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Demand Response of Electric Hot Water Heaters for Increased Integration of Solar PV

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***Abstract*—Integration of solar photovoltaic (PV) systems onto the electric grid provides clean sources of electrical power. However, utilities must implement mitigation strategies to avoid large ramp rates. This paper evaluated the potential for an electric water heater (EWH) to improve daily gird operations on an actual feeder. The actual feeder supplies power to about 2,900 homes and has a 6MW PV array. The control strategy included on/off commands, modulation of the hot water tank set point, and used partitioning techniques to reduce the load efficiently. The experiment successfully controlled the EWHs so that the the net load peaks observed in the morning were reduced, and the evening ramp rates were decreased.**

***Index Terms*—photovoltaic degradation**

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. Demand side management controls offer a cost effective means to optimize and temporary 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 thousands of residential electric water heaters (EWH) to shift demand.

Centralized control of residential EWH 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. Integration of smart grid technologies, such as the internet of things, must work with intelligent algorithms to control home appliances appropriately. Advanced control is required because of the inherent variable power draw from residential homes. Appliances such as EWH offer a high peak power potential [2] and have been integrated into existing utility company incentive programs.

Existing incentive programs offered by utility companies entice customers to minimize their overall energy consumption and reduce power draw during critical grid operations. Existing programs have incentivized customers to allow the utility to control the EWH. For example, Xcel Energy paid customers $2 per month for a whole year if they allowed their EWH to be disconnected for 6 hour periods during hot summer or cold winter days. The 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 [3].

In addition to utility integration, research studies have shown that EWH can provide balancing services for the grid. For example, Diao et *al.* [4] modeled 147 residential hot water heaters and tested centralized and decentralized controllers for frequency support. EWH have been considered good candidates for real-time DR to shift loads and balance wind generation. Pourmousavi et *al.* simulated the control 1,000 residential EWH for DR by modulating the temperature set point [5]. The present work also performed a simulation of EWH. The intent was to control the EWH to improve the integration of solar photovoltaics (PV) on the electric grid.

The integration of solar PV on the grid creates a scenario where the net load is reduced during the day and then experiences a sharp increase as the solar irradiance decreases. This situation is often referred to as the duct curve [6]. The sharp increase in demand requires utility companies to turn on costly power generators quickly. The implementation of targeted DR activities can improve grid operations and stability during these high ramp rate situations. This paper evaluates the potential for EWH to decrease the ramp rate and improve the integration of solar PV on the grid.

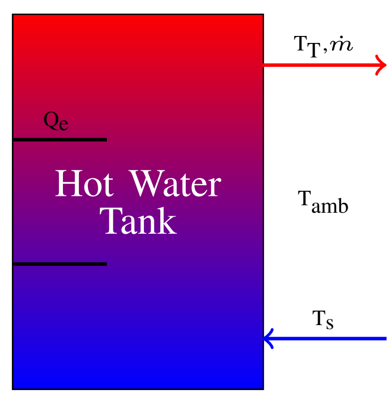

Fig. 1. The electric hot water heater was modeled using a first order differential equation. The variables included tank mass and temperature, inlet temperature, heating element power, and mass flow rate.

II. Methodology

The present work used actual demand and PV data from an electric feeder. The feeder is 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 for DR. The EWHs were simulated inside a control aggregation model. The intent was to reduce the overall demand on the feeder in the morning and evening to decrease the ramp rates caused by the PV power production.

A. Electric Water Heater Model

The EWH was model used a single node approach where the temperature in the tank was assumed to be constant. A first order differential equation was used to solve for the tank temperature and has been used often in past literature [4], [7]. The first-order differential equation is as follows:

$$M\frac{dT_T}{dt} = Q_e + \dot{m}C_p(T_s - T_T) + UA(T_{amb} - T_T) \quad (1)$$

where
M: mass of water in the tank (kg)
T_T: tank temperature (°C)
Q_e: heating element power (Watts)
T_s: inlet temperature (°C)
T_{amb}: ambient temperature (°C)
$\dot{m}$: mass flow rate (kg/s)
C_p: specific heat of water (4.18J/g°C)
U: heat transfer coefficient (W/m^2K)
A: Area of the tank surface (m^2)

B. Electric Hot Water Simulation

The simulation of the 2,900 EWH used random draw profiles based on past statistical analysis of residential use [8]. A random 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 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.

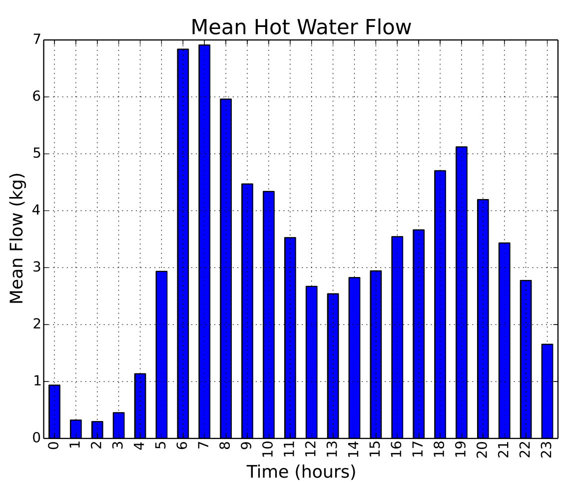

Fig. 2. The average hot water flow at each hour of the day peaked in the morning around 7:00. It then decreased during the middle of the day and then peaked again around hour 19:00.

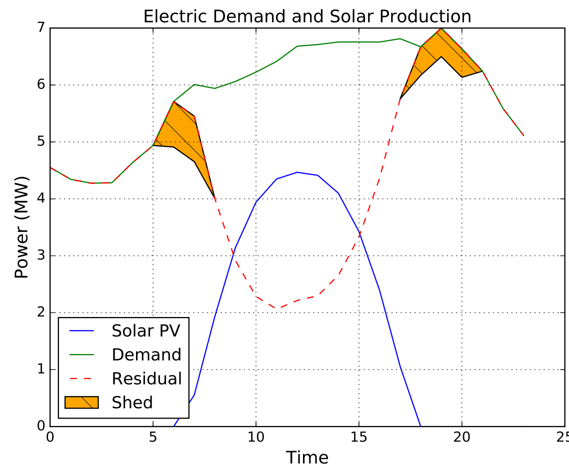

Fig. 3. The DR control strategy attempted to reduce the load at the shoulders of the residual curve. The intent was to reduce the ramp rates caused by the increase or decrease in PV power production.

C. Demand Response Control

The control of thousands of EWH has the potential to shed considerable load. EWH draw about 4.5kW of electricity when charging. The control of the EWH is complicated because the charging times do not all match. Therefore, this experiment implemented a control strategy that used the temperature set point and on/off command. The strategy attempted to reduce the electrical load at the shoulders of the residual curve as shown in Figure 3. The intent was to reduce the ramp rates caused by the increase or decrease in PV power production.

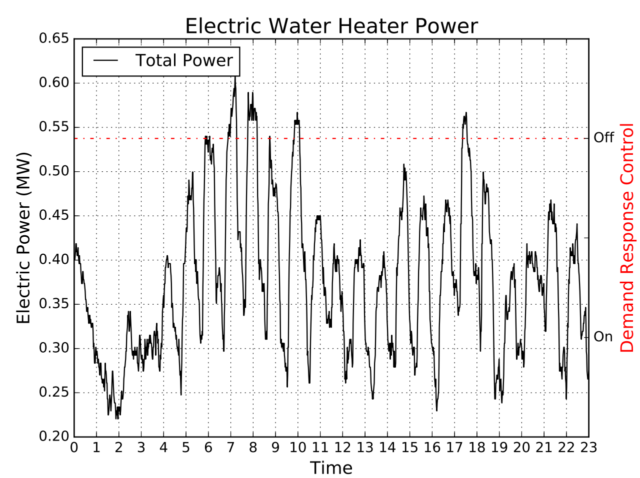

Fig. 4. The electric power profile for the 2,900 water heaters peaked around 07:00 and 18:00.

III. Results

The experiment results include electric demand profiles for normal and DR controlled operations. The normal operations was performed first to develop a baseline profile. Then the DR control scenario was implemented to define the potential reduction in load. Finally, the DR results were subtracted from the baseline to produce a profile that was compared with the actual demand on the feeder.

A. Normal Operations

The simulation effort began with a representative model of EWH and the associated draw profiles. The model simulated 2,900 water heaters without DR control. The peak demand for all of the EWH was simulated to be 0.6MW around 07:00 in the morning and about 0.55MW in the evening as shown in Figure 4. Therefore, there is a potential to shed around 0.5MW during the morning and evening when the net peak is at its highest.

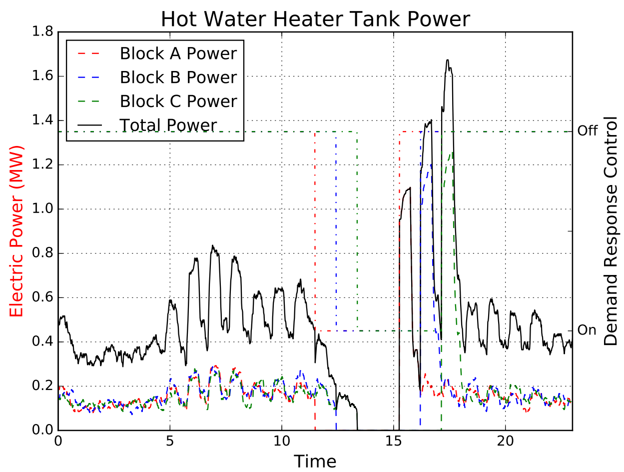

Fig. 5. The control of 2,900 EWH by separating the devices into three bins and then staggering the on/off commands reduces the peak rebound from 4MW to 1.6MW.

B. Demand Response Control

The DR controller was set up to shed load when the PV power was increasing and decreasing. The DR controller output on/off commands and also defined the internal water temperature set point. It als considered a partitioning of EWH so that the rebound would not be significant. For example, without partitioning and no set point control the peak rebound for the EWHs was estimated to be around 4MW. The partitioning control strategy was able to reduce the peak down to 1.6MW as shown in Figure 5. The DR control strategies were able reduce the load and improve the ramp rate of the "Duck Curve" as shown in Figure 6. The load was reduced in the morning by 0.45MW and the rebound increased demand slightly. However, it did not create a large peak. The evening ramp rate was decreased and as a result created a peak at hour 20:00.

IV. Conclusion

The experiment was able to model EWH and integrate DR control effectively. The control strategies used on/off control, modulated the set point, and implemented a partitioning approach to reduce the rebound. The control successfully altered

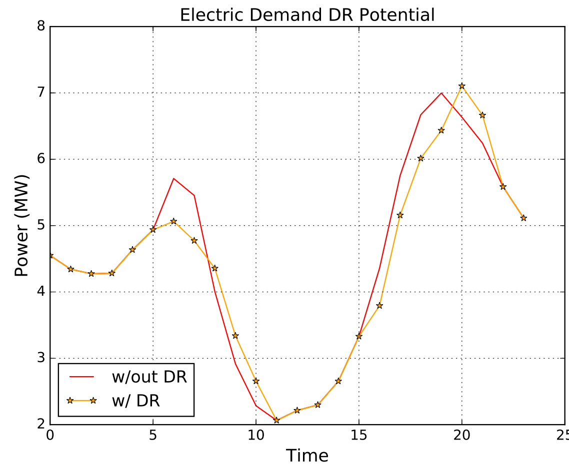

Fig. 6. The demand response control was able to shed load in the morning and decrease the ramp rate in the afternoon. The peak load was increased to just over 7MW.

the demand profile to improve the integration of solar PV for this feader. The morning peak was reduced and the afternoon ramp rate was decreased.

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