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Dynamic SetPoint Control of Electric Hot Water Heaters for Increased Integration of Solar Photovoltaic Systems

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***Abstract*—The integration of solar photovoltaic (PV) systems onto the existing grid provides a clean source of electrical power. However, PV systems can only produce power during the day and is often intermittent. Utility companies must implement mitigation strategies that account for large ramp rates and high variability. The strategies include the control of dispatchable resources that can react quickly to abrupt changes in demand and generation. For example, electric water heaters (EWH) can be controlled to help grid operations. This paper reports on a simulation effort that evaluated the potential for EWH to more closely follow solar power generation to decrease ramp rates and smooth PV variability. The experiment implemented an dynamic setpoint controller that synchronized the charging of EWH with the sun. The simulation results were coupled with actual feeder data that support 2,900 residential homes and had a 6MW PV system. The approach successfully synchronized the EWH with the PV generation and maintained a comfortable temperature for the occupants.**

***Index Terms*—electric water heaters, demand response, photovoltaic**

I. Introduction

The balance between electrical consumption and production offers significant challenges for today's grid. The integration of renewable energy sources, electro-mobility, and increased demand requires sophisticated control methods to balance the overall system in real-time. Demand side management controls offer a cost effective means to optimize and temporarily reduce electrical power. For example, energy efficiency can permanently reduce demand, time of use rates can optimize schedules to shift demand, demand response (DR) can shed loads quickly, and spinning reserves can provide frequency control services [1]. This paper examined the potential for advanced control of thousands of residential electric water heaters (EWH) to synchronize demand with solar photovoltaic (PV) generation.

Advanced control of residential systems, such as EWHs, can provide significant benefits for the electric grid. The residential sector has the potential to provide about half of the total peak demand reduction in the United States [2]. Existing and past incentive programs offered by utility companies have enticed customers to minimize their overall energy consumption and reduce power draw when needed to improve grid stability. Existing programs, described by Ericson [3], have successfully incentivized customers to allow the utility to control their EWHs. For example, Xcel Energy paid customers $2 per month for an entire year if they allowed their EWH to be disconnected for a 6 hour period during hot summer and cold winter days. This program included 280,000 EWH and was able to reduce demand by 330 MW in 2001. An Australian program was also implemented successfully and reduced demand during peak operations by 389 MW using 355,000 EWH. Current and past incentives programs were typically designed to shed peak load at the expensive of occupant comfort. This paper investigates the potential to implement a program that controls EWHs based on solar PV production while avoiding occupant discomfort.

Synchronizing the electric power demand of EWHs with the sun can improve the integration of PV on the grid by leveling the net power profile. The net power is the difference between the electrical load and the PV system generation. The net load profile often has a large valley in the middle of the day caused by the generation of electricity from PV systems [4]. As a result, there is a large increase in demand as the sun sets. The utilities must account for this significant increase in demand and often rely on expensive generation plants. Instead, utilities can implement a program that dynamically controls EWH setpoints. The dynamic setpoint control algorithm uses the measured irradiance as an independent variable. The algorithm has the potential to fill the net load profile valley and smooth intermittent solar PV generation.

This paper describes an experiment that simulated the control of EWHs using the dynamic setpoint algorithm. The paper is structured into four main sections: background, methodology, results, and conclusions. The methodology provides an overview of the EWH model and water draw profile. It also discusses the impact that solar generation has on the grid and defines the dynamic setpoint control algorithm. The results section provides a discussion and supporting graphs from the simulation effort. The conclusions section describes the key findings and potential next steps.

II. Background

Considerable work has been conducted to evaluate the control of EWHs to support grid services. Research studies have shown that EWH can be used for demand side management. Sepulveda et *al.* successfully implemented a particle swarm optimization algorithm to control 200 simulated EWHs [5]. The simulation results showed that the EWH control was able to shift the residential load and reduce morning and evening peaks by 100kW and 150kW respectively. Another study evaluated the charging and discharging impacts on exergy [6] to improve peak shaving control. This study determined what customers are most likely to be drawing power during the utility's peak. This helped the utility company determine which customers were eligible for the program. Another study performed by Pourmousavi et *al.* simulated the control 1,000 residential EWH for demand response (DR) by modulating the temperature set point [7]. The research paper defined multiple control cases, such as set-point control based on time of use pricing, that can provide peak shaving benefits for the utility. In addition to peak shaving, research studies have shown that EWH can provide balancing services for the grid. For example, Diao et *al.* [8] modeled 147 residential hot water heaters and tested centralized and decentralized controllers for frequency support.

III. Methodology

The present work used a model to simulate EWHs and actual demand and PV data from an electric feeder. The feeder was comprised of 4 substations that support about 2,900 residential buildings. The feeder was observed to have a maximum electrical load of about 11MW. It also had 6MW PV array connected to one of the substations. The PV array provided about 20% of the energy on an annual basis. The experiment assumed that each of the homes had a EWH that could be controlled. The EWHs were simulated inside a control aggregation model written in Python programming language. The simulation effort evaluated the potential of hot water storage charging to occur during peak solar PV generation and also react to intermittent behavior.

A. Electric Water Heater Model

EWH models have been discussed frequently in past literature. The tanks have commonly been modeled using a single node approach where the temperature in the tank was assumed to be constant. This type of model applied a first order

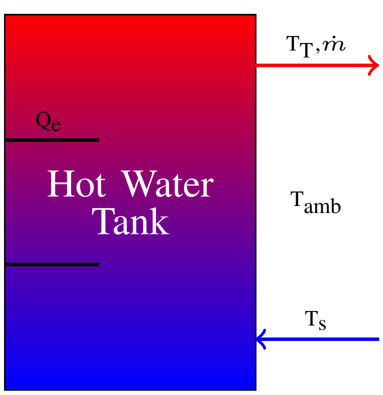

Fig. 1. The electric hot water heater was modeled using a state space model. The variables included tank mass and temperature, inlet temperature, heating element power, and mass flow rate.

differential equation that solved for the tank temperature [8], [9]. The present work modeled the dynamic EWH system using a state space model. Unlike the single node approach, the state space model considered the thermal stratification. EWH storage tanks experience stratification, shown in Figure 1, where the cold water is on the bottom and the hot water is on the top.

The state space model used in this experiment was created to simulate model predictive controls by Jin *et* al. [10]. The approach divides the tank into vertically stacked isothermal nodes. The model then calculates the energy balance for the nodes using:

$$C_i \frac{dT_i}{dt} = Q_{in_i} - Q_{loss_i} - Q_{draw_i} \tag{1}$$

where Q_{in} is the heating element thermal power,
Q_{loss} is the thermal loss, and
Q_{draw} is the thermal power lost to the house.

The state space model was used to solve the non iterative part of Equation 1. State space models represent physical systems using a first-order differential equation and a set of inputs, outputs, and state variables. In this case, the equations were developed using:

$$\dot{x}(t) = A(t)x(t) + B(t)u(t) \tag{2}$$

$$\dot{y}(t) = Cx(t) \tag{3}$$

where the state variable x is a vector of the thermal tank node temperatures T_i ($x = [T_0, T_1, ..., T_{11}]$) and the control variable u is a vector that contains the ambient temperature (T_a), inlet temperature (T_{in}), and the heating element control signal represented by $s_{element}$ ($u = [(T_a, T_{in}, s_{element}])$. The state space model, described in Equations 2 and 3, was converted to a discrete time state space model in order to incorporate temperatures and flow rate. The simulation effort used a 50

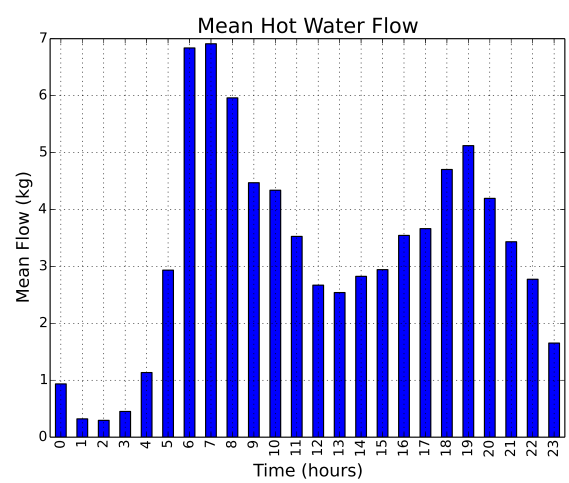

Fig. 2. The average hot water flow at each hour of the day peaked in the morning around 7:00. It then decreased during the middle of the day and then peaked again around hour 19:00.

gallon tank with two 4,500 Watt heating elements for each of the residential buildings. The model also depended on a realistic draw profile to simulate the thermal and electrical performance.

B. Electric Hot Water Draw Profiles

The simulation of the 2,900 EWH used random draw profiles based on past statistical analysis of residential use [11]. A generator was used to created unique profiles that represented actual use at one minute intervals. The mean of all the profiles for each hour of the day is shown in Figure 2. The average flow profile was very low in the early morning and quickly increased to a peak around 07:00. The profile then decreased during the middle of the day and peaked again around hour 19:00.

C. Electric Grid

The integration of solar PV systems presents many complications. Locations where there is a high penetration of PV

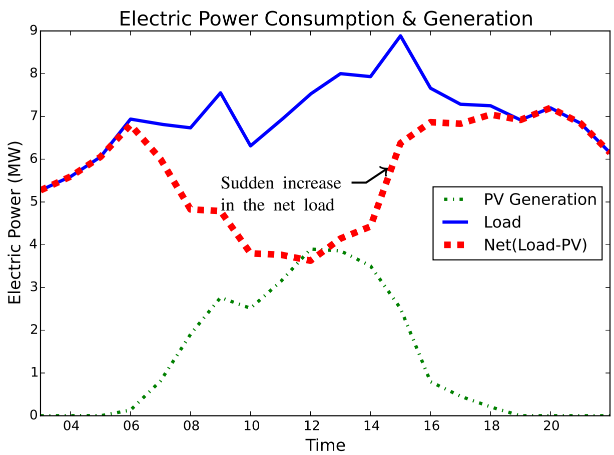

Fig. 3. The net load is the difference between the load and the PV generation. The net load has a large rampe rate at the end of the day when the sun sets and demand increases. The change may require utilities to turn on expensive generation stations.

requires the utility to react quickly to large changes in the net load. The net load is the difference between the load and the PV generation as shown in Figure 3. The increase in demand coupled with the rapid reduction in solar power generation as the sun goes down at the end of the day can cause instability on the electric grid. This situation may require the deployment of an expensive generation station to rapidly come online and accommodate the load. EWHs have the potential to mitigate this issue by synchronizing their charging with the solar production.

The synchronization of the EWHs with the sun can also help with the intermittent generation of power caused by clouds. The variability in solar generation, shown in Figure 4, can cause large fluctuations in the net load. The variability has been addressed in past literature with batteries [12], hybrid storage [13], heating/cooling equipment [14], and others. The different approaches have attempted successfully to smooth the PV output using various storage devices. The present work used EWH to match the load with the solar generation. The approach used a control signal for the hot water tank setpoint temperature that was dependent on the solar irradiance.

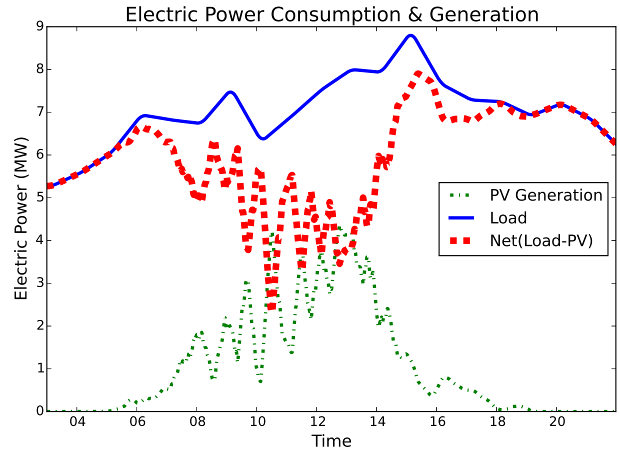

Fig. 4. The net load, which is the difference between the load and the PV generation, can have rapid fluctuations caused by solar intermitenacy due to clouds. The variability can cause instabilities on the grid.

D. Setpoint Control

The control of EWHs can provide services that improve the viability of solar PV on the grid. Solar energy at the earth's surface can change rapidly throughout the day as clouds move across the sky. The changes can have an impact on the grid in locations where there is a high penetration of PV. The dynamic setpoint control of EWH can help synchronize the solar power with the load and simultaneously maintain occupant comfort.

The control of the simulated EWHs, that typically have a static setpoint temperature, were altered to have a dynamic setpoint. The setpoint temperature is the reference temperature that is compared with the actual water temperature to determine the control of the heating element inside the EWH. If the water temperature (T_{water}) is less than the setpoint temperature (T_{sp}) by more than 2.7°C than the heating element is turned on as shown in Equation 4:

$$\text{Heating Element} = \begin{cases} \text{On}, & \text{if } T_{water} < T_{sp} - 2.7°C \\ \text{Off}, & \text{otherwise} \end{cases} \quad (4)$$

The dynamic setpoint, used in this experiment, was a nonlinear function:

$$T_{sp} = 12(E/1300)^3 + 45 \quad (5)$$

where E is the measured irradiance (W/m^2). In this experiment the static set point temperature was set to be 49°C. The nonlinear function, plotted in Figure 5, is a third-order equation where the setpoint temperature is set to be 45°C at low solar irradiance and slowly climbs to 49°C at 700 W/m^2. Between 700 and 1200 W/m^2 the function increases from 49°C to about 54.5°C. The nonlinear set point control is necessary so that the heating element in the EWH does not turn on at low irradiance unless it is necessary for occupant comfort. The set point temperature can exceed 52°C at high irradiance so that the tank can maintain a comfortable temperature throughout the night and morning.

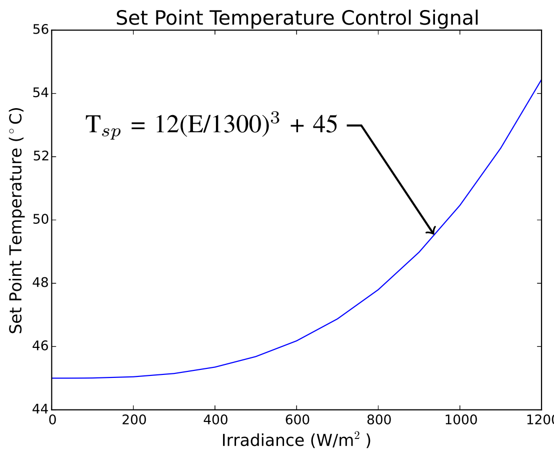

Fig. 5. The control algorithm increases the temperature set point based on a nonlinear function that increases from 45°C to 54.5°C exponentially.

E. Experiment

The simulation of 2,900 EWHs was conducted in a coordinator manner to compare a typical operations with two different dynamic setpoint control scenarios (Table I). The first test was the baseline simulation that modeled all of the EWHs with a static set point of 49°C. The second test modeled

TABLE I
CONTROL SCENARIO TESTS

Test	Name	Control Type	
		Static Set Point (49°C)	Dynamic Set Point
0	Baseline	2,900	0
1	Solar Control A	1,933	967
2	Solar Control B	967	1,933

1,933 EWH with a static set point of 49°C and 967 with the dynamic nonlinear set point defined by Equation 5. The third test decreased the number of EWHs controlled using the static set point of 49°C to 967 and applied the dynamic set point to 1,933 EWHs.

IV. RESULTS

The experiment simulated three different scenarios as described in Section III-E. The EWH results from each scenario was combined with the actual PV and load data from a feeder. The results include an overview of typical water draw and electric demand profiles. The typical operations simulation was performed first to develop a baseline profile that could be compared with the results from the proposed dynamic setpoint control algorithm. The dynamic setpoint control algorithm was simulated in three different scenrios where it was applied to 33%, 66%, and 100% of the EWHs in the 2,900 homes.

A. Typical Control of Electric Water Heater

The electric feeder had a load profile that peaked to about 10MW in the afternoon and dropped below 4MW in the early morning, as shown in Figure 6. Over the three day period the PV generation fell to zero during the night and reached a maximum of 3.8 MW over the three day period. The simulation of typical EWH operating conditions had a

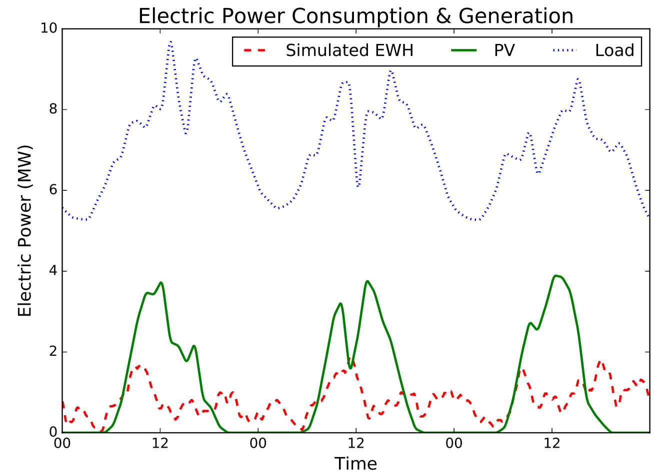

Fig. 6. Under normal operating conditions the load peaked to about 10MW in the late afternoon and dropped to around 4MW in the early morning. The PV generation reached a maximum value of 6MW during the day and dropped to zero at night. The electric water heater simulation had a peak load in the morning around 07:00 and then a smaller peak around hour 19:00.

profile that peaked to about 2MW around hour 08:00.

The electric power draw from the 2,900 EWHs followed closely with the hot water draw. The total power for all 2,900

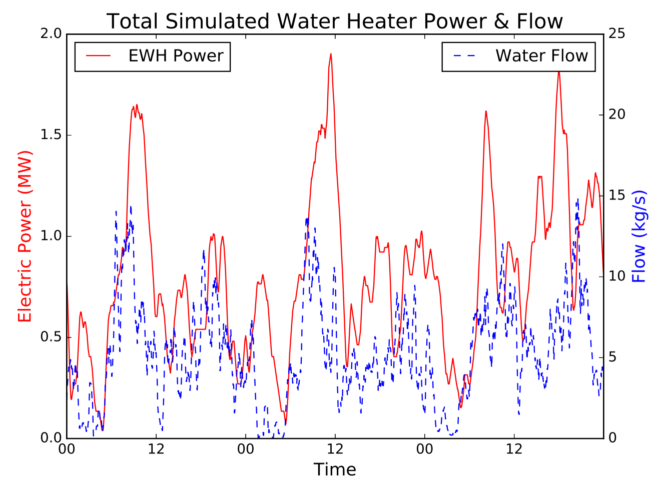

Fig. 7. The three day period in August had a peak power draw of about 1.9MW. The water flow reached a high of about 15kg/second for the 2,900 simulate EWHs.

EWHs increased and decreased with the water flow, but was slightly offset as shown in Figure 7. The offset indicated that time to charge the thermal tank expanded beyond the usage of the hot water. The tanks were charged right after the water temperature dropped below the setpoint value.

B. Dynamic Setpoint Control of Electric Water Heater

The control algorithm was able to synchronize the EWH electrical demand with the solar generation as shown in Figure 8 that plots a four day period in August. In this case,

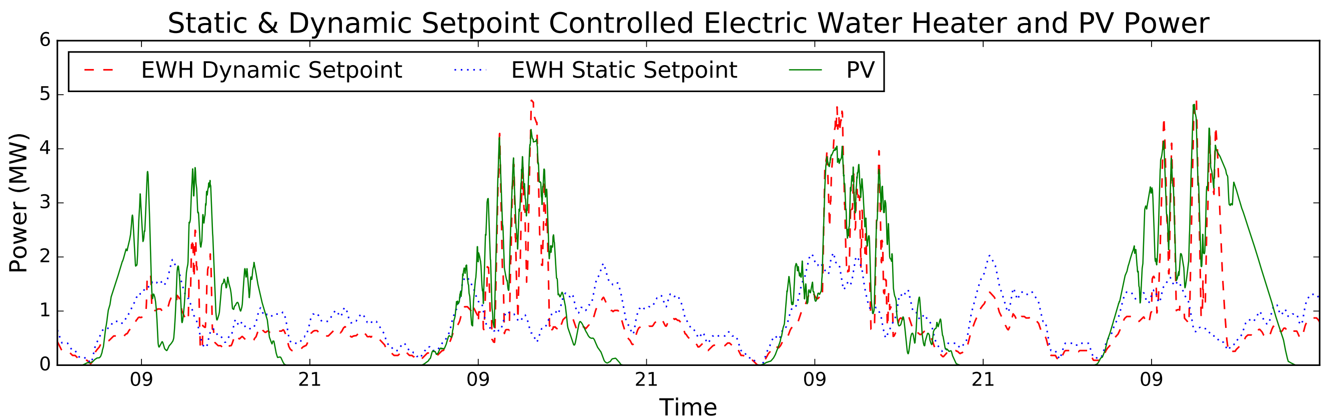

Fig. 8. The uncontrolled electric water heater charging power does not match well with the PV generation profile under normal conditions. The nonlinear set point control algorithm applied to 33% of the residential homes synchronizes consumption with PV generation over a four day period.

the simulation controlled about 960 of the 2,900 EWHs using the dynamic setpoint control algorithm. The power consumed by the 967 EWHs increased and decreased with the generated solar power. During the night the overall EWH power draw was less than the EWHs controlled using a static setpoint. The

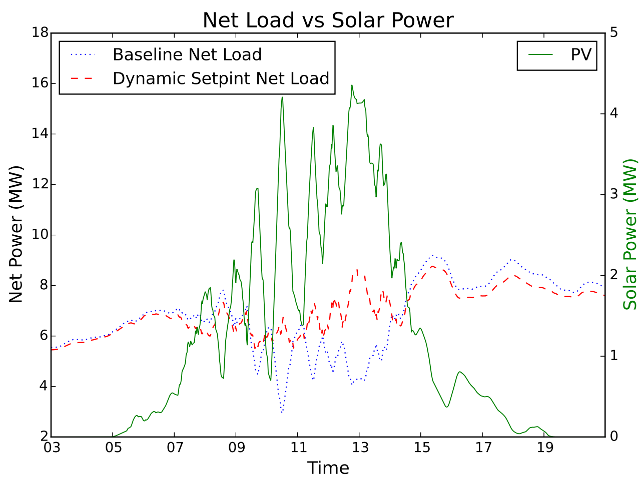

Fig. 9. The solar irradiance dependent set point algorithm was able to fill in the valley created by the PV production and smooth the variability.

reduced power demand during the night was because the tanks had been charged to a higher set point than normal during the day. The EWH power demand was combined with the net load to evaluate the impact on the variability and end of day ramp rates.

The control of the 967 EWHs affected the net load by increasing demand during the day and then decreasing it during the night. This result was computed by first subtracting the baseline EWH demand from the measured net load and then adding the results from test 1. The new load profile, shown in Figure 9, filled in the valley and decreased the magnitude of the intermittent spikes. The approach eliminated the large ramp rate that had occurred at night fall in the baseline simulation.

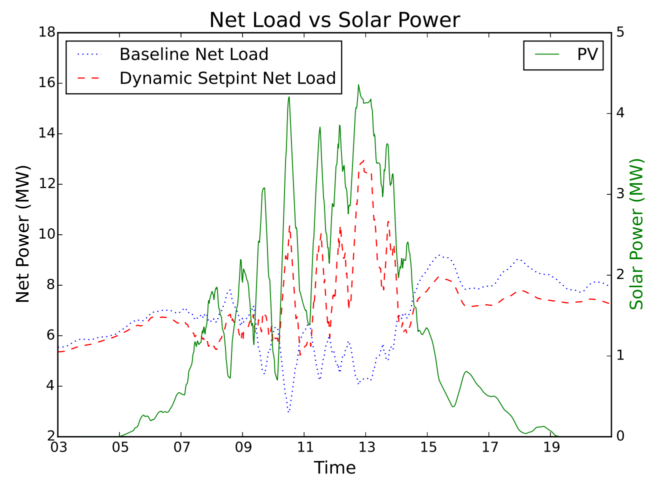

Fig. 10. The dynamically controlled setpoints for 67% of the EWHs allowed the net load to follow the solar PV generation profile well. It also decreased the overall load at night by about 1.1MW between hour 16:00 and midnight.

The second test, that controlled 1,933 EWHs with a dynamic setpoint and 967 with a static setpoint, was able to follow the PV generation profile well (Figure 10). The net load was much higher than the baseline during the day and it followed the variable output of the PV system well starting at 11:00 in the morning. The control algorithm was not able to follow the solar generation as much in the morning. However, in the afternoon the net load increased from a max value of 8MW in test 1 to a maximum load of 16MW. The night time demand differential also increased.

The simulation calculated the average temperature at the top and bottom of the tank. During the same four day period between August 4th and 7th that is plotted in Figure 8 the average temperature at the top of the tank did not drop below 50°C as shown in Figure 11. Additionally, the bottom temperature did not drop below 47.5°C. The average temperature in the EWHs that were synchronized with the sun remained within a comfortable range for users.

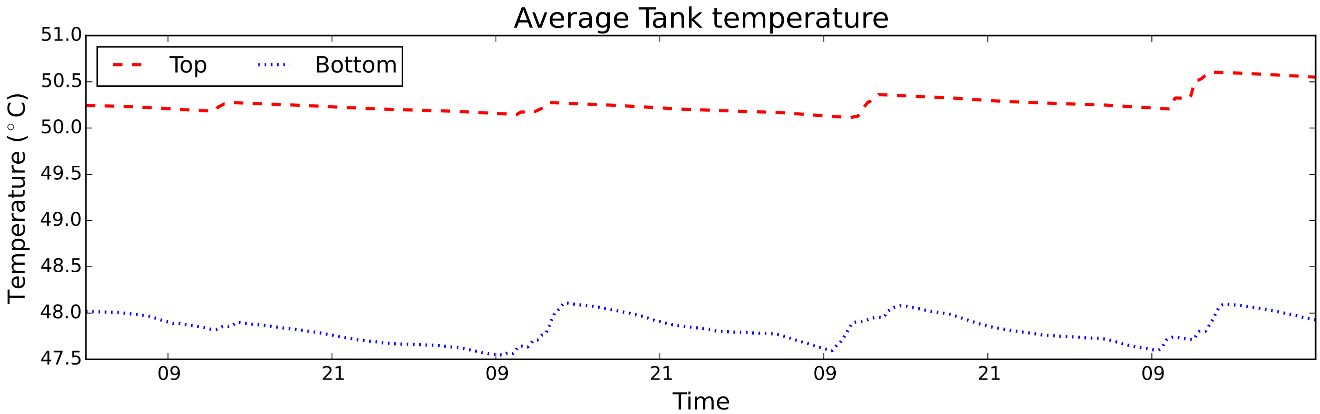

Fig. 11. The simulation effort calculated the top and bottom temperatures in the hot water tanks. The temperatures stayed within a range that maintained occupant comfort through the four day period. The top temperature did not drop below 50°C and the bottom temperature stayed above 47.5°C.

V. Conclusion

The experiment simulated 2,900 EWHs using two different control approaches. The first approach emulated typical operations of an EWH and used a static setpoint. The second approach used a dynamic setpoint control algorithm that changed the setpoint based on the measured irradiance. The simulation effort found that the dynamic control of EWH setpoints can be used to synchronize the tank charging with solar PV generation. The approach mitigated the sudden increase in the net load that occurs when the sun sets. It also addressed the need to smooth the variability of PV by matching the electric power draw of the EWH with the intermittent solar generation.

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