Realistic user behavior modeling for energy saving in residential buildings

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***Abstract*—Due to the high costs of live research, performance simulation has become a widely accepted method of assessment for the quality of proposed solutions in this field. Additionally, being able to simulate the behavior of the future occupants of a residential building can be very useful since it can support both design-time and run-time decisions leading to reduced energy consumption through, e.g., the design of model predictive controllers that incorporate user behavior predictions. In this work, we provide a framework for simulating user behavior in residential buildings. In fact, we are interested in how to deal with all user behavior aspects so that these computer simulations can provide a realistic framework for testing alternative policies for energy saving.**

***Keywords*-user behavior; energy consumption; energy saving**

I. Introduction

Traditional energy optimization methods have not considered the study of the non-deterministic nature of the human behavior when providing solutions in this field, but new human-centric paradigms are emerging gradually. This means that new human-centric approaches are currently under an intensive research and development phase. Therefore, and mainly due to the high costs of live research in this field, performance simulation by means of computers seems to be an appropriate and cheap method to accurately assess the quality of these new approaches.

Our idea is shared by the community. For example, building simulation by means of computers is very important since every building is different in many ways [3], [4] e.g., with respect to location and exterior environment, kind of construction and building envelope, space usage and interior environment, the Heater-Ventilation-Air Conditioning (HVAC) system, and so on. We think that simulating user behavior is also an important aspect of the building simulation since a) users influence the overall heat gain in a room, and b) comfort level objectives may only be satisfied when people are present. Thus, realistic simulation and prediction of user behavior may contribute significantly in energy saving. In our opinion, a simulation which cannot take into account these presence and thermal changes cannot be considered realistic enough to derive precise conclusions.

This is what happens in most existing approaches: stochastic processes determined by human behavior like lighting control, occupancy, activities performed, etc., are forced to operate on a fixed schedule, or according to control rules similar to the sequences that run the mechanical systems involved such blinds, windows, and so on. This is a compromise between the strengths of software tools designed to simulate buildings and the predictable mechanical controls. However, in actual buildings, we know that manual control decisions can deviate substantially from what these simplified models dictate. Until now, not much attention has been paid on this field of research. According to Oldewurtel et al. [9], the main reason for research on realistic user behavior being rarely carried out until now are primarily the difficulties and costs of obtaining a precise model and the fact that energy costs played a minor role in the past. But now the situation is different.

We aim to provide a framework for simulating user behavior in residential buildings, which may be used as a design and testing tool for efficient energy management. In fact, we are specially interested in taking into account all the aspects concerning user behavior (people presence in the different rooms, activities performed, use of lights and electrical devices, natural ventilation, use of domestic hot water, and so on) so that truly realistic scenarios can be replicated in a computer simulator. Such simulation framework is beneficial both as a design tool (e.g., for incorporating user behavior predictions into model predictive controllers), as well as a testing tool (e.g., for testing the performance of alternative heating controllers under realistic scenarios).

The rest of this paper is structured as follows: Section II presents related work on energy data management concerning user behavior in residential buildings. Section III describes our proposal for user behavior modeling from a stochastic perspective. In Section IV, we explain how we have built our user behavior models for simulating realistic scenarios. In Section V, we evaluate the benefit of the predictions to energy saving. Finally, Section VI presents concluding remarks and future work.

II. Related work

According to prior work, there are two main ways to address the problem of saving energy in modern buildings. The first of them depends highly on human intervention since it proposes manual control purely based on consumption feedback from the utility companies, domestics systems, and so on. The second way does not depend on people since tries to automatically supervising the buildings by sensing and controlling their energy usage.

One of the standard approaches to control energy usage includes model predictive controllers. However, user behavior predictions are not usually part of such formulations [7]. We think that including some kind of models concerning the habits of the home occupants could improve existing predictive strategies. Our opinion is based on many works such as: Wood & Newbotough [12] achieved a good percentage of reduction in energy consumption of occupants by changing their behavior. Hoes et al. [4] show that electrical energy consumption in buildings is not only linked to their operational and space utilization characteristics, but also to the behavior of their occupants. Yu et al. [13] tried to identify the impacts of occupant behavior on building energy consumption. The results obtained give hints to prioritize efforts when modifying user behavior in order to reduce costs. Rijal et al. [11] proposed a model which was designed to include the interaction of an average user of an office space with good results. Bourgeois [1] found that a realistic treatment of the control of lighting device can result in significant reductions in energy use. Ouyang and Hokao [10] investigated energy-saving potential by improving user behavior in 124 houses in China, results obtained showed that effective promotion of energy-conscious behavior could reduce energy consumption. Finally, some pilot projects demonstrated that low energy systems, such as natural ventilation, shading to control solar heat gains and glare, day lighting to dim lights, and demand controlled ventilation, especially need the interactions and collaboration from occupants [5].

Until now, not many solutions for saving energy have considered using behavioral information from home occupants, but other many factors which can be taken into account in order to improve energetic efficiency. Some of these factors are fixed and some are dynamic. Fixed factors can be collected in advance by simply asking occupants. Then, experts can suggest the best ways to exploit them. There are three main groups of factors: related to the house placement, related to home occupants and related to the nature of the house subsystems. Regarding dynamic factors we can mention most of physical conditions, i.e. house characteristics, seasonal statistics, weather forecasts, and so on. In this work, we aim to include a new factor to the group of that dynamic aspects, i.e. user behavior models that can allow simulating realistic scenarios.

III. Stochastic modeling of user behavior

Nowadays, the traditional control approaches concerning residential buildings are pushed to their limit by new and very demanding building technologies. One of the possible solutions is related to the emergence of a new paradigm for applying smart technology to residential buildings often called home automation [8]. Most of the related work focuses on model predictive control methodologies for controlling, e.g., cooling, electrical devices, heating, lighting, and ventilation in independent building zones. To be more formal, we can say that model predictive controllers use a model to predict the future evolution of the housing subsystems and compute optimal control actions by optimizing a cost function (related to energy saving, comfort and safety in this case) depending on these predictions. In the near future, model predictive control should become even more important to ensure efficient and correct building functionality. For example, as the outdoor temperature is supposed to be an influential factor for the building heating subsystem, some kind of weather forecast could be used by the model predictive controller to automatically adjust the indoor temperature.

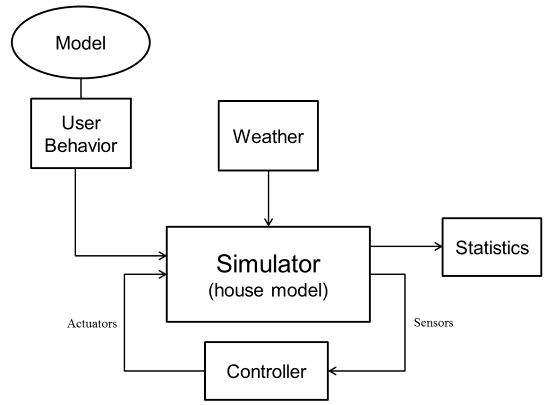

Figure 1. Example of a simulation scenario designed to test the possible benefits from using a given control strategy. If user behavior is not taken into account, the simulation could not be considered realistic

However, costs of live research are very high, so researchers test their strategies in advance using a simulator. If the results from these simulations seem to be promising, then these strategies can be implemented in the real world. In order to perform simulations, researchers have to take into account home simulators that can meet their requirements.

Figure 1 shows a simulation scenario designed to test the possible benefits from using a given control strategy. If real weather data or user behavior are not taken into account, the simulation could not be considered realistic. Most of priorly developed simulators include capabilities to work with past weather data or even future weather forecasts. Most of them also include capabilities to model user behavior. However, as we already mentioned, these models are quite static, i.e. they are based on fixed behavioral patterns. In this paper, instead, we take into account the non-deterministic nature of human behavior so that simulations can reflect what happens in the real word more accurately.

Emerging empirical models of user behavior tend to be based on statistical algorithms that predict the probability of an event, for example: opening a window, given certain environmental conditions. Our modeling strategy is based on observations of real environments in real buildings that allow statistical correlation between activities and person who perform the activity, time of day, season, indoor conditions, and so on. In other words, we treat user behavior in a residential building as a stochastic (i.e. probabilistic) process where the odds of events are based on several factors. For example, if we observe that a person has waken up at 7am in workday, our model assumes that this pattern will happen regularly and adds some stochastic changes depending on a randomness coefficient. Of course, this pattern is only valid for a working day, not for weekends or holidays.

IV. Performance simulation of realistic scenarios

Taking into account user behavior when performing simulations concerning energy consumption is important since people living in a house produce internal loads as a result of their activities. This means that if these internal loads are not taking into account the simulations performed cannot be considered realistic. Therefore, we have that internal loads are those factors that coming from the user behavior can affect the dynamics of a house. Internal loads includes but are not limited to: user presence, user activity, use of electric appliances, use of lights, natural ventilation and use of domestic hot water. These kind of internal loads can be modeled using schedules. Schedules are a way of specifying how much or many of a particular quantity is present or at what level a physical variable should be set. In order to perform the simulations we are going to use two main software tools: EnergyPlus [15], Building Controls Virtual Test Bed (BCVTB) [14] and Matlab. The strategy that we propose has a total of 9 steps. We exclude from this list house modeling, since we suppose the user has a realistic model on the house in which the simulation is going to be performed. These steps are going to explained in more depth in the following subsections.

A. Preparation of data structures

First of all, it is necessary to prepare the data structures we are going to use to work with the data in main memory. We need data structures for storing and working with values representing presence of people in each of the rooms of the house, activity of the people in each room, percentage of lights that are switched on each time step, percentage of electric power that is on each time step, enumeration of opening/closing windows along the day, and use of domestic hot water (dishwasher, shower, washing machine, and so on).

B. Automatic capture of time step

The time step is automatically captured from the house model. This implies that all data from the controller has to be automatically adjusted. We are prepared to work with time steps ranging from 1 hour to 1 minute. This value depends on the degree of resolution researchers want for their strategies.

C. Definition of the randomness coefficient

One of the major characteristics of user behavior is it lack of predictability. However, but we admit regularities in the occurrences of activities performed by people under certain circumstances. For this reason, we need to work with a randomness coefficient that allows the systems to change the patterns of the people living in the house.

D. Input parameters

It is necessary to define the parameters for the controller, i.e. the control signals to control the actuators. This task seems to be trivial, but it is really very tedious when performing it manually: it is necessary to define the parameters to be submitted in the controller, to define the parameters to be received in the simulator, and to define the nature of the values to be transmitted using the BCVTB environment. For this reason, we have automatized this task so that users only have to define these parameters once.

E. Output parameters

It is important to define the output parameters that the controller will read from the simulator, i.e. the sensors that monitor the physical conditions of the house and environment. The problem is analog to that concerning the input parameters. This means that it is necessary the parameters to be monitored in the simulator, to define the parameter that the controller will read, and the nature of the data to be transmitted using the BCVTB environment. For this reason, we have also automatized this process. Now, it is possible to define the output parameters only once. A software routine will accordingly update this information in the rest of modules.

F. Conversion from user schedule to physical vectors

Monitoring behavior from occupants along with changes in the home is a critical task when using human-aware systems. This monitoring process is responsible for capturing relevant contextual information for activity recognition systems and tries to guess what kind of activity is happening. However, the simulator does not accept events described in natural language. This means that the conversion from real user schedules to physical vectors is of vital importance for the correct simulation of truly realistic scenarios. The idea is simple: people gives us an exhaustive list of their activities at home, we extract the behavioral patterns, and on basis of these patterns we automatically process this list and transform into physical values. This list has to describe activities in a very precise way: the day and date these activities were performed, the people (age, gender) who performed them, the rooms in which these activities were performed, the lights or electrical devices which supported them, and so on. We use conversion tables for generating the physical vectors. For instance, a person who is sleeping is supposed to produce less heat that a person who is making some exercise. Or the effects of a person using a oven are going to be completely different from the effects of a person listening the radio.

G. Consideration of official/unofficial holidays

It is necessary to define the holidays to include the effect of the house shutdown during certain periods of the year. Holidays defined in this way are used for the whole simulation. It is possible to use an external file for specifying the official and unofficial holidays that our framework should take into consideration. The possible holiday dates are defined in the holiday schedule and the actual holidays to be used in the simulation

H. Value acquisition and interpolation

The values are always specified in the form of one value per hour, i.e. vector of 24 numeric values. However, when working with these values internally it is necessary to adapt them to the granularity required. The reason is sometimes it could be possible that users want to visualize statistics with a different level of granularity. In order to perform a simulation correctly, the controller, the environment for transmitting the data and the simulator have to be synchronized. This can be achieve by interpolating the current values. Since the simulator works with average values, the interpolation of the vales has not any negative effect.

I. Value submission and reception

The final step involves the submission/reception of the values to/from the simulator from/to the controller. This process is performed by means of sockets. It is necessary to specify the nature of the values to be transmitted in three different places: the controller, the simulator, and the environment that is going to be used to transport these values. It is also necessary to identify the kind of day we are simulating, since it is the behavior of a person during a workday is not going to be the same that during a weekend or a holiday. We have designed our solution so that it is only necessary to specify these values in one place only. Then, a routine will update the necessary information in the other places accordingly. Obviously, this step has to be repeated iteratively until the end of the simulation.

V. Evaluation in Energy Saving

Having developed a framework for realistic simulation of user behavior, a follow-up question is *how predictions based on such simulated user behavior data may improve energy saving in residential buildings.* In order to assess the potential benefit of user-behavior predictions into energy saving, we designed controllers for radiator-based heating systems that may incorporate predictions of user-behavior. The designed controllers fit into the general *model-predictive control* (MPC) framework [6], where periodically (e.g., every $T_{\rm opt} = 1$ hour) the controller optimizes the use of the heater over an optimization horizon (e.g., $T_{\rm hor} = 6$ hours), while only a small part of the derived *optimal policy* is implemented each time (e.g., the policy corresponding to the first 1 hour). Every time instance at which the controller optimizes (i.e., at times $t = T_{\rm opt}, 2T_{\rm opt}, ...$), it collects measurements of the observed phenomena (e.g., room and outdoor temperature, people's presence, etc.) and updates its predictions about the evolution of these phenomena (e.g., the evolution of the room temperature and the future occupancy). Thus, the MPC implementation provides a feedback mechanism for correcting/improving potentially inaccurate predictions.

We implemented a standard MPC framework for controlling the temperature of a single thermal zone in a typical residential building. Implementation was possible in the simulation environment Energy Plus [15] where the evolution of the room temperature can be observed under different heating control strategies. The controller is designed to minimize a weighted sum of the heating energy cost and the comfort cost (defined as the Euclidean distance of the room temperature $T_{\rm room}$ from the desired temperature $T_{\rm des}$) over the optimization horizon $T_{\rm hor}$.

Figure 2 demonstrates two different MPC experiments run over a period of 2 months (October-November in Linz, Austria). In the first one, current measurements of occupancy are used as predictions for the whole optimization horizon $T_{\rm hor}$ (worst predictions), while in the second one perfect occupancy predictions are used. Thus, these two experiments set the bounds with respect to the benefits derived from incorporating user behavior predictions. For both experiments, the heating-comfort cost has been plotted for different scaling factors of comfort. Lastly, in both experiments, the controller uses accurate weather predictions and an identified model for the evolution of room temperature. Thus, this setup allows us for assessing the benefit of user-behavior predictions in energy saving.

The corresponding costs of standard hysteresis controllers (i.e., one that operates only under people's presence and one that it is always on) is also demonstrated. Note that the incorporation of accurate occupancy predictions may lead to up to 32% reduction in the total heating cost at a comfort level corresponding to the standard hysteresis controller. Energy is also saved even without accurate user behavior predictions due to the rest of the predictions incorporated in the model predictive controller (i.e., weather and room temperature predictions).

VI. Conclusion

User behavior is one of the most significant sources of uncertainty in the prediction of building energy use by simulation programs due to the complexity and inherent uncertainty of people behavior. With the trend towards smart controllers that reduce energy consumption, taking into account the behavior of home occupants actively involved is

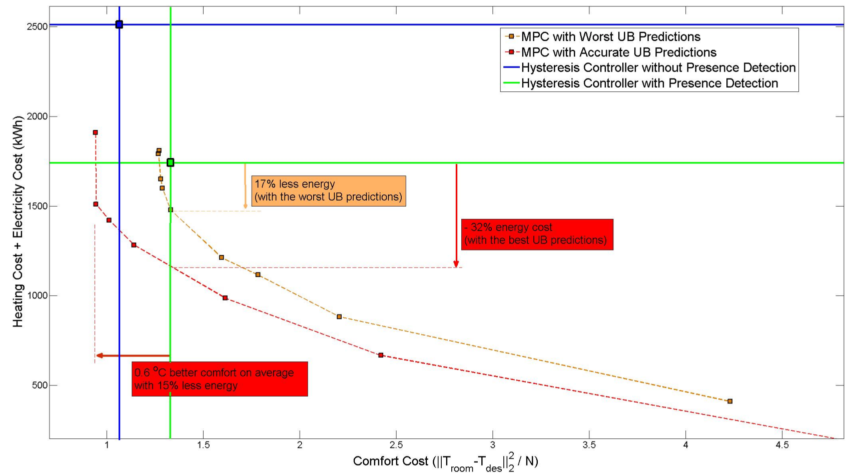

Figure 2. Comparison of energy cost as a function of the comfort level for different controllers.

a key to achieve realistic simulations leading to get solutions for high energy performance without scarifying occupant comfort or productivity. In this work, we have presented our ongoing research on user behavior modeling for simulation of realistic scenarios leading to optimization of energy consumption. In fact, we have tried to take into account all the aspects concerning user behavior (presence, activities, use of lights and electrical devices, natural ventilation, use of domestic hot water, and so on) so that truly realistic scenarios can be replicated in a computer simulator. In this way, accurate research can be carried out but without incurring in the high costs of live research.

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