Case Study Review: Prediction Techniques in Intelligent HVAC Control Systems

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ABSTRACT

Heating, ventilation, and air conditioning (HVAC) is a type of service that consumes energy and usually results in greenhouse gas emissions. Likewise, HVAC is a critical service that provides comfortable, healthy and productive indoor environments for building occupants. As growing energy consumption of HVAC systems and demands of indoor thermal comfort, researchers are exploring intelligent control to relieve this increasing pressure on the buildings and facilities. This paper summarizes the control structure, provides a review on prediction techniques of intelligent HVAC-related systems, and also presents control methods that used this forecasted information to minimize energy consumption and maximize thermal comfort.

KEYWORDS

HVAC; energy savings; thermal comfort; prediction and learning; optimization

1 INTRODUCTION

HVAC systems are comprised of sophisticated and multi-input multi-output engineered equipment that provides space heating and cooling energy as well as fresh air to occupied buildings (Hordeski, 2001). However, the design of HVAC control systems is becoming complex due to the increasing pressure on buildings and facilities to achieve energy conservation in addition to enhancing thermal comfort. The complexity can be attributed to several factors. Firstly, energy savings is strongly influenced by weather conditions, occupants' presence schedule, usage rate, and building characteristics, many of which vary stochastically (Braun, 2003). Secondly, thermal comfort preferences are subjective, affected differently by occupants' health levels, ages and genders, living areas and so on.

Local control, such as two-position (i.e. on and off) control and proportional, integral and derivative (PID) control, is widely used in present-day HVAC systems. This type of controller, however, is designed mainly to ensure indoor climates are conditioned to expected set-points (e.g. indoor temperature, relative humidity, and CO2 concentration) with limited capability regarding energy savings and thermal comfort in applications. In the research literature, one of the advancements in building control theory that has yielded promising results towards the improvement of both energy savings and occupant comfort is 'prediction' – the ability to forecast future exogenous parameters that affect HVAC operation, such as weather, occupant presence, and preferences. The weather forecast was used to optimize set points for energy savings (ASHRAE, 2011). Real-time and forecasted occupants' presence data was employed for demand-driven HVAC control (Erickson and Cerpa, 2010). The information on thermal preferences over time can drive HVAC system to offer person-centric comfort environments (Manna et al., 2013).

To explore this research trend, this paper selects and reviews ten intelligent HVAC-related systems according to three criteria. Firstly, they were developed in buildings spanning three different typologies: dwellings, office buildings, and classrooms. Secondly, these intelligent systems have used various prediction techniques together with optimal control, rule-based control, or other advanced control methods to respond automatically to climate and occupant presence as well as thermal preferences. Thirdly, most of them have been evaluated by measurements in real building contexts. Meanwhile, this paper not only analysis the control structure and algorithms in detail but also discuss the advantages and disadvances in this area.

The subsequent sections of this paper are arranged as follows. Section two gives an overview of the reviewed control systems, otherwise called projects in this paper, and summarizes their control structures. Section three presents algorithms exploited by these control systems in terms of predicting climate and occupants' presence as well as thermal preferences. Section

four reviews the various employed control strategies that use predicted information to improve HVAC operation. Finally, the conclusion of the study is provided in Section five.

2 THE OVERVIEW OF INTELLIGENT HVAC-RELATED CONTROL SYSTEMS
2.1 Project introduction
The development of intelligent HVAC control is an emerging topic, aiming to provide more comfortable indoor climates and require less energy use. This section introduces reviewed intelligent systems featuring various degrees of prediction with or without learning capacity, including six HVAC control systems and four ambient intelligent systems that integrated heating and cooling control.

To start, the NEUROBAT (Morel et al., 2001), a heating controller, was integrated with predictive capacities to allow itself adapt to climate, building characteristics and occupants using artificial neural networks (ANN). When compared to "advanced" and "low cost" controllers respectively, it achieved 13% and 55% energy savings both in a selection of residential houses and commercial buildings in Switzerland.

An HVAC control system developed by Dong et al. (2010; 2014) employed a model predictive control (MPC) and took account into the prediction of climate and occupancy patterns to obtain energy savings and maintain the indoor temperature. The experiment was implemented in a solar decathlon house used as offices at Carnegie Mellon University. Test results showed that energy savings of 26% for heating and 17.8% for cooling were achieved when compared to a control system based on scheduled control. Similarly, the OptiControl Project (Gwerder et al., 2013; Oldewurtel, 2011) developed an MPC HVAC system by incorporating the prediction of climate, room occupancy and electricity prices. The test was carried out in a typical Swiss office building, equipped with a central air handling unit and water-based heating and cooling systems. In their qualitative benefit-cost assessment, the MPC system realized best comfort and energy savings when compared to five rule-based HVAC controllers, and required highest development and engineering as well as instrumentation costs.

A heating and cooling control system developed by Ferreira's team (2012) combined ANN and model-based predictive control (MBPC) for energy conversation and thermal comfort. Compared with the same HVAC system without the intelligent control, this control system saved 37% energy when tested in classrooms of the University of Algarve.

Dalamagkidis et al. (2007) simulated an HVAC control system using reinforcement learning to balance energy and thermal comfort based on energy evaluation and thermal preferences. The simulation showed that a larger energy consumption was caused by changing control policy and a greater weight of comfort when compared to a two-position controller and a fuzzy proportional, derivative (PD) controller. They suggested longer training time and more information of environment can improve control performance. Another HVAC control system that developed by the MASBO project (Booy et al., 2008; Chee et al., 2007) aimed to create a person-centric comfort indoor environment using multi-agent technology for learning and predicting occupants' preferences (e.g. temperature, humidity).

Similarly, another four ambient intelligent systems are introduced in this paragraph. In a residential house located in Marshall, Colorado, the ACHE system (Mozer et al., 1997; Mozer, 1998) aimed to offer a comfortable living space with learning occupants' behavior and preferences. The system combined occupancy predictor and optimal control to reduce energy consumption with the regulation of indoor air temperature, ventilation, lighting, and water temperature. For an office building located at Swiss Federal Institute of Technology in Lausanne, Guillemin (2003) developed a shading, electric lighting, and heating control system. Compared to a manual controller, its lighting and heating system showed 26% energy savings by integrating predictive features (e.g. forecasted outdoor weather and indoor temperature). In an attempt to manage the energy of appliances at residential buildings, AIM project (Capone et al., 2009; Barbato et al., 2009) monitored, learned and predicted occupants' presence and preferences for heating, cooling and lighting control. The iDorm project (Doctor et al., 2005; Hagras et al., 2004) used embedded agents to create a person-centric comfortable dormitory in University of Essex. The fuzzy logic was used in the agents to learn and predict occupants' needs for lighting, heating, appliance, and entertainment's systems, and then generate rules to control the actuators in this multi-use space.

2.2 The control structure of intelligent HVAC systems

On the assessment of these intelligent systems, it is found that the following block diagram showed in Figure 1 can characterize the 'intelligent' components of these systems into two layers: 1) prediction, 2) energy and comfort improvement.
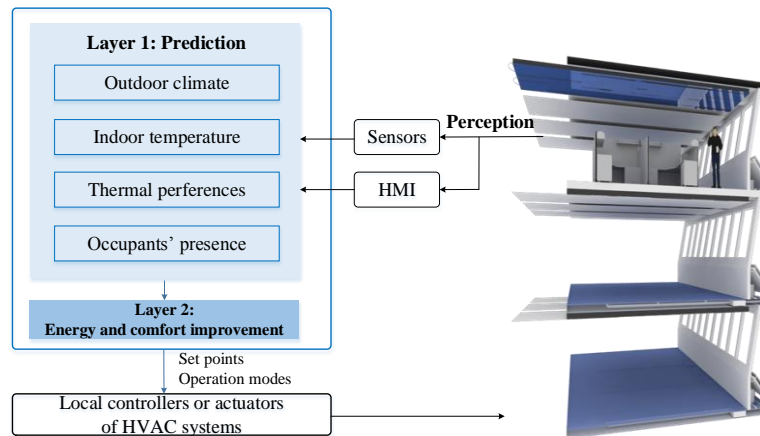

Figure 1. General block diagram of HVAC systems with prediction

The first layer, prediction, yields forecasted information of occupants and environment with the data collected by sensor networks and Human Machine Interface (HMI). The second layer incorporates these predictions to optimize or determine time-dependent set points or operation modes for the local controller or actuators in HVAC systems. Regarding the HVAC-related control in these systems, prediction algorithms in the layer one and control methods in the layer two are summarized in Table 1. The following two sections present and discuss these algorithms and methods that utilized in these two control layers across the reviewed projects.

Table 1. Comparison of HVAC-related control

Projects	Layer 1: Prediction				Layer 2: Improvement of Energy or Comfort
	Outdoor Weather	Indoor Temperature	Occupants' Behavior		
			Presence	Thermal Preferences	
NEUROBAT	ANN	ANN		Fuzzy Logic	Cost function with dynamic programming
Dong's system	Hammerstein Wiener, Gaussian Process	Resistance-capacitance network(RCW)	Semi-Markov Model		MPC
OptiControl	MeteoSwiss weather forecast and local validation	Dedicated RCW	Non-homogenous Poisson process model		MPC
Ferreira's system	ANN	ANN		ANN	MPC
Dalamagkidis's system				Adaptive simulator	Reinforcement learning
MASBO				Multi-agents	Rule-based control
ACHE		First order RCW	ANN with lookup table		Cost function with exhaustive searching
Guillemin's system	ANN	Two-node RCW			Proportional control
AIM			Statistical method	Statistical method	Rule-based control
iDorm				Fuzzy logic	Fuzzy logic

3 PREDICTION IN THE INTELLIGENT HAVC SYSTEMS

The reviewed systems used different methods with or without learning capacity to implement predictive features in their HVAC systems, such as advanced control (e.g. fuzzy logic), physical models, statistical models, machine learning, among which machine learning was used mostly. This section presents research into predictions of climate (e.g. outdoor climate and indoor temperature) and the occupants' behavior (e.g. presence and thermal preferences).

3.1 Outdoor climate

The outdoor weather forecast is required for an HVAC system with MPC, and also be used as inputs of indoor climate prediction models for other optimal control algorithms. The outdoor

climate prediction in the reviewed projects considered local outdoor solar radiation, temperature, humidity, and wind speed for HVAC control.

ANN, used as supervised machine learning here, was employed in three reviewed systems for outdoor climate prediction. The NEUROBAT (Morel et al., 2001) used two ANN models with Levenberg-Marquart algorithm for the outdoor climate prediction. Regarding the prediction of external solar radiation over a six-hour timeframe, they compared eight prediction models (e.g. two reference modules, three linear modules, two stochastic models and an ANN model). The ANN model with learning capacity offered the authors' best prediction. The inputs of this model included time, maximum outdoor temperature variation and so on. Meanwhile, the authors also compared four models (e.g. a reference model, two linear models, and an ANN model) for the prediction of external temperature from one hour to six hours. The ANN model also gave a better prediction than other means. In a similar manner, Guillemin's system (2003) used an ANN model with one hidden layer, four neurons, and the Levenberg-Marquart training algorithm to predict relative solar radiation. The ANN's inputs included solar radiation data and maximum solar irradiance value. Also, Ferreira's project (2012) utilized three radial basis function ANNs to predict outdoor air temperature, air humidity, and global solar radiation respectively. Meanwhile, the authors employed a multi-objective genetic algorithm to determine the number of neurons.

Dong et al. (2010; 2014) assumed the prediction of short-term outdoor climate was important for their HVAC system. So, they used Hammerstein-Wiener models to forecast hourly outdoor temperature and solar radiation, and employed a machine learning method – Adaptive Gaussian Process to predict outdoor wind speed based on learning from previous samples.

Different from above local outdoor climate predictions with machine learning or stochastic processes, the OptiControl project (Oldewurtel, 2011) used local weather forecast data (i.e. outside air temperature, wet bulb temperature, and solar radiation) from MeteoSwiss directly. The weather forecast was delivered hourly for following three days with an update cycle of twelve hours. The project's researchers integrated Gaussian noise into an error model to reduce weather disturbances and measured local weather data to avoid errors caused by the distance between the building location and MeteoSwiss.

3.2 Indoor temperature
This section summarizes two main types of models exploited in the reviewed HVAC control systems for the prediction of indoor temperature. The first type is the building thermo-physical model, and the second type is the thermal behavioral model (Morel et al., 2001). The inputs of these models could be historical, current and forecast outdoor climate data; previous and current indoor climate data; control operation signals.

Building characteristics primarily decide the response of the internal space of a building to the outdoor weather. Influential factors include the various construction materials, sizes of internal space, geometries, and so on. These, in turn, contribute to a building's overall thermal mass, insulation, infiltration resistance, etc. A building physical model that incorporates characteristics of a building can predict indoor climate (Crawley et al., 2008). In general, building thermo-physical models are usually thermodynamic models based on resistance-capacitance (RC) networks. Many of the reviewed studies have made use of the RC-based method to predict the indoor temperature in HVAC control systems.

For examples, the ACHE system (Mozer et al., 1997) used a first-order RC equation as the thermal model of the house and its furnace to predict indoor air temperature. Measured outdoor air temperature, current indoor air temperature, and operational status were the inputs of this model. In Guillemin's research (2003), a physical room model based on two nodes was employed: one node was used for indoor temperature and the thermal capacity of furniture, and the other one was for thermal mass of walls, floor, and ceiling. This model also incorporated the additional factors such as the internal thermal gains caused by occupants and electrical equipment. Similarly, Dong's team (2010; 2014) and the OptiControl project (Gwerder et al., 2013; Oldewurtel, 2011) utilized dedicated multi-node RC thermal models of buildings to predict indoor climate.

One of the disadvantages of deploying RC models is that the RC structure and its parameters need to be tailored and validated for each unique application. That leads to high

implementation costs. As an alternative, two of the reviewed HVAC control systems proposed machine-learning-based thermal behavioral models to learn automatically from datasets for the indoor temperature prediction.

NEUROBAT (Morel et al., 2001) built up an inhabited building behavior module using ANN. It could predict indoor air temperatures over a six hour period using data on the following parameters: 1) forecasted outdoor air temperature and solar radiation, and 2) indoor air temperature, heating power offered by a sample vector. Also, Ferreira (2012) exploited two sets of radial basis function ANNs to predict indoor air temperature and humidity for its HVAC system. The inputs of ANNs included indoor and outdoor air temperature and humidity, outdoor global solar radiation, and indoor air temperature set points. They showed appropriate forecast accuracy when tested both in summer and winter.

3.3 Occupants' presence
Scheduled presence profiles are suitable for some public spaces that are occupied regularly or invariably. In reviewed projects, the NEUROBAT project (Morel et al., 2001) and Guillemin's system (2003) used scheduled timetable for occupants' presence. However, in most indoor thermal zones, occupants' presence is stochastic. The poor anticipation of occupants' behavior can increase building energy use by over one third (Nguyen and Aiello, 2013). To maximize the energy savings, the following projects used statistical methods and machine learning to predict occupants' presence for the HVAC control.

Three of reviewed intelligent HVAC control proposed daily occupancy prediction (i.e. short-term vacancy and presence). The ACHE project (Mozer, 1998) developed an occupancy predictor using the data from motion detectors. It tested three diverse occupancy predictor approaches: a lookup table, an ANN, and an ANN with look-up table respectively. The test showed the ANN with look-up table generated the best prediction. The look-up table recorded the possible structures of occupants' schedule, and ANN with three layers learned and informed the rest of the uncertain structures. Inputs to this ANN included the present time of day, the day of the week, the average proportion of time that the studied building zone was occupied in the 10, 20, 30 minutes from the current time of day to the previous three days. Different from ACHE's occupancy predictor, more sensors were exploited in Dong's HVAC system (2010) to collect data on acoustics, illumination, motion, CO2 concentration, temperature, and relative humidity for evaluating the occupants' presence and the number of occupants. The occupant number prediction employed a Gaussian Mixture Model to classify the changes of the selected features and used a method from machine learning - a Hidden Markov Model to estimate the number of occupants. Meanwhile, a daily occupancy predictor was exploited using a Semi-Markov Model. In addition, the AIM project (Capone et al., 2009; Barbato et al., 2009) developed a presence profile to predict occupants' behavior for each thermal zone. In an initial observation period spanning several weeks or months (off-line mode), daily data of room occupancy and vacancy were collected by sensor networks, and then were clustered by cross-correlation to generate daily presence profiles based on the probability distribution. Moreover, these statistical profiles can be updated online by Local Updating Algorithm (LUA).

Different from above daily occupancy prediction, the OptiControl project recommended the prediction of long-term vacancies (such as annual leave, business trips, and holidays, etc.) for indoor climate control in commercial buildings. This may have been for good reason, researchers in the OptiControl project (Oldewurtel, 2011) investigated the importance of the occupancy prediction and simulated energy savings potential from the prediction of the long-term vacancy in HVAC systems. They concluded that adapting HVAC control to account for long-term occupant vacancies could yield an energy conservation potential of 34% in some scenarios. They analyzed five-year occupancy data of a Swiss commercial building and employed a prediction method similar to that used by Wang et al. (2005) (e.g. a non-homogeneous Poisson process model with two exponential distributions). The difference is OptiControl project used that in the prediction of vacant days to instead of the vacancy prediction in minutes and hours.

3.4 Occupants' thermal preferences
The fuzzy logic technique was widely explored in research on building control, Kolokotsa (2007) reviewed applications of fuzzy logic on buildings regarding thermal comfort, indoor

air quality, visual comfort, energy savings, and so on. Two surveyed intelligent systems exploited this technique to achieve the indoor thermal comfort. The occupant's adaptation blocks in NEUROBAT (Morel et al., 2001) used fuzzy logic to produce comfort temperatures based on occupants' set points. The iDorm system (Doctor et al., 2005; Hagras et al., 2004) employed fuzzy logic to learn occupants' preferences like indoor air temperature and lighting levels, then generate rules for control.

Another three projects used various algorithms to achieve local occupants' thermal preferences. In the AIM project (Capone et al., 2009; Barbato et al., 2009), occupants' temperature set point for each room was collected by sensor networks. Statistical temperature profiles were produced together with presence profile at the end of the observation period, and were updated online by LUA. For some purposes including HVAC control, the MASBO project (Booy et al., 2008; Chee et al., 2007) used personal agents to learn occupants' preferences - temperature and humidity. It observed the environment with a wireless sensor network recorded occupants' interactions (i.e. set points) by a thermostat, managed a profile of occupants' preferences that stored in the agent as a parameter vector (i.e. indoor temperature, humidity, and air quality), and adjusted rule set to meet occupants' personal requirements. In Dalamagkidis's simulated HVAC system (2007), an Adaptive Occupant Satisfaction Simulator (AOSS) was used to explore occupants' comfort satisfaction. This AOSS combined indoor and outdoor conditions together with occupants' satisfaction scales.

However, many open spaces within commercial buildings are shared by multiple occupants, each with their own intrinsic preferences on thermal comfort. Different from above projects, the OptiControl project (Oldewurtel, 2011) did not learn and predict local occupants' preferences by HMI for its studied commercial building. Instead, it used two ranges of thermal comfort (i.e. narrow and wide ranges) to achieve energy savings and avoid comfort violence frequently. An exponential weighted moving average function of previous measured outdoor air temperature data was used to calculate the actual indoor thermal comfort range at a relevant time, and the calculation of this moving average was the same as described in EN 15251(CEN, 2007). For another type of open area application – classrooms, Ferreira's project (2012) used a radial basis function ANN with five neurons to regress a Fanger's Predictive Mean Vote (PMV) index function for predicting mean thermal sensation.

4 IMPROVEMENT OF ENERGY SAVINGS AND THERMAL COMFORT
This section presents the control methods that were used to optimize or determine real-time HVAC operations based on the forecasted information from the prediction layer.

4.1 Optimal control
The term 'optimal control' on controls of an HVAC system here refers to an application that maximizes the cost-effectiveness of an HVAC system without sacrificing thermal comfort and air quality requirements. Wang et al. (2008) reviewed prominent optimal control methods and discussed their relevant strength and weaknesses. A few relevant optimal control studies on energy efficient and comfort were found in reviewed intelligent HVAC-related systems, and are presented in this section.

In the ACHE system (Mozer et al., 1997; Mozer, 1998), a cost function was used to express the expected average cost for the studied residential heating system. The cost function was comprised of two components. One is the energy cost based on the use of electricity and gas resources for primary energy needs, which mainly depended on the control decision. The other component was the discomfort cost incurred when occupant thermal comfort requirements would not be met, which relied on occupancy status and indoor temperature. This discomfort cost used an economic loss model covered the salary and productivity loss per hour for the residential household. Also, the control system exhaustively searched for the minimum expected cost from a set of decisions generated by the control. Similarly, NEUROBAT (Morel et al., 2001) used another cost function to optimize energy cost and discomfort cost over six hours based on predicted indoor temperature, sample vector of heating power, and comfort temperature. The energy cost was attributed to the primary energy consumption of heating systems, and the discomfort cost was inferred from occupants' perceived deviations away from the PMV. A dynamic programming algorithm was used to calculate the optimal heating command.

MPC, a constrained optimal control, was used as the basis for the optimization of energy consumption with comfort constraints in a number of HVAC control systems (Samuel et al., 2011). In Dong's system (2010), OptiControl project (Oldewurtel, 2011), and Ferreira's HVAC system (2012), MPC was employed to optimize control operations in a certain time horizon based on the forecasted information from the prediction layer (e.g. indoor and outdoor climate, occupancy, and electricity price) together with thermal constraints.

Reinforcement learning, a type of machine learning, can also be used as an optimal control method for improving decisions after a period of online learning (Wang and Ma, 2008). Meanwhile, this optimal control needs little computing resource and only requires enough space for data storage (Yang et al., 2015). Dalamagkidis' simulated HVAC system (2007) utilized reinforcement learning to balance energy and comfort with three penalties: an energy penalty based on the evaluation of energy consumption, an indoor thermal comfort utilized AOSS signal, and a penalty of indoor air quality based on a formula of CO_2 concentration.

4.2 Other control methods
Different from above optimal algorithms used in reviewed projects, Guillemin (2003) utilized a proportional control to replace the optimal control in his system in consideration of the computing limitation of controllers. The proportional control applied a formula that contained predicted outdoor solar gains and room occupancy to balance energy and comfort. Additionally, AIM (Mozer et al., 1997; Mozer, 1998) and MASBO (Booy et al., 2008; Chee et al., 2007) projects set control rules to adjust systems for achieving energy saving and occupants' thermal preferences according to predicted data of occupants' presence and thermal preference. Aslo, iDorm project (Hagras et al., 2004) used rules that generated by the fuzzy logic to offer person-centric thermal comfort environments.

5 CONCLUSION
This paper provided a review of selected ten intelligent HVAC-related control systems that integrated prediction with or without learning processes. Most of them have proven their potential for energy savings and comfort improvement in real settings. It was found that prediction of environmental conditions and occupant behaviour opened up possibilities for the performance improvement of HVAC control, such as:
- Allowing for more efficient shut off of systems for energy savings according to the occupancy status
- Intelligently pre-awake systems before rooms are occupied.
- Automatically adjust room climate set points according to occupants' thermal preferences
- Effectively optimize energy consumption and thermal comfort within permissible bounds

Going forward, with continuing progress in the development of building sensing technology and networks, building data may become increasingly more available - and at a lower cost - for analyzing characteristics of environments and occupants' behavior. Meanwhile, the performance of prediction at HVAC control systems could be improved to acceptable levels through advancements in algorithms, such as machine learning.

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