JouleSense: A Simulation based Platform for Proactive Feedback on Building Occupants' Energy Use

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Abstract: A significant amount of energy in the buildings can be saved by inducing efficient occupant behavior. The occupant's awareness tools that have been shown to be effective in achieving energy efficiency gains depend on various computational and estimation algorithms. This paper proposes an energy feedback scheme that relies on a model based, building thermal simulation in order to identify the areas for efficiency improvement. By leveraging the specific mathematical formulation of those models and a dedicated open-source solver, improved computational speed, reduced cost and enhanced interoperability is obtained. This combined with the integration into a building management system (BMS), permits real-time sensing and feedback. Unlike similar studies, this work's outcome allows the creation of the energy awareness tools that rely solely on validated thermal model simulation, thus increasing their accuracy and potential in the future smart buildings.

1 INTRODUCTION

As the urban population has continued to increase in the recent years, the sustainable urban development initiatives have motivated the research efforts for reducing the energy use in the building sector. Broadly, there are two major approaches for reducing the energy use in buildings.

The most prominent one is the *passive* approach. It focuses firstly on the improvement of the building thermal envelop by incorporating improved isolation and thermal storage material like the phase changing ones. Secondly, it promotes the wide adoption of energy efficient appliances through citizen awareness campaigns.

The second approach calls for *active* involvement towards energy efficiency through the deployment of smart building infrastructure. In this approach, ubiquitous computing and embedded electronics play a significant role by providing fine grained energy monitoring and actuation capabilities. There are two strategies in the active approach. In the first one, the smart building automation technologies are deployed to achieve optimal energy use while maintaining a comfortable indoor environment without human intervention. The other focuses on bringing user in the loop for improving energy efficiency by facilitating user awareness through targeted feedback on his consumption (Mattern et al., 2010). This study focuses on the development of a platform based on the latter approach.

A significant amount of energy in the buildings can be saved by inducing efficient occupant's behavior (Yu Zhun Jerry et al., 2011). Direct feedback to building occupants through the use of in-house displays in the form of real time energy consumption data has been shown to reduce energy use by up to 20% (Wood and Newborough, 2003). These savings are a result of two major factors: the high dependence of energy consumption on the usage patterns of the occupants and the fact that decision to invest relies solely on their willingness (Darby, 2010). Thus, efficiency gains can be realized by inducing behavioral changes on people through appropriate feedback on their energy consumption. In fact, studies have shown that feedback to drive people towards energy efficient behavior can be effective if it is frequent, uses an interactive element and offers multiple options to the occupant (Fischer, 2008).

At the heart of all the energy feedback based tools lies a computational algorithm, the complexity of which varies greatly depending on the approach utilized, the nature of feedback provided and the available ubiquitous computing at the occupants' living

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spaces (Spagnolli et al., 2011). Recent years have seen the rise of data science based tools to deliver personalized actionable energy reports for the occupants in order to help them save energy (Zeifman, 2012; Chen and Cook, 2012; Birt et al., 2012). These techniques mostly deploy disaggregation algorithms on smart metering data in order to achieve appliance level breakdown of energy consumption.

However, these techniques necessitate the existence of a usually large input dataset. Moreover, they frequently involve complex calculations in order to extract various patterns from this data, thereby requiring considerable computational power and time, nowhere near the capabilities of current embedded electronics. Therefore, a key limitation of these solutions is that such information is provided after a significant gap of time and after the energy has been consumed.

This paper presents an integrated simulation based platform for providing proactive energy savings recommendations to building occupants with regard to their heating equipment by leveraging the power of Internet of Things (IoT) enabled sensing technologies, validated thermal models and a custom, optimized simulation engine.

2 BACKGROUND THEORY

2.1 Choice of Modeling Approach

The ability of our integrated tool to deliver accurate feedback rests on the underlying thermal model. The proposed system needs to be tailored to the physical properties of the building in question and hence should be able to capture the interactions between physically connected spaces in the building. This paper represents such a thermal model of the building using a network of resistances and capacitances. A typical building is made up of ceilings, floors, facade and internal walls as well as windows. All these different elements can both store heat and transfer it through various mechanisms. Apart from these elements, room air and other mass (ex. furniture) also participate in the above-mentioned processes. So a useful representation is to model the heat storage using capacitors and the heat transmission using resistors. This work is built on the well-studied and proved lumped capacitance method. (Maasoumy et al., 2011; Fraisse et al., 2002). The choice of this modeling approach has been motivated by the following considerations:

1. The resulting model should be descriptive enough to capture all the relevant dynamics to give reliable and accurate results. For this, it was necessary to model each room and wall with at least one node.
2. It should have reasonable data needs and be computationally efficient to allow for near real time applications.
3. Finally, it should be dynamically customizable for various buildings with minimal overhead.

2.2 Developing an Electrical Network

An equivalent electrical network has been developed in order to represent the thermal processes in the building. For this, each node is assigned to every room and wall (if the wall has multiple layers then an equal number of nodes can be assigned to the wall), which is then connected to the ground via a capacitor, C.

Heat transfer in a typical building takes place through the three processes: conduction, convection and radiation. Heat conduction across walls under steady state condition can be described by

$$Q_{cond} = \frac{k \cdot A \cdot (T_2 - T_1)}{L} \tag{1}$$

where Q_{cond} is the conductive heat transfer rate, k is the thermal conductivity, A and L is the area and the thickness of the wall accordingly, with T_1 & T_2 the temperatures on the two sides of the wall. Convective heat exchange also takes place from the surface of the walls and the room air. This rate of heat transfer is given by

$$Q_{conv} = h \cdot A \cdot (T_s - T_{air}) \tag{2}$$

where Q_{conv} is the conductive heat transfer rate, h is the convective heat transfer coefficient, T_s is the surface temperature and T_{air} is the temperature of the surrounding air . In addition to these, heat transfer also takes place via radiation exchange that occurs between the internal surfaces of the wall, between facades surfaces and the sky and irradiation from the sun. The heat exchange between the internal surfaces of the walls is neglected. This is justified since walls of rooms are almost at the same temperature and therefore net heat exchange between them can be neglected. Further, long-wave radiation exchange with the sky can be modeled using a combined convective and radiative heat transfer coefficients for the external surfaces as has been proposed in (Gyalistras and Gwerder, 2009). Heat gain from solar radiation can be modeled as direct heat inputs to room air and wall surfaces.

All the above mentioned heat transfer mechanisms, can now be represented using an electric analogy. In such a model, voltage source plays the role

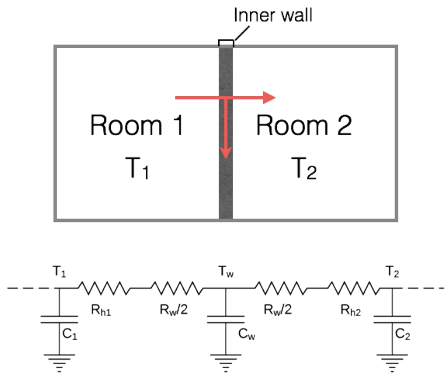

Figure 1: Electrical equivalent circuit to represent thermal processes in an internal wall.

of the temperature of a building element or room, whereas current represents the heat flow. Since resistance is defined as the ratio of potential difference over current, the resistance associated with conduction is

$$R_{cond} = \frac{(T_2 - T_1)}{Q_{cond}} = \frac{L}{k \cdot A} \tag{3}$$

and the one associated with convection

$$R_{conv} = \frac{(T_s - T_{air})}{Q_{conv}} = \frac{1}{h \cdot A} \tag{4}$$

Furthermore, heat storage capacity of walls and rooms can be represented using heat capacitance of capacity

$$C = m \cdot c_p \tag{5}$$

where m is the mass and c_p is the specific heat capacity.

In addition, external and internal heat gains can be easily added to our model. Internal heat gains and radiators can be modeled as direct power inputs to the room node. This basically translates into an appropriate current source at the room nodes. For a detailed description for modeling other heat gains, the reader can refer to (Lehmann et al., 2013).

It is important to note that in deriving this model, the following assumptions were made:

1. Heat transfer across the walls has been assumed to take place perpendicular to the surface. Thus, there is no variation in temperature over a surface.
2. Spatial variations in the temperature of the room have been ignored; therefore, one node is sufficient to represent a complete room.
3. The heat capacity of room air has been assumed to constant at 1.007 $^{kJ}/_{kg \cdot K}$. This is a justified assumption since this value is 1.006 $^{kJ}/_{kg \cdot K}$ and 1.0007 $^{kJ}/_{kg \cdot K}$ at 250 K and 300 K accordingly.

We demonstrate the modeling procedure using a test case shown in Fig. 1. In this example, there is an internal wall of area A, thickness L and thermal conductivity k. The heat transfer coefficient on the side of room 1 is h_1 and that on the side of room 2 is h_2. In an equivalent thermal circuit, there are three different nodes with potentials T_1, T_2 and T_w that correspond to the temperatures of air in both the rooms and the wall respectively. Note that the node for the wall temperature has been assigned to the centerline of the walls. These nodes are connected to the ground via the capacitors

$$C_{1,2} = \rho_a \cdot v_{1,2} \cdot c_a \tag{6}$$

$$C_w = \rho_w \cdot A \cdot L \cdot c_w \tag{7}$$

where ρ_w represents the density and c_w the specific heat capacity of the wall, ρ_a, c_a are the respective ones for air and $v_{1,2}$ the volume of each room. Eq. 6 represents the heat storage capacity of air in both rooms and Eq. 7 corresponds to the heat storage capacity of the wall. The heat transfer across the wall has been modeled using the resistances

$$R_{h;1,2} = \frac{1}{h_{1,2} \cdot A} \tag{8}$$

$$R_w = \frac{L}{k \cdot A} \tag{9}$$

The Eq. 8 represents the convective thermal resistance and the Eq. 9 corresponds to the conductive thermal resistance. This resistance of the wall has been split across the centerline resulting into two thermal resistances of $^{R_w}/_2$.

An important advantage of using the aforementioned approach is that all its parameters have physical interpretations. This direct relation allows us to examine the effect of changing any parameter in a physical building by changing the relevant parameter in the electrical network. Additionally, this permits our proposed tool to provide energy savings strategies to the building occupants.

3 SYSTEM ARCHITECTURE

However, the aforementioned simulation is computationally heavy and the simulators commonly used in the literature are built for use in specialized mathematical software like Matlab®. As a result, the control and automation modules built around those simulation cores are also written in the same software language (Sturzenegger et al., 2014). The problem with the use of such expensive proprietary software packages is that the tools developed in such environments get restricted to just lab level research projects and do not achieve commercial adoption.

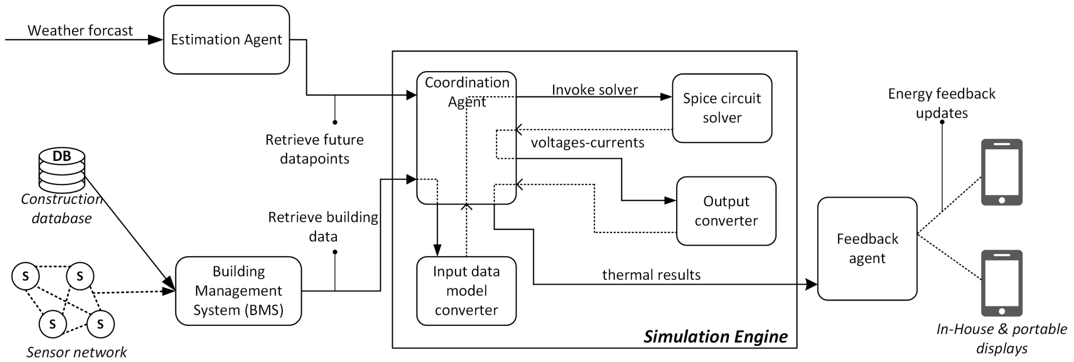

Figure 2: Architecture of the platform developed in this work.

This study presents an alternative approach for providing the same thermal simulation outputs in terms of accuracy but with increased performance and usability. The dedicated numerical solver deployed in the literature, is replaced by a circuit simulation engine. Since the problem and model formulation scrutinized in Section 2 fits excellently with the purpose of a circuit simulation engine, an increase in performance in the numerical operations required for those models is expected along-with a reduction in overall cost due to the free availability of the software.

The integrated tool presented in this paper is composed mainly of the following four discrete agents: the weather related estimation agent, the building management system (BMS), the simulation engine and the feedback agent. Fig. 2 shows the complete architecture of the platform with all the agents interconnected.

The BMS developed in (Lilis et al., 2015) is a hybrid platform which integrates the sensing and actuation end devices with building structure data in a common environment. A Representational State Transfer (REST) Application Programming Interface (API) provides accessibility interface to all the dynamic (real-time sensing) and static (building structure) data. In addition, the API provides the means of action through the installed actuators. The sensing capabilities include among other, temperature, humidity, luminosity, presence and individual powers of electrical loads. By leveraging the advancements in embedded electronics and networks they provide increased granularity in indoor living space sensing and acting.

The weather estimator provides the necessary future environmental data of the neighboring simulated zones for use in the thermal simulation model. In order to generate the relevant outputs it takes into consideration the historic values of the zones and the weather prediction from external sources. Using an experimental solar heat gains model, it is possible to estimate within an acceptable error the future temperature data-points of the neighbor zones.

The feedback agent generates intelligent insights and recommendations for the occupant by analyzing the data provided by the simulation engine. As an input, it receives the predicted time series temperature data from the simulation engine, and runs appropriate analysis on it. Its task is to provide the high abstraction level outputs that could be leveraged by the user devices and in-house displays in order to provide the desired user awareness. The feedback agent is completely decoupled from the inner-workings of the simulation engine and any intermediate steps. In addition, it is totally independent of the particular structure of the building and the smart sensing and actuation infrastructure present in it. This is highly important since it facilitates the creation or reuse of universal energy awareness applications that have been already proposed or implemented in the literature. Therefore, by keeping the compatibility of the simulation engines output with current literature solution the potential impact grows beyond the limits of this study.

Finally, the core of this work focuses on the design and validation of the simulation engine as seen in Fig. 2. This simulation engine comprises of a dedicated circuit simulator SPICE, a coordinator agent and a software utility to convert output of the solver into usable format. The coordinator agent firstly retrieves data from BMS structure database (DB) in order to create the resistance-capacitance thermal model of the building and automatically synthesizes all its parameters from the building structure data as has been described in Section 2. Subsequently, it gathers the environmental data from the weather estimator and real-time DB of BMS and creates the dynamic controllable sources of the circuit. The output at this stage is a *netlist* file compatible with the spice based solvers which describes the circuit to be simulated in full detail. In the next stage, the coordinator agent

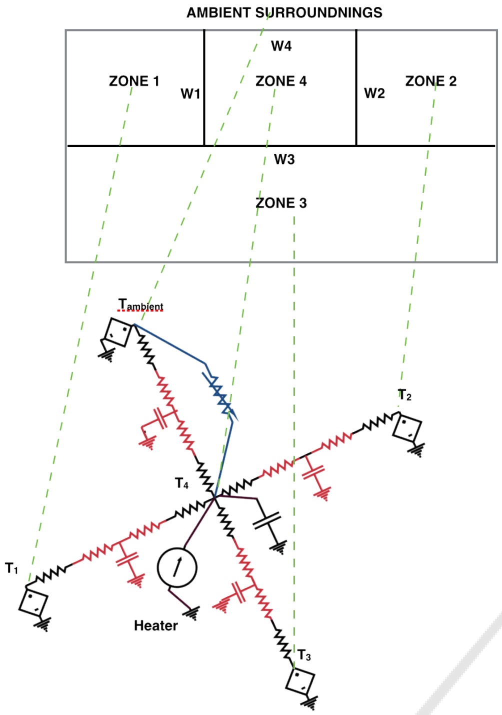

Figure 3: Schematic of the hypothetical room used for validation along with the equivalent R-C network representation.

launches an LTspice (Linear Technology, 2015) console instance and supplies the generated *netlist* file to perform circuit simulation. Once the simulation terminates, the coordinator agent invokes the conversion utility to convert back the circuit related raw outputs to the physically meaningful ones. Eventually, the feedback agent pulls these outputs to run its analysis and generate insights for the occupants.

Therefore, with the help of the four agents developed in this work, our platform, JouleSense, is able to provide proactive energy savings recommendations to the occupants. To use the platform in a new building, the building structure has to be provided through the BMS interface together with the necessary sensors and actuators. Once the system is ready, the occupant only interacts with the platform through the mobile interface by using the feedback agent and by receiving the suggestions. By the time a new request is generated for the feedback agent for the updated predicted thermal dynamics, the simulator engine is invoked and the entire aforementioned process is executed.

4 VALIDATION

In order to validate our model, the authors performed a comparison of the results of the model with that of state-of-the-art Matlab based building resistance-capacitance modeling (BRCM) tool (Sturzenegger et al., 2014). This tool has been experimentally validated extensively over several months for model predictive control on a real and fully operating office building in the OptiControl-II project (Gwerder and Gyalistras, 2013). Thus, it provides a good basis to validate the accuracy of the proposed tool.

For this, a hypothetical test room, Zone 4, has been defined as shown in Fig. 3. Two other rooms and a corridor surround this room. Further, for the sake of simplicity floor and ceilings are assumed to have adiabatic boundary conditions. However, they can be also simulated if need be, by two additional circuit branches of capacitances and resistances using the building material and structure specs of the floor and ceiling.

The temperature profiles of these rooms and corridor along-with the outside temperature have been used as boundary conditions for the corresponding walls. This time series temperature data was collected from the sensors deployed in one of the EPFL campus buildings for the month of September 2015. Further, the room is considered to be unoccupied, with no furniture and no deliberate ventilation. The material properties used for the simulation are described in the Table 1. A window was placed on wall 4 which connected the zone under consideration to the external environment. The U-Value of the window was taken to be 0.51 $W/K{\cdot}m^2$ with an area of 6.43 m^2. Furthermore, a radiator has been assumed to be present in the room which is modeled as a current source to the room node.

The results of the simulation performed have been shown in the Fig. 4 that demonstrates the comparable accuracy of our platform with respect to the state-of-the-art tool.

Table 1: Building material and structure specs.

Wall	W1	W2	W3	W4
Specific Heat Capacity $J/kg{\cdot}K$	1000	1000	1000	1000
Specific resistivity $m{\cdot}K/W$	4.76	4.76	4.76	1.49
Density kg/m^3	700	700	700	1600
Thickness m	0.1	0.1	0.1	0.27
Area m^2	13.40	13.40	9.19	9.19

The combination of the free circuit solver with the integrated BMS provides a low cost, yet accurate environment for developing third party applications to realize energy savings through targeted occupant

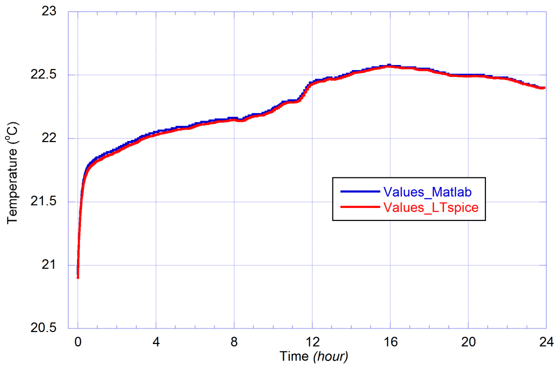

Figure 4: Comparative accuracy of this work's solver vs state-of-the-art Matlab based tool.

feedback. These applications can leverage the feedback agent analysis and the near-real time low computationally requiring thermal simulation engine.

A specific agent, called time-to-target-temperature has been developed. It leverages the ability of this tool and demonstrates its usage. This agent provides an estimate of the time taken by a specific building zone to achieve the desired temperature. Currently, a mobile application is used as a frontend to a desired temperature set-point from the user. The feedback agent invokes the simulator engine through a RESTful API and receives a time series of predicted temperature data. It then looks up the time to reach the desired temperature in the time series and displays the output to the user through the application. A prototype screen-shot of the application is visible in Fig. 5. The execution time of the entire process is in the order of 1 sec and hence fast enough for full scale implementation. This agent can also be leveraged by third party applications to generate various insights for the user. For instance, the information of the time it takes to achieve the desired temperature, can help occupants save energy since they tend to set higher set-point temperatures believing that it leads to faster heating (Gupta et al., 2009). This inevitably leads to energy waste if the temperature is not turned down. Another application envisioned in this paper is an energy savings recommendation engine. It invokes the simulator agent multiple times and finds the most optimum control set-points and actuator positions. It achieves that through sequential thermal simulations for all the different cases and by calculating the energy consumption in each case with the help of time-to-target-temperature agent. The most efficient configuration is recommended to the occupant over the mobile application.

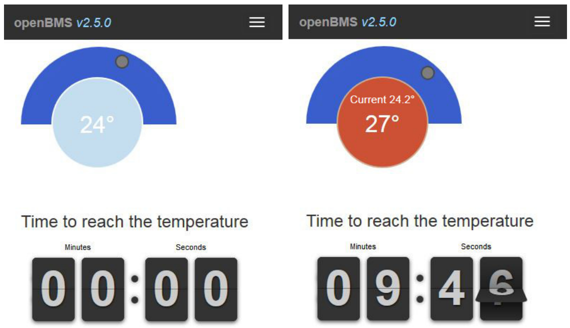

Figure 5: The initial prototype of the time-to-temperature user awareness application integrated with openBMS both in steady state and in operation.

5 CONCLUSIONS

As future work, we envision the porting of the open source of SPICE to ARM architecture in order to integrate our optimized awareness tool in low power embedded electronics, thus, eliminating the need for cloud computing.

In this work, an integrated simulation based framework is presented. It allows the development of applications for near real time feedback to building occupants. This approach is validated by comparison with state-of-the-art tools in accuracy, speed and usability. Its capabilities are highlighted by the development of the feedback agent: time-to-target-temperature. We argue that the strength of our approach lies in the flexibility, affordability and usability aspects of this platform; facilitating the creation of an energy awareness application ecosystem encouraging efficient occupant behavior.

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