Home Energy Management System for off-grid Tiny House

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Abstract

Home Energy Management Systems (HEMS) are becoming more popular in on-grid settings, where they help homeowners lower electricity bills. This project proposes to develop a HEMS that will optimize the energy consumption of an off-grid Tiny House in Richmond, CA for the purposes of avoid energy shortages while limiting deviations from optimal operating temperature. We begin by assuming perfect predictions of insolation, ambient air temperature, and occupant behavior-driven demand. We then develop a Model Predictive Control (MPC) system to control operation of a heat pump and radiant floor system, using parameters estimated from specifications of the materials and equipment used within the house. Proper parameter identification and validation of the model will occur once a data stream from the fully built house exists (Summer/Fall 2016).

I. Introduction

A. Motivation and Background

The rising global demand for energy accompanied by the threat of global warming necessitates cost-effective solutions for reducing both total energy demand and the carbon content of that energy. In the residential sector, cyberphysical home energy management systems (HEMS) have the ability to optimize residential energy use in order to improve user comfort, reduce cost, and minimize CO2 emissions [8]. This is performed by combining streaming data with control and demand response (DR) algorithms.

Numerous HEMS algorithms have recently been developed in both academic and operational settings [9] [5] [7]. The majority of these programs are well-suited to the "on-grid" environment, where cost is the clear choice for an objective, and there are no constraints on total energy demand. In an "off-grid" PV+battery system, however, there are no operational costs yet finite battery size limits energy usage. Furthermore, the ideal minimization objective is not cost but an inherently subjective measure of occupant discomfort due to decreased usage of typical HVAC, water heating, lighting, and plug loads. For this reason, among others, off-grid HEMS are presently less developed then their on-grid counterparts. While the off-grid market is smaller, an accurate HEMS for the energy-constrained situation that is adaptive to user preferences and behavior has the potential for widespread use in off-grid settings.

B. Literature study

Our main resources were the homeworks and notes of this class. Apart from that, we completed a literature review on the topics of tiny houses, HEMS and optimal control. [9], [5] and [7] provided important background information for HEMS in general, demand response, and consumer behavior. By drawing off of this past work, we were able to choose the simplifications of our theoretical model that enabled us to develop a computationally feasible dynamic program. [6] and

[1] provided past examples of energy management optimization frameworks for solar powered buildings.

C. Focus of this Study

We developed a Dynamic Program (DP) to optimally control the Energy and Resource Group (ERG)'s Tiny House In My Backyard (THIMBY) project, an off-grid, solar-powered, 200 sq ft. house being designed and built on the Berkeley Global Campus in Richmond, CA. We will incorporate weather forecasts and predicted occupant-driven demand to control HVAC, water heating, and refrigeration loads. Ultimately, we intend to use the model to make suggestions to homeowners for necessary load reduction in times of low solar input and low battery levels. Within the context of this class project, however, we will focus simply on automated control of heating and cooling, while assuming that user behavior is fixed. Furthermore, we will assume that this fixed user-driven demand, the ambient temperature, and solar insolation are all perfectly predictable over our prediction interval. Specifically, our MPC system addresses the following objectives:

- Analysis and Modeling: Understanding the physical behavior of the house and identifying negligible aspects in order to simplify and linearize the system. Listing reservoirs, parameters and states.
- Parameter Identification: Setting up the linear-in-the-parameters form for future analysis once data sets from the tiny house are available.
- Optimal Control: Build a dynamic program that minimizes the difference of the desired temperature and the temperature set by the dynamic program. The dynamic program will account for constraints on the state of charge of the battery, temperature in the hot water tank and temperature of the floor.

II. Technical Description

A. The Tiny House

As previously mentioned the Tiny House is a off-grid, solar powered, 200 square feet house placed on a trailer. The utilities of the house is carefully picked to minimize the energy demand but also see to the comfort of the users. Furthermore, the energy source for the house is xx square feet photo-voltaic panels providing xx kWh to the Tiny House. The energy demanding features of the house are the hot water demand, radiant floor heating system, refrigerator, poop oven and other user dependent demands such as the usage of plugs. The poop oven is a component of the house with the purpose of disinfecting the effluent from the toilet by heating the later. Both domestic hot water usage and the radiant floor heating system are components that require heated water. Thus a hot water tank will be installed inside the house of which the heating system consists of a heat pump.

B. Nomenclature

The following notations will used throughout the report:

$$\begin{aligned}
C &:= \text{Thermal Capacitance} \\
R &:= \text{Thermal Resistance} \\
I &:= \text{binary on/off indicator} \\
\beta &:= \text{solar irradiance on building surfaces} \\
fl &:= \text{floor}
\end{aligned}$$

$$
\begin{aligned}
s &:= \text{non-floor building surfaces} \\
tnk &:= \text{hot water tank} \\
a &:= \text{indoor air} \\
\infty &:= \text{outdoor ambient air} \\
RF &:= \text{radiant floor heating system} \\
HP &:= \text{heat pump} \\
shw &:= \text{shower demand} \\
fr &:= \text{fridge}
\end{aligned}
$$

Uncontrollable Inputs:
- $P_{PV}(t)$ - Energy supply from PV panel
- $T_{\infty}(t)$ - Ambient outdoor temp
- P_{dem} - Non-heating related (uncontrollable) power demand
- P_{shw} - Power demand due to usage of showers (causes demand from pumps + pulls a given amount of thermal energy out of the hot water tank)

Controlled Inputs:
- $I_{RF}(t)$ - Radiant floor heating system on/off status
- $I_{HP}(t)$ - Heat pump Water Heater on/off status

Outputs
- $T_tnk(t)$ - Hot water tank temperature
- $T_a(t)$ - Operating temperature of house (function of air temperature, floor temperature, and "other surface" temperature)
- $E(t)$ - Battery Energy level
- $T_fl(t)$ - Floor temperature

Reservoirs and associated level variables:
- Thermal energy in hot water tank - T_{tnk}
- Thermal energy of indoor air - T_a
- Energy level of battery (electric) - E_{batt}
- Thermal energy of radiant floor heating system- T_{fl}
- Other surfaces (i.e. walls/ceiling) (thermal) - T_s

C. Thermal Model

A proper thermal model is essential, since most of the measurable outputs will be temperatures. Additionally, the objective and is to minimize a temperature difference. The thermal model includes the operative temperature in the room and the temperatures of the fridge and the hot water tank. All three heat transfer phenomena occur in the house: conduction, convection and radiation. Conduction and convection are both linear, whereas radiation is a non-linear effect that is not explicitly included. However, as a later step in the modeling process simplifications will be made in order to get rid off non-linearity.

The operative temperature is the main comfort variable, since it includes the heat exchange of the user and the house in form of convection and radiation. The parameter ζ usually depends on the flow velocity of the air. Since this is usually not known, a common assumption of $\zeta = 0.5$ is made (ISO 7730). The radiant temperature is the temperature of the surfaces facing the user weighted by their surface area.

$$T_o = \zeta T_a + (1 - \zeta) T_{rad} \tag{1}$$

$$T_{rad} = \frac{T_s A_s + T_{fl} A_{fl}}{A_s + A_{fl}} \tag{2}$$

The evolution of the temperature of some of our reservoirs — namely the floor, "other surfaces" (incl. walls and roof), indoor air, and refrigerator — are described as follows:

$$C_{fl}\frac{dT_{fl}}{dt} = \gamma_{fl} R_{solar} + \alpha_{fl} I - \frac{1}{R_{fl,\infty}}(T_{fl} - T_\infty) - \frac{1}{R_{fl,a}}(T_{fl} - T_a) + O_{fl} P_{th,fl} \tag{3}$$

$$C_a\frac{dT_a}{dt} = \alpha_a I + \frac{1}{R_{fl,a}}(T_{fl} - T_a) + \frac{1}{R_{s,a}}(T_s - T_a) + \frac{1}{R_{t,a}}(T_t - T_a) + \frac{1}{R_{\infty,a}}(T_\infty - T_a) + \frac{1}{R_{r,a}}(T_r - T_a) + P_{th,r} O_r \tag{4}$$

$$C_s\frac{dT_s}{dt} = \gamma_s R_{solar} + \alpha_s I - \frac{1}{R_{s,\infty}}(T_s - T_\infty) - \frac{1}{R_{s,a}}(T_s - T_a) \tag{5}$$

$$C_r\frac{dT_r}{dt} = \frac{1}{R_{r,a}}(T_a - T_r) - P_{th,r} O_r, \tag{6}$$

where
γ_i denotes the proportion of insolation absorbed by reservoir i,
$P_{th,fl}$ and $P_{th,r}$ denote the thermal power provided by the radiant floor and the refrigerator,
$H_{i,j}$ denotes the heat transfer rate between reservoir i and j,
C_i denotes the heat capacity of reservoir i,
α_i denotes the fraction of internal gains that are transferred to reservoir i, and
I denotes the internal gains defined by the following function:

$$I(t) = \beta_c C + \beta_r O_r + \beta_f O_f + \beta_{sh} U_{sh} + \beta_{pl} U_{pl} + \beta_{st} U_{st} + \beta_t U_t + \beta_l U_l \tag{7}$$

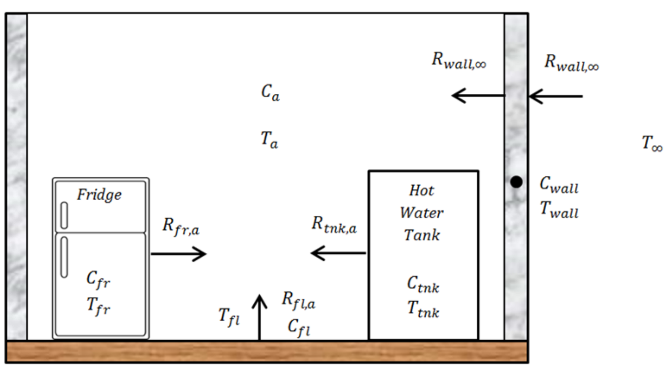

Figure 1: *Thermal Model for the Tiny House air temperature.*

The heating of the Tiny House is maintained by a floor radiator system connected to the water tank through a heat exchanger. The system of equations for the thermal energy in the water tank (stated reservoir) will thus be connected to the thermal energy of the air in the house. The incoming heat fluxes occur through an electric heating system whereas the outgoing heat fluxes will occur due to hot water usage (showers, taps etc.), thermal losses to the heat exchanger and efficiency heat losses. Since the hot water tank is place within the house there will also be a heat flux between the tank and the air in the room. The thermal system is illustrated in figure 2 and the accompanying equations can be seen below.

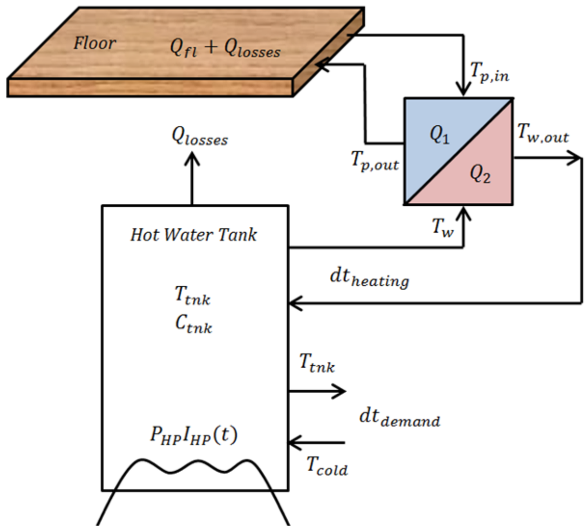

Figure 2: *Thermal Model for hot water tank.*

In order to build a dynamic program that runs smoothly we will however set up the thermal model without the fridge and the poop oven. We will further assume that all heat transfer occurs linearly, that there is no radiative heat transfer and that the efficiency of the battery as well as the heat pumps are constant. Additionally, we will neglect internal gains, inverter losses, thermal losses, power draw of pumps and heat transfer between shower and air as well as hot water tank and air. This results in a simplified model defined in the following equations and as shown in figure 3 and 4. Since the house is not build yet, the parameters given in the equations had to be estimated by using the thermal properties of the materials as well as the geometry of the house. These values are helpful for simulation purposes, but will be replaced later by parameters obtained through parameter identification.

$$\begin{aligned} C_{tnk}\dot{T}_{tnk}(t) = &\Bigg(I_{HP}(t)e_{HP}P_{HP} - \frac{1}{R_{tnk,a}}[T_{tnk}(t) - T_a(t)] \\ &- I_{RF}(t)\frac{1}{R_{tnk,fl}}[T_{tnk}(t) - T_{fl}(t)] - I_{shw}(t)P_{th,shw}\Bigg) \end{aligned} \tag{8}$$

$$\begin{aligned} C_a\dot{T}_a(t) = &\Bigg(\frac{1}{R_{fl,a}}[T_{fl}(t) - T_a(t)] + \frac{1}{R_{s,a}}[T_s(t) - T_a(t)] \\ &+ \frac{1}{R_{tnk,a}}[T_{tnk}(t) - T_a(t)]\Bigg) \end{aligned} \tag{9}$$

$$\begin{aligned} C_{fl}\dot{T}_{fl}(t) = &\Bigg(I_{RF}(t)\frac{1}{R_{tnk,fl}}[T_{tnk}(t) - T_{fl}(t)] \\ &- \frac{1}{R_{fl,a}}[T_{fl}(t) - T_a(t)] - \frac{1}{R_{fl,\infty}}[T_{fl}(t) - T_\infty(t)]\Bigg) \end{aligned} \tag{10}$$

$$C_s\dot{T}_s(t) = \left(-\frac{1}{R_{s,\infty}}[T_s(t) - T_\infty(t)] - \frac{1}{R_{s,a}}[T_s(t) - T_a(t)]\right) \tag{11}$$

$$\tag{12}$$

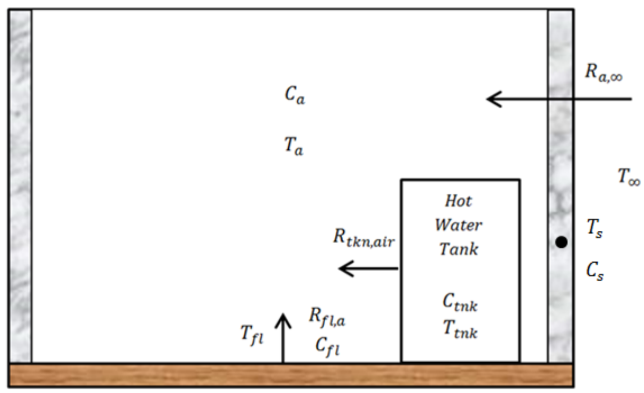

Figure 3: *Simplified Thermal Model for inside air.*

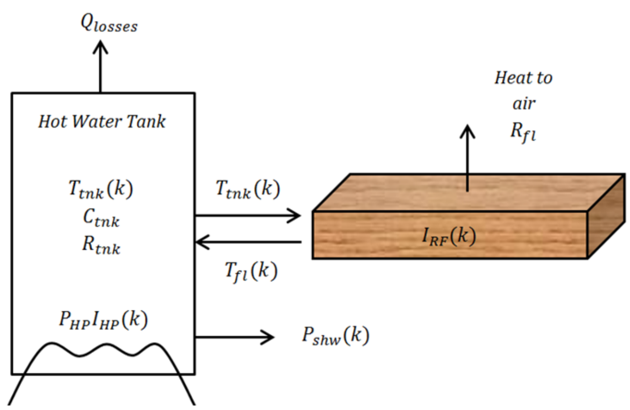

Figure 4: *Simplified Thermal Model for hot water tank.*

D. Dynamic Program

The dynamics described in Section C are jointly non-linear in the states and inputs (see, for example, Equation 8). In fact, given the complex relationship between ambient temperature, PV production, and the various states within the house, it is likely that our feasible set of states at any point in time is non-convex. While this means that convex programs will fail, DP provides a means for near-optimal control of our system. Using the aforementioned dynamics, we construct the following DP:

Cost function:

$$\min_{x(k),u(k)} \quad \sum_{k=0}^{N-1} \frac{1}{2}(T_a(k) - T_{targ})^2 \tag{13}$$

subject to

$$E_{batt}^{min} \le E_{batt}(k) \le E_{batt}^{max}, \qquad k = 0, \ldots, N-1 \tag{14}$$

$$E_{batt}(N) \ge 0.95 E_{batt}(0) \tag{15}$$

$$T_{tnk}^{min} \le T_{tnk}(k) \le T_{tnk}^{max}, \qquad k = 1, \ldots, N \tag{16}$$

$$T_{fl}(k) \le T_{fl}^{max}, \qquad k = 1, \ldots, N \tag{17}$$

$$-P_{batt}^{max} \le P_{batt}(k) \le P_{batt}^{max}, \qquad k = 0, \ldots, N-1 \tag{18}$$

$$E(k+1) = E(k) - \Delta t P_{batt}(k), \qquad k = 0, \ldots, N-1 \tag{19}$$

$$\begin{aligned} &P_{batt} = -e_{batt} S(k) + \frac{I_{HP}(k) P_{HP} + P_{dem}(k)}{e_{batt}}, \\ &\quad \forall P_{batt}^{min} \le P_{batt}(k) \le P_{batt}^{max}, \qquad k = 0, \ldots, N-1 \end{aligned} \tag{20}$$

$$\begin{aligned} T_{tnk}(k+1) = {} & T_{tnk}(k) + \frac{\Delta t}{C_{tnk}} \Big(I_{HP}(k) e_{HP} P_{HP} \\ & - \frac{1}{R_{tnk,a}}[T_{tnk}(k) - T_a(k)] - I_{RF}(k) \frac{1}{R_{tnk,fl}}[T_{tnk}(k) \\ & - T_{fl}(k)]) - I_{shw}(k) P_{th,shw} \Big), \qquad k = 0, \ldots, N-1 \end{aligned} \tag{21}$$

$$\begin{aligned} T_a(k+1) = {} & T_a(k) + \frac{\Delta t}{C_a} \left(\frac{1}{R_{fl,a}}[T_{fl}(k) - T_a(k)] \right. \\ & \left. + \frac{1}{R_{s,a}}[T_s(k) - T_a(k)] + \frac{1}{R_{tnk,a}}[T_{tnk}(k) - T_a(k)] \right), \qquad k = 0, \ldots, N-1 \end{aligned} \tag{22}$$

$$\begin{aligned} T_{fl}(k+1) = {} & T_{fl}(k) + \frac{\Delta t}{C_{fl}} \left(I_{RF}(k) \frac{1}{R_{tnk,fl}}[T_{tnk}(k) - T_{fl}(k)] \right. \\ & \left. - \frac{1}{R_{fl,a}}[T_{fl}(k) - T_a(k)] - \frac{1}{R_{fl,\infty}}[T_{fl}(k) - T_\infty(k)] \right), \qquad k = 0, \ldots, N-1 \end{aligned} \tag{23}$$

$$\begin{aligned} T_s(k+1) = {} & T_s(k) + \frac{\Delta t}{C_s} \left(-\frac{1}{R_{s,\infty}}[T_s(k) - T_\infty(k)] \right. \\ & \left. - \frac{1}{R_{s,a}}[T_s(k) - T_a(k)] \right), \qquad k = 0, \ldots, N-1 \end{aligned} \tag{24}$$

Initial Values:

$$E_{batt}(0) = E_0 \tag{25}$$
$$T_{tnk}(0) = T_{tnk,0} \tag{26}$$
$$T_{fl}(0) = T_{fl,0} \tag{27}$$
$$T_a(0) = T_{a,0} \tag{28}$$
$$T_s(0) = T_{s,0} \tag{29}$$

Value function:

$$V(x(k), u(k)) = \min_{u(k)} \frac{1}{2}(t_a(k) - t_{targ})^2 + V_{k+1}(x_{k+1}) \tag{30}$$

Boundary condition:

$$V(x(N), u(N)) = \frac{1}{2}(T_a(N) - T_{targ})^2 \tag{31}$$
$$\tag{32}$$

where

$$x(k) = [T_{tnk}(k), T_{fl}(k), T_a(k), T_s(k), E_{batt}(k)]^T \tag{33}$$
$$u(k) = [I_{HP}(k), I_{RF}(k)]^T \tag{34}$$
$$T_{targ} := \text{target air temp} = 20\,^{\circ}\text{C} \tag{35}$$
$$E_{batt}^{max} = 2.304 \times 10^7\,\text{J} \tag{36}$$
$$E_{batt}^{min} = 0\,\text{J} \tag{37}$$
$$P_{batt}^{max} = 3300\,\text{W} \tag{38}$$
$$e_{batt} := \text{battery 1-way efficiency} = 0.96 \tag{39}$$
$$e_{HP} := \text{heat-pump conversion efficiency} = 2 \tag{40}$$
$$P_{dem} := \text{user-controlled (i.e. non-heat pump) electrical demand} \tag{41}$$
$$\tag{42}$$

The cost function (equation 13) aims to minimize the squared difference of the target temperature and the indoor air temperature. To model the state of charge of the battery the energy level of the battery is utilized in order to avoid non-linearity as seen in equation 14 and 15. Furthermore, the inequality constraint defined by equation 15 is set as we do not want the energy level of the battery to move outside the limits of 5 % of the initial value.

E. Uncontrollable inputs forecast

A simple bottom-up approach was used to model energy and water demand based on time of the day. For the electricity power demand, the energy consumption profile of a group member's household was pulled from PG&E records to extract an average daily energy demand profile, which was then scaled to correspond to the number of electric loads in the tiny house. In addition, we assumed that two 10-minute showers would be taken each morning from 7am to 7:20am, using a total of 16 gallons of 110deg F water.

Hourly PV production and ambient outdoor temperature inputs were calculated using the National Renewable Energy Laboratory's PVWatts tool [3]. The output we created using PVWatts relied on Typical Meteorological Year (TMY3) data from Oakland International Airport to produce hourly temperature and irradiance estimates, which were then input to their PV production model using a South-facing 2.28kW array tilted at 57deg.

The uncontrollable inputs for a 24 hours period are represented in Figure 5 below.

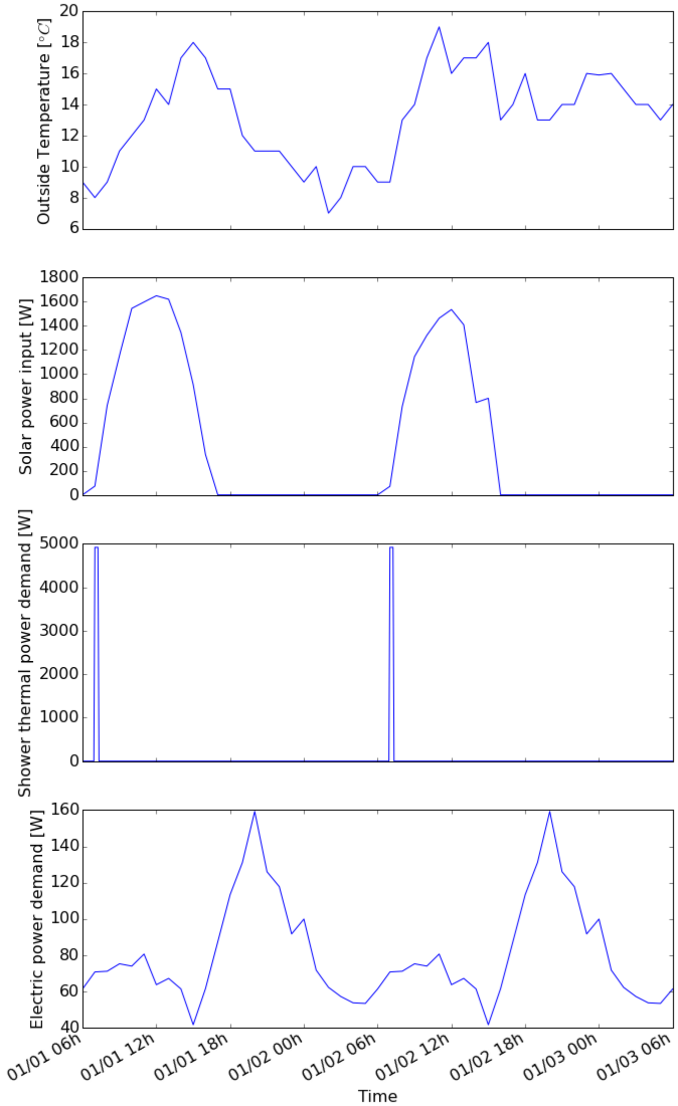

Figure 5: *Uncontrollable inputs for a 48h period*

III. Results and Discussion

The presented dynamic program was run for different time horizons, from 6 hours to 48 hours. Figures 6 to 9 below show the evolution of inside temperature, tank temperature, floor temperature, and battery energy as a function of time. The deviation from target temperature at each time step is also represented on a separate graph.

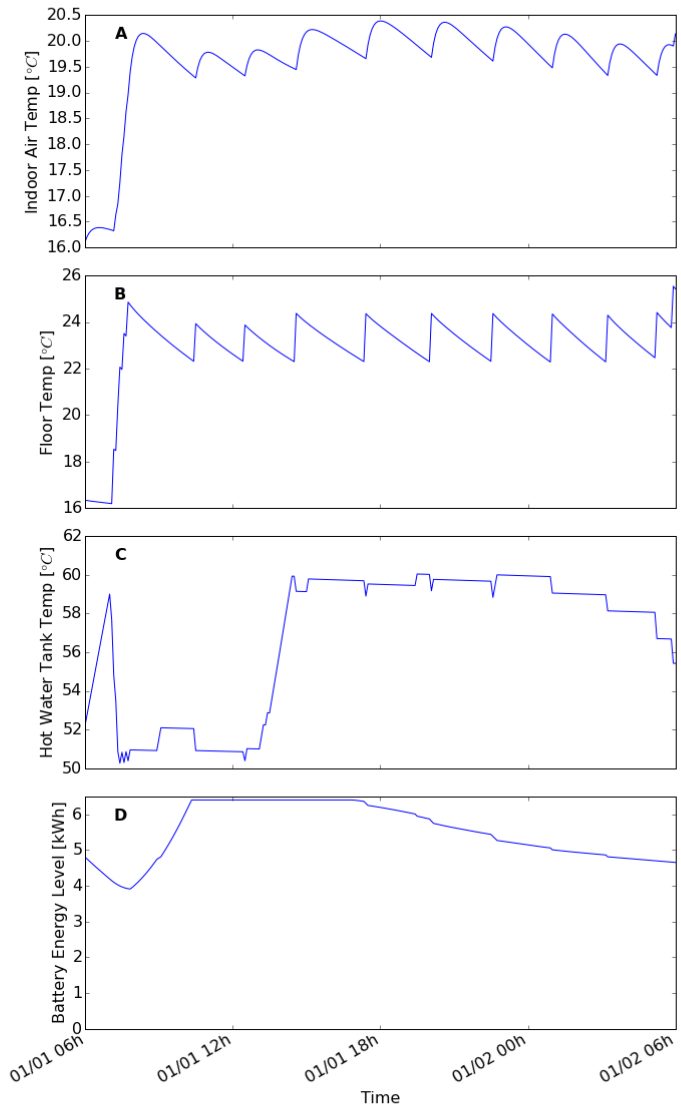

Figure 6: *Evolution of 4 states within a 24h-horizon simulation.*

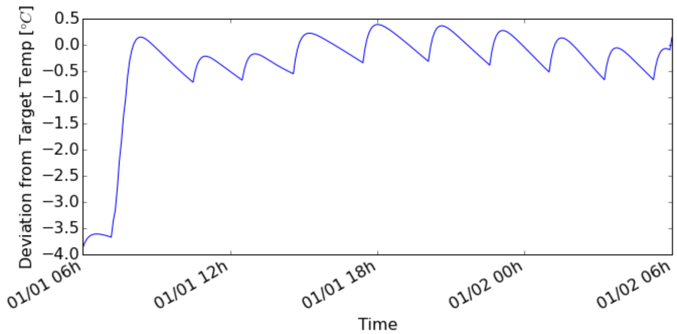

Figure 7: *Deviation from target temperature within a 24h-horizon simulation.*

These first results validate the algorithm and provide an in-house temperature profile with a mean square root error of 0.29 °C. As expected, the indoor air temperature fluctuates around the target temperature of 20 °C, after a transitory state of around 1 hour.

The floor temperature increases are correlated with activated floor heating ($I_{RF} = 1$), which in turn leads to increase of indoor temperature. As specified in the algorithm, the floor temperature does not go above the chosen comfort limit of 27 °C.

Solar power input during the day is sufficient to cover electricity demand, and thus this time period corresponds to a charging of the battery. Past 6pm, the battery is the only source of power and is thus discharged progressively.

Similarly, the tank temperature also starts increasing after 12pm to anticipate decrease of available solar power and future use of radiant floor heating. The tank tem The effect of showers can also be seen in the peak increase of tank temperature that occurs at 7am for the first day.

A constraint was put on the battery final energy level to be no less than 95% of the initial energy level, and can directly be checked by looking at the battery energy level at the final time step. This constraint is crucial as it ensures resource availability even at night. For these simulations, the initial state of charge of the battery was set to 0.75, but it is interesting to notice that this value can be lowered to one that is more realistic with the data frame considered (6am to 6am the next day). Indeed at the end of the night, it can be expected that the battery will have been significantly discharged and will thus start the next day with a low energy level.

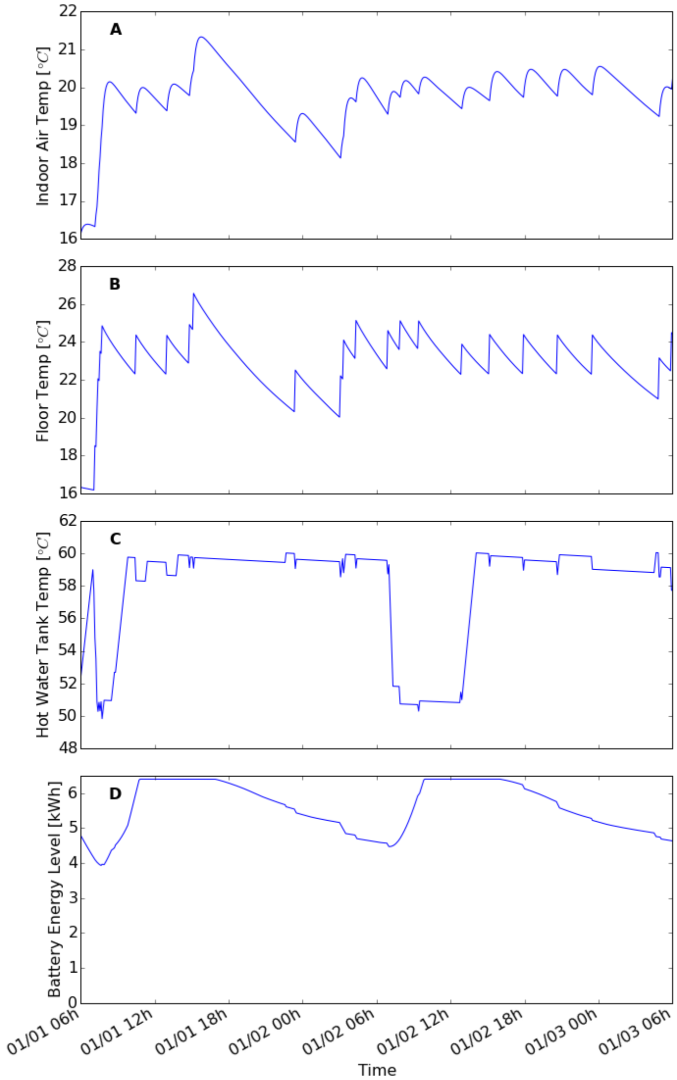

Figure 8: *States evolution for a 48h horizon optimal control*

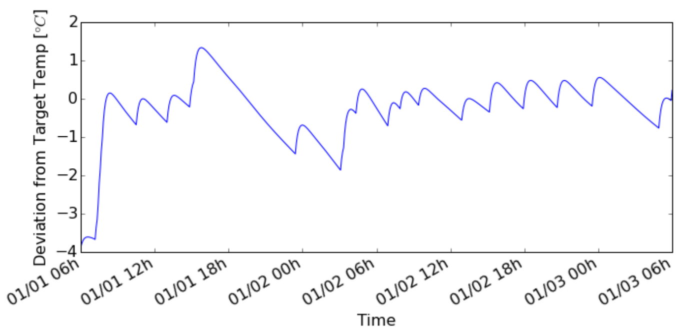

Figure 9: *Deviation from target temperature for a 48h horizon optimal control*

The same behavior is observed for the 48h time horizon, with a root mean square error of 0.85 °C.

IV. Summary

The envisioned Home Energy Management System innovates from the classical on-grid HEMS, as the end goal of the system is no longer to minimize costs of electricity withdrawn from the grid but rather to make sure that the homeowners will be able to satisfy their vital energy consumption needs at all time. A dynamic program suitably represents the energy dynamics within the tiny house, given parameters estimated using specifications of materials and equipment used in the house.

Several actions will be taken once the tiny house is built. Parameter identification will better estimate the parameters used in the dynamic program. After applying these parameters, the performance of the simplified system can be validated. If not satisfying, it can be improved by taking into account neglected effects step by step (e.g. energy recovery ventilator (ERV), radiative heating, temperature-dependent efficiencies). Furthermore, model predictive control will be used to iteratively solve the control problem for varying inputs at consecutive timesteps. Weather forecasts will take the place of a Typical Meteorological Year dataset to allow us to control the house with knowledge of future temperature and cloud cover. Furthermore, an online learning algorithm will better predict non-heating electrical demand. Ideally, this will allow active user input. Finally the HEMS can be enhanced to influence the user's behavior by providing information and advising during critical energy supply phases. This would result in a better use of resources throughout critical phases.

References

[1] Colin, C., El Alami, K. and Nouet, W.
"Predictive Energy Demand Side Management for a Residential Photovoltaic and Battery Solution", Berkeley, 2015

[2] DeWitt and Roeschke
"Optimal Refrigeration Control for Soda Vending Machines", Berkeley, May 2015.

[3] National Renewable Energy Laboratory
"PVwatts", http://pvwatts.nrel.gov/pvwatts.php.

[4] Pipattanasomporn, Kuzlu and Rahman
"An Algorithm for Interlligent Home Energy Management and Demand Response Analysis", *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp 2166-2173, December 2012.

[5] Semigran and Tsim
"Bay Area Smart Home Cost Optimization with Photovoltaic Electricity", 2014.

[6] Sun, C., Sun, F. and Moura, S.
"Nonlinear Predictive Energy Management of Residential Buildings with Photovoltaics and Batteries", Berkeley, Summer 2015.

[7] Zhou et al.
"Real-time Energy Control Approach for Smart Home Energy Management System", *Electric Power Components and Systems*, vol. 42, no. 3-4, pp. 315-326, 2014.

[8] WattTime
"Connecting Clean Energy to the Internet of Things", http://www.watttime.org.

[9] Zipperer et al.
"Electric Energy Management in the Smart Home: Perspectives on Enabling Technologies and Consumer Behavior", August 2013.