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Learning based personalized energy management systems for residential buildings

Mallikarjun Soudari [a], Seshadhri Srinivasan [b,*], Subathra Balasubramanian [a], Juri Vain [c], Ulle Kotta [d]

[a] Department of Instrumentation and Control Engineering, Kalasalingam University, Krishnan Koil, India
[b] Berkeley Education Alliance for Research in Singapore, Singapore 138602, Singapore
[c] Department of Computer Science, Tallinn University of Technology, Tallinn, Estonia
[d] Institute of Cybernetics, Tallinn University of Technology, Tallinn, Estonia

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ABSTRACT

This investigation presents a personalized energy management system (PEMS) for heating, ventilation and air-conditioning (HVAC) systems in residential buildings based on economic model predictive control (EMPC) integrated with occupancy and occupant behaviour. The major building blocks of the PEMS are: weather forecasting tool, occupancy predictor, occupant behaviour model, cost-generator, and Economic Model Predictive Controller (EMPC). The occupancy is modelled using Hidden Markov Model (HMM), whereas Adaptive Neuro Fuzzy Inference System (ANFIS) is used to model the occupant behaviour. The cost generator computes the energy cost as the sum of personalized costs computed by using ANFIS model, time-of-use charges predicted from load-curve information, and fixed energy cost. The EMPC optimizes the energy consumption using a constrained optimization routine including the comfort margins specified by the occupant in a receding horizon manner. Performance of the PEMS is illustrated using experiments on a laboratory scale HVAC system. Our results show that the proposed controller not only reduces the energy consumption by 9.7–25%, and cost (from 8.2% to 18.2%), but also maintains the temperature within the personalized comfort band. The novelty of the proposed approach is the integration of demand response, occupancy and occupant behaviour within the PEMS framework. As a result, the proposed controller reduces energy, cost and peak-demand.

1. Introduction

Occupants play a vital role in determining energy use in building heating, ventilation and air-conditioning systems (HVAC). Haldi et al. [1] proved that building thermal dynamics is intrinsically linked to its occupants, which itself is directly influenced by the perceived environment comfort. In a recent survey [2], the authors argue that understanding building-human interaction can lead to about 40% energy savings in HVAC systems. Further, the authors stressed the need for integrating user activity and external factors for predicting occupant behaviour. Therefore, it is essential to explore the potential of personalized energy management systems (PEMS) to design intelligent energy saving controllers.

The occupancy and occupant preference depends on numerous external time-varying factors such as climate, type-of-day (normal, working, weekend), time-of-the day, and solar insolation. Further, individual behaviour of the occupants also varies from one individual to another. Consequently, the main challenge lies in obtaining a realistic yet adaptable model for occupancy and occupant behaviour to be used in design of PEMS. Further, as electricity markets are getting deregulated, not only energy consumption, but also the duration of energy consumption needs to be considered in PEMS design. This means that, in addition to energy savings, PEMS should also change consumption or its pattern during peak-load and high cost periods (also called demand response). To our best knowledge, PEMS performing energy savings, demand response and cost reduction integrating occupancy prediction and occupant behaviour have not been investigated in literature.

Main contribution of this investigation is the development of a PEMS for HVAC systems in residential buildings that is based on economic model predictive controller with strong emphasis on occupancy behaviour model and demand response (DR), integrated in PEMS. The novelty is in integration of DR in PEMS framework. The

* Corresponding author.
E-mail addresses: s.m.arjuns4u@gmail.com (M. Soudari), seshadhri.srinivasan@bears-berkeley.sg (S. Srinivasan), b.subathra@klu.ac.in (S. Balasubramanian), vain@ioc.ee (J. Vain), kotta@cc.ioc.ee (U. Kotta).

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latter means that personal comfort margins are respected, learned and integrated into the DR framework, allowing to perform peak-shaving based on Real Time Pricing (RTP). This connection has not been investigated before. Existing PEMSs are primarily designed to improve the energy efficiency and comfort, but do not address DR, as a rule.

Integrating occupant behaviour within PEMS requires sophisticated controllers that can incorporate different information in their design, and model predictive controllers (MPC) have proved to be a good choice. They can optimize energy savings based on information about building model and predictions on thermal influences, and have been studied by many researchers. Morari et al. [3] first combined numerical weather forecast with HVAC predictive control that resulted in significant energy savings. Later, the information on occupancy [11–17], thermal storage [5–7], energy cost [19–22], and occupant behaviour [25] has been used to design energy management systems in buildings. Though, the aim of reducing energy consumption in these investigations is well motivated, the resulting controllers can lead to energy peaks raising grid stability issues [20]. To overcome energy peaks, demand response algorithms based on real time pricing [27], and using economic model predictive controllers have been studied (e.g., [20–24]). EMPC provides a methodology to perform DR by integrating cost information and this makes it more suitable for deregulated electricity markets where the energy prices change depending on the market conditions.

Stochastic modelling methods have been used to predict occupancy in majority of studies. The tools such as adaptive Gaussian process, Hidden Markov Model, episode discovery, Semi-Markov Model and Blended Markov Chain have been suggested in different papers, see [9,10] and references therein. The role of the occupant behaviour in HVAC MPC design has been investigated only in [25], up to our knowledge. The authors studied the use of Hidden Markov Model (HMM) to model occupancy. However, this recent paper does not address the problem of reducing peak-demand. Our goal is to combine occupant behaviour model with DR. For occupancy prediction, we use HMM in a feedback mode, i.e., the future probable states are estimated based on current measurements on occupancy in the building. HMM has been used due to its ability to model temporal correlations of occupancy and environmental factors in consecutive time-steps. In [26], it has been shown that the presence of temporal information significantly improves the occupancy prediction capability. The role of EMPC integrated with information on occupancy prediction and occupant behaviour for designing PEMS reducing energy consumption, cost and peak-demand has not been investigated.

In [34], Adaptive Neuro Fuzzy Inference System (ANFIS) has been used to model energy consumption patterns to be applied later for designing the demand response algorithm. Motivated by this, we decided to model occupant behaviour as set-point changes (not patterns as in [34]) using ANFIS mainly due to its ability to combine learning capabilities of artificial neural networks with decision making capabilities of fuzzy inference systems. As the occupant behaviour is influenced by environmental and economic factors, the ANFIS learns the occupant behaviour from historical information using the neural network part. Decisions on set-point changes are made using the fuzzy part. Thus, the hybridization of ANN and fuzzy are required for implementing learning based decisions and ANFIS is used to this extent. The output of the ANFIS is the predicted set-point changes that are related to the MPC via cost that charges the comfort of the consumer based on the predicted set-points.

The MPC requires the building model that captures the thermal influences due to external temperature and occupancy. A disturbance variable in this model is assumed to describe the heating due to occupancy over a certain period, whereas weather forecasts are used to capture the interactions of the building temperature with the environment. The least squares method is used to estimate the building model parameters. Since the disturbance term varies non-linearly in time, this investigation uses Radial Basis Function Neural Network (RBFNN) for estimating the disturbance term. This method is known to be standard and successful to approximate nonlinear functions. The building model thus obtained is semi-parametric regression model, wherein the least squares approach obtains the parameters of the model, whereas the non-parametric part is described using the RBFNN model.

The paper is organized into seven sections including the introduction. Section 2, presents the PEMS Organization. The building thermal model is presented in Section 3, while Section 4 presents the occupant behaviour prediction. The economic model predictive controller is introduced in Section 5, and the experimental results of the PEMS in Section 6. Conclusions are drawn from the obtained results in Section 7.

2. PEMS organization

The main components and data-flow in the PEMS shown in Fig. 1 are: (i) forecasting tool, (ii) occupancy estimator, (iii) behaviour model, (iv) cost generator and (v) EMPC. The forecasting tool is a software that interfaces with the web to generate forecast on temperature, humidity, global solar radiation (GSR), etc., and also has repository of intelligent control algorithms (ANFIS, RBFNN, HMM) that are required for modelling the occupancy, and occupant behaviour. The behaviour model uses forecast information on temperature, humidity, GSR, predictions on occupancy from HMM, information on current hour of the day, historical information on activity, and type of the day to predict the occupant behaviour model using ANFIS. The output of the ANFIS are the rules of the fuzzy inference system (FIS) that model the occupant behaviour. The occupancy estimator uses the HMM model of the type of day, using historical information from DB. The occupancy is estimated as possible future state and current measurements are used to correct the HMM predictions. The HMM therefore works in a feedback mode. The cost generator uses the predictions on set-points from the occupant behaviour model, load-curve information and information on fixed energy cost to compute the cost for the next 24 h. To predict the occupant behaviour, the ANFIS uses the forecast and historical information. Finally, the EMPC uses the building thermal model, an optimizer, information on constraints, and cost information as objectives to reduce peak-demand, energy cost and consumption. The constrained optimization problem is solved over a prediction horizon and the first among the control inputs is applied in a receding horizon manner.

In addition to the above components, the PEMS uses simple sensors, embedded controllers and other hardware. The proposed PEMS is implemented in a laboratory that is equipped with a single-stage compressor HVAC system. The building model, measurement system, occupancy prediction, and occupant behaviour models are used to design the EMPC, which is the main building block of the PEMS. The PEMS integrates predictive controller with ANFIS to forecast human behaviour.

3. Building thermal model

The test-bed used in our investigation consists of a HVAC equipment with single-stage compressor controlled with simple thermostat, limit-switches on the door to measure occupancy using a simple counter algorithm ported on an embedded board (Arduino Uno), and temperature sensors are mounted through out the building. The HVAC system has two units, internal and external. The internal unit houses the blower fan, while the outer unit has the compressor and condenser coils. The single-stage compressor