adapted for a CCHP plant. The inference-based control utilizes time and utility tariff ontologies along

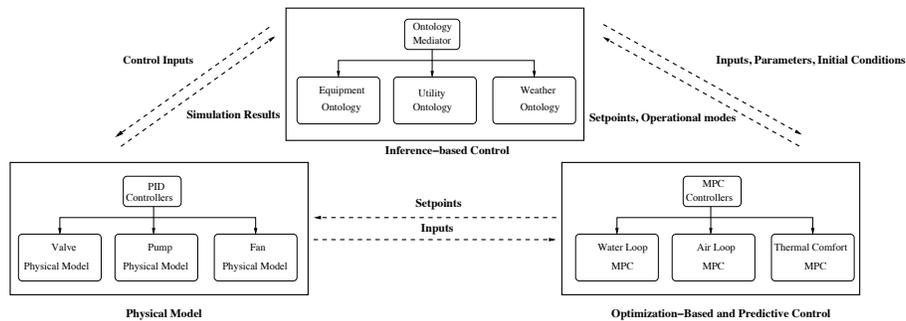


Figure 9: Hybrid control architecture for building simulations.

with rule sets enabling temporal reasoning to obtain the appropriate rates in three different locations. The inferred outputs from the ontology provide inputs and a set of initial conditions to the MPC. The simulation results reveal that the inferred initial conditions from the ontology yield better results and faster computation time for MPC as compared to the guessed initial conditions. Moreover, modeling with ontologies and rule sets will provide an easy to use, scalable, and adaptive framework to capture the regulations and constraints of the domain, i.e., it is convenient to modify or add new rate tariffs without changing the underlying control implementation. Another advantage is that unlike the mathematical constraints, the rules are defined in English-like syntax that is also machine readable. Lastly, the inference-based rules can potentially play the role of a preprocessor for MPC simulations. We expect that a mature implementation of cross-disciplinary control will employ semantic models and inference-based rules from a multiplicity of domains (e.g., building, equipment and occupants), and enable inference of information from heterogeneous domains. This inferred information will be an input to physical control models such as MPC for better control outcomes.

## Acknowledgment

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Subscript	Description
<i>CHW</i>	Chilled water
<i>i</i>	Chiller number
<i>P</i>	Pump
<i>L</i>	Load/campus
<i>T</i>	TES
<i>w</i>	Water
<i>f</i>	Fuel
<i>S</i>	Supply water stream from chiller/to campus
<i>R</i>	Return water stream to chiller/from campus
<i>a</i>	Top layer in 2-zone TES model
<i>b</i>	Bottom layer in 2-zone TES model
<i>in</i>	Inlet stream to TES/HRSG
<i>out</i>	Outlet stream from TES/HRSG
<i>GT</i>	Gas turbine
<i>ST</i>	Steam turbine
<i>grid</i>	Electricity grid
<i>elec</i>	Campus electricity load
<i>cooling</i>	Campus cooling load
1	Steam used to derive ST
2	Steam used for campus load heating
<i>c</i>	TES charging mode
<i>d</i>	TES discharging mode

Symbol	Description
<i>T</i>	Temperature ( <i>K</i> )
<i>Q</i>	Cooling consumed/produced ( <i>kW</i> )
<i>W</i>	Power consumed/produced ( <i>kW</i> )
<i>ṁ</i>	Mass flow rate ( <i>kg/s</i> )
<i>m</i>	Mass flow( <i>kg</i> )
<i>ρ</i>	Density of water ( <i>kg/m<sup>3</sup></i> )
<i>δ</i>	Thermal storage control (∅)
<i>c<sub>p</sub></i>	Specific heat capacity ( <i>kJ/kg – K</i> )
<i>A</i>	Area of TES tank ( <i>m<sup>2</sup></i> )
<i>c</i>	Unit cost of energy source ( <i>\$/kWh</i> for electricity) and ( <i>\$/kg</i> for fuel)

Acronym	Description
BIM	Building Information Models
CPP/CPR	Critical Peak Pricing/Rebate
DL	Descriptive Logic
HVAC	Heating, Ventilation and Air-Conditioning
IFC	Industry Foundation Classes
MPC	Model Predictive Control
OWL	Web Ontology Language
RDFS	Resource Description Framework Schema
RTP	Real Time Pricing
TES	Thermal Energy Storage
TOU	Time of Use
XML	Extended Markup Language

## Nomenclature