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PURSUIT

Simulation of a Smart Home Energy Management System with Dynamic Price Response

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With the continuing development of the smart grid combined with the fluctuating nature of the electricity market, the development of demand-side management with controllable loads have been greatly emphasized. Due to the large amount of household loads in the residential sector, managing the energy usage of individual homes has received much interest. This paper presents a simulation of a previously proposed hardware design of a smart home energy management system (SHEMS). The report will focus on the data collection and processing functions of the proposed design and will implement them onto standard household loads, such as the electric water heater and the electric vehicle charging station. Overall, we found that the simulation of the loads saves consumers a significant amount of money when a SHEMS is implemented.

Index Terms— Smart Home Energy Management System (SHEMS), dynamic pricing, peak shaving, real-time pricing (RTP), machine learning algorithms, optimization strategies, load simulation, cost reduction

NOMENCLATURE

XT(t)	Temperature in Electric Water Heater at time t, ºC
a	Thermal Resistance of Tank Walls, W/ ºC
XA(t)	Ambient Temperature at time t, ºC
PEWH	Power of Electric Water Heater, W
PEV	Charging Power of the Electric Vehicle, W
RTP(t)	Real-Time Price at time t
m(t)	Status of Electric Water Heater, ON/OFF
SEV(t)	Status of the Charging Station at Time t: 0, 0.5, 1
af	Frequency Parameter of the Charging Station
ae	Energy Parameter of the Charging Station
f	Frequency of the Status of the Charging Station
Avol	Capacity of Battery generated by array A, kWh
Bvol	Electric Vehicle Battery Capacity, kWh

Introduction

The price of electricity in the competitive energy market fluctuates constantly. With the recent implementation of the smart grid and the volatile nature of the electricity market, the reduction of electricity cost and usage on the demand side has become a pressing need [1]. Lack of real-time pricing technologies (RTP) that allow electricity market operators to respond quickly to price changes hinders the development of demand side management. This delay in electricity management response largely occurs due to the fact that electricity, unlike other commodities, cannot be stored for long periods of time [2]. Real-Time Pricing is a dynamic rate that reflects the real-time state of supply and demand of electricity, changing price throughout the day and with the seasons [3]. Due to advancements in technology during the past few years—with the development of sophisticated communication technologies and advanced metering infrastructures (AMI)—RTP has grown from being an abstract concept to a feasible application in some power system technologies [4]. With RTP, consumers can work more closely with electricity suppliers to develop and use optimized control strategies to monitor their loads in an effort to be more active in the electricity market [1]. Increased consumer participation in markets will lead to the enhanced reliability of systems. as well as the reduction of price volatility [5]. To facilitate this, smart home energy management systems (SHEMS) have been developed in an effort to reduce the consumer's total electricity payment and to achieve a demand response, which is critical to the continuing development of the smart grid.

Previously, the concept of a smart home with integrated energy meters as part of a home-based system was proposed as a potential method to reduce energy costs [6]. With this in mind, the concept of the SHEMS was developed. Ongoing research has investigated the integration of features such as ZigBee communication protocols [7] and wireless touch-screen interaction [1] into the SHEMS concept. Currently, several SHEMS systems are in development by leading vendors, such as Intel, Siemens, and Control4 [8]. SHEMS research will continue to evolve, as it is more consumer-centric and more defined in terms of its connection to utilities and the residential factors that surround it [8].

Electricity usage varies throughout the day. At certain peak times, the amount of electricity used reaches high levels, potentially causing problems for the electricity infrastructure. Demand response aims to have the smart grid respond to the levels of electricity usage so that usage does not increase to dangerously high levels. Figure 1 shows the peak load and cost graph as generated from [9] and [10].

Demand side management is an important consideration. As the graph indicates, the costs for the peak load reduction program have exponentially increased in past years, while the potential and the actual peaks have only slightly increased. New methods to enhance the effectiveness of the energy savings of the program while reducing the total costs should be taken into consideration. Development of SHEMS is a possible solution to this growing problem. It is anticipated that the use of the SHEMS system to optimize and control residential loads will directly flatten electricity demand peaks, as a result of demand response [1].

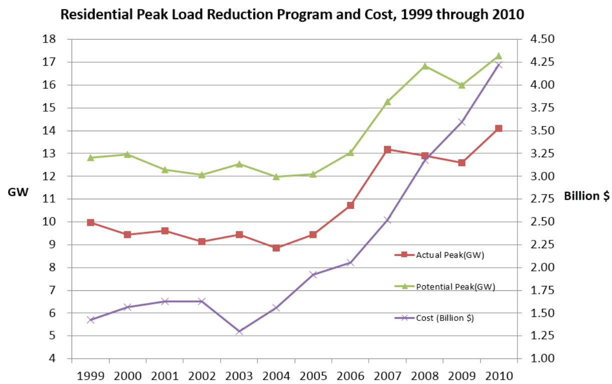

Fig. 1: Residential Peak Load Program Reduction Costs

Current SHEMS prototypes and designs have failed to incorporate all necessary requirements in proposed models. Some prototypes are focused entirely on the hardware design and do not take into account the machine learning algorithms required to achieve the responsive load management based on consumer preferences and RTP [1]. On the other hand, other simulation studies are focused more on software—including machine learning algorithms and dynamic price responsive mechanisms—but were not thorough in the design of the hardware [1]. The development of a functional— yet consumer-friendly— SHEMS system requires a new approach from existing systems [8]. In regards to the numerous models currently in the market, customers are usually unaware of their presence, and are thus misinformed about the functionality of SHEMS [8]. Consumers must be aware of SHEMS before they become viable for domestic use.

In a previous paper, a design for a SHEMS with Dynamic Price Response was proposed, focusing on both the hardware and the software required to become feasible. The proposed software design focused on data collection of the real-time pricing data and consumer preferences, processing the collected data with machine learning algorithms and pattern recognition, and controlling of the loads based on load optimal strategies generated in the processing stage [1]. This new SHEMS design works through direct load control, which will achieve more in terms of demand response via direct load controlling.

In this paper, the simulation of the mentioned system was implemented using MATLAB to demonstrate how users of the SHEMS can save money and energy through demand-side management on various commonly used household loads. In doing so, the authors hope that consumers will gain a better understanding of the SHEMS and its potential advantages in their daily lives. This simulation focuses on collecting the real-time price data and processing the data to create optimizable control strategies for each household load. MATLAB was used to develop models of the loads and to load optimal strategies in order to demonstrate that the SHEMS can save users' money and reduce the electricity peak load at critical times throughout the day.

Methodology

The main purpose of simulating the SHEMS with a MATLAB GUI is to demonstrate how consumers can save money by implementing it in their households. This is accomplished by demonstrating the use of several home appliances most commonly used by households with and without the SHEMS. Figure 2 shows a block diagram detailing the process of simulating the SHEMS. By taking real-time pricing data from the wholesale market along with user inputs and appliance models, the GUI can return accurate results to the user. Through this work, the consumer's perception of the SHEMS can be enhanced by highlighting its ability to save money and by increased public awareness of the system.

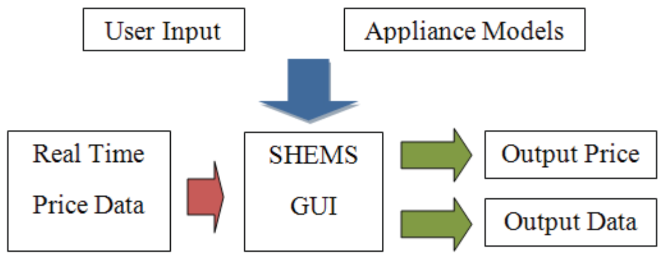

Fig. 2: Block Diagram for Designing the Simulation

Certain districts in the power market of the United States have compiled RTP of electricity prices. For the simulation, the RTP data was taken from the New York Independent System Operators, which gathers price data in cost per mega-watt hour every five minutes over a 24-hour period [11]. Upon examining the data gathered from the website, it was found that the prices were not taken at the assumed five minute time intervals, and that there was duplicate data gathered at certain times. Before it could be used, the data had to be filtered to eliminate the duplicate data as well as the times not synchronous with five minutes. The filtered data was used in all subsequent experiments to model a 24-hour period. Once the program to collect the data was compiled and tested, models for appliances were created and tested via MATLAB. Once affirming their efficacy, a GUI was created to incorporate RTP and the household loads together.

Appliance modeling

The appliances that were modeled are the electric water heater and a charging station for an electric vehicle. They were subsequently built with MATLAB and simulated under normal conditions and with the influence of the SHEMS. By incorporating RTP data into the models, they can be made more accurate for the simulation.

Electric Water Heater (EWH)

Electric water heaters function by heating water up to a certain high temperature. Then, regardless of the amount of hot water being used, the water cools down to a lower temperature level. Once it reaches that low temperature, the water goes into a heating cycle again. Aside from modeling the electric water heater without the influence of the SHEMS, we also aimed to model the electric water heater and how it functions ideally with the SHEMS implemented. This required the development of an optimization strategy based around the nature of the SHEMS. To that end, the electric water heater must function both in and out of acceptable price limits. Under influence of the SHEMS, the electric water heater first checks the price to see whether it is above or below a certain user-defined price limit. If it is at or below the limit, the water heater will heat up to this set, user-defined temperature. However, if it is above the limit, the water heater will heat and cool around a specified water temperature to ensure quick heating when the water is needed.

To achieve a more accurate model, the EWH also takes into account a typical water usage curve for an entire day as shown in Figure 3. The data of the curve was taken from Laurent and colleagues [12]. By implementing the water usage curve, the accuracy of the electric water heater model was optimized, modeling water usage and its effect on the temperature of the heater over time.

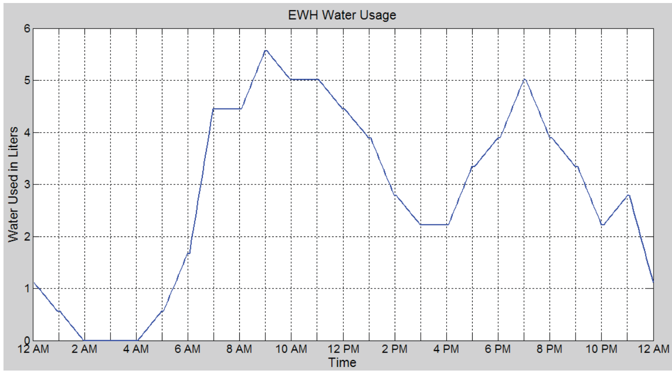

Fig. 3: Typical Household Water Usage Plot

The electric water heater also required accurate models for the heating and cooling of water, respectively. The cycles of heating and cooling were modeled with differential equations—equations that model the change of a variable over time based on several parameters. For the simulation, important parameters included the resistance of the tank's wall, the ambient temperature at the current time, the current temperature, and the power of the heating element of the EWH. The equations for heating and cooling that were used in the model are shown in (1) and (2), respectively. They were based on the elemental EWH load model as presented in [12] which allow for the physical parameters of the water heater to be reflected in the model.

$$\frac{dX_T}{dt} = -a \cdot (X_T(t) - X_A(t)) + P_{EWH} \tag{1}$$

$$\frac{dX_T}{dt} = -a \cdot (X_T(t) - X_A(t)) \tag{2}$$

Table I shows the specifications of the electric water heater used in the experiment. The parameters are taken from the EWH model proposed in the previous hardware design proposal [1].

TABLE I: Water Heater Characteristics

Water Heater Type	Electrical
Power Rating of Heating Element	4.5 kW
Tank Surface Area	2.8 m^2
Tank Volume Capacity	40 Gallons
Thermal Resistance of Tank Wall	0.005 W/ ºC

To calculate the total price for the water heater, the data points for the times at which the

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EWH was heating the water had to be taken into consideration, along with the RTP at the time. This was accounted for with the status of the EWH, *m(t)*. By having it set to 0 when not heating and 1 when it is heating, the prices for when the EWH is actually using electricity are accounted for. The pricing algorithm used for the Electric Water Heater is shown in (3).

$$P_{total}(t) = \int_0^{24} P_{EWH} \cdot RTP(t) \cdot m(t) \qquad (3)$$

Electric Vehicle Charging Station

The parameters for the electric vehicle to be charged were based on the Nissan LEAF, and they are shown in Table II [13].

TABLE II: Electric Vehicle Parameters

Charging Power Rate	Approx. 6 kW
Battery Volume	24 kWh
Time to Fully Charge	Minimum of 4 hours

The charging station functions by charging the battery of an electric car up to full capacity. The normal model charges the battery at the full power rate at the beginning of the charging period specified by the user while the model influenced by the SHEMS charges the battery at certain intervals to ensure that the price is optimally low. To improve upon the SHEMS model, we decided to incorporate three stages of operation for the charging station: off, which is represented by 0, charging at half of the power rate, which is represented by 0.5, and charging at the full power rate, which is represented by 1. The normal charging station has only two modes of operation: 0 for off and 1 for charging at full power. By using two different modes for the status of the charging, the SHEMS model can better demonstrate its effectiveness at saving money for the consumer.

For this simulation, it was decided to take into account the price of two corresponding days. This was done using the price data for one day and copying sections of it to create a mock 48-hour pricing array to model two consecutive days starting from 12:00 PM from the previous day, 24 hours for one whole day, and ending at 12:00 PM the next day. The optimization equation utilized in the simulation was specifically formulated for the electric vehicle as a whole. Thus, the model must take into account overnight charging. As a result, using the RTP pricing array for two days is reasonable for the simulation.

Optimization Equation for the Charging Station

The electric vehicle simulation proved difficult due to the variations for the charging status of the station. An optimization equation with a generic algorithm for the SHEMS model was devised to represent the charging station's on-off cycle. Using this equation is essential to processing an accurate simulation that results in the lowest price while ensuring that the car battery gets charged to 100%. The optimization equation accounts for the total price generated by an array, the frequency of switching the charging station on and off, and the amount of power generated with the array. The frequency must be considered in order to ensure that the battery's lifetime is not reduced by turning the machine on and off too often. This method generates the array that charges the battery at the lowest price. By assigning constants next to the appropriate parameters, the importance of the parameters can be adjusted according to the user's preferences.

Generic Algorithm for the Charging Station

The electric vehicle simulation utilized a generic algorithm to work in conjunction with the optimization equation to provide the best result. A generic algorithm (GA) is an intelligent search algorithm that helps model the biological concept of natural selection through population growth and mutation. These algorithms are widely used to find a good solution for optimization problems in many power system equations [14]-[17]. In a previous paper, a GA was utilized as a solution to a payment cost minimization model factoring in wind power [18]. Based on the results of the model, we hoped that the same method could be used in this simulation for the charging station. For the optimization equation, finding the best solution may not be possible due to time constraints and the number of possible solutions. Using a generic algorithm helps by finding a good solution as a tradeoff between analyzing numerous other options and the time to evaluate each possible solution. Beginning with randomly generated solutions, the generic algorithm evaluates them through a number of iterations, or generations. Each solution is evaluated by a fitness function, and the good solutions are crossed over and slightly mutated. Crossing over good solutions improves them, while mutating them allows for variety. This process repeats for all the generations, resulting in a solution that provides the best result in terms of the lowest price and the frequency of turning the station on and off [19]. The optimization equation used for the model is shown below:

$$f(x) = P_{RTP,total}(t) + a_f \cdot f + a_e \cdot | A_{vol} - B_{vol} | \tag{4}$$

In preliminary tests, the parameters a_f and a_e were tested with various values to obtain the best result for the optimization equation. These parameters help assign importance to the appropriate parameters for frequency and energy consumption, respectively. After testing with different values, the parameters were set to constant values, $a_f = 100$ and $a_e = 1000$ to ensure that the best value for the generic algorithm can be achieved.

Similar to the EWH, the charging station required its own algorithm to calculate the price, taking into account only the points when it is charging. With the unique setup of the status for the electric vehicle charging station, the algorithm can account for the times when the battery is being charged at the full power rate or half the power rate. The resulting pricing algorithm that was used is shown below:

$$P_{RTP,total}(t) = \sum_{t=T_{START}}^{T_{END}} P_{EV} \cdot RTP(t) \cdot S_{EV}(t) \tag{5}$$

Once the models for the EWH and the electric vehicle charging station were thoroughly developed using the equations above, a GUI for the electric water heater was created. An additional GUI was created, combining both the EWH and the charging station.

Development of the GUI

The graphical user interfaces were designed with MATLAB. The idea behind the design was to incorporate an easy-to-use interface to increase awareness of the SHEMS while demonstrating how users can save money through its usage. Figure 4 shows the GUI created specifically for the electric water heater load model. This prototype for the EWH served as a template for all subsequent models.

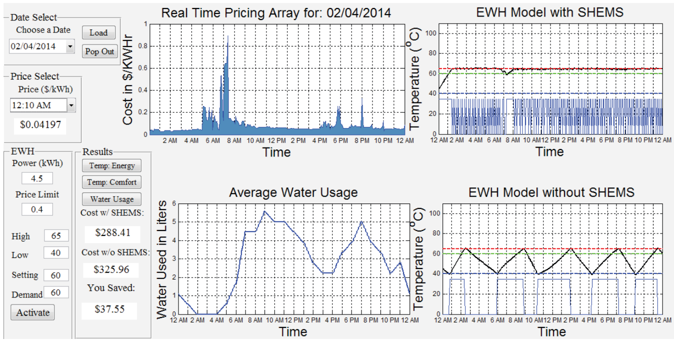

Fig. 4: GUI model for the Electric Water Heater

The prototype GUI shows an informative display with easy-to-use controls on the right of the screen. To activate it, the user first chooses a specific date to load the RTP data. Then, the user can set the temperatures for the water as well as upper and lower temperatures for the water heater. Then, the user activates the water heater, and the GUI takes the parameters and returns a result and a price for the electric water heater usage with and without SHEMS. This shows how much money can be saved. The graphs display the real-time pricing data from the date selected, the average water usage curve, and the Electric Water Heater temperature chart with and without the SHEMS pricing strategies.

Elements were taken from the prototype to create a new, easy-to-use GUI combining the EWH and the electric vehicle charging station, allowing the user to easily navigate it and learn more about the SHEMS. It also displays the results of both household loads to present the amount of energy and money used together, highlighting the benefits of the system as a whole. Figures 5, 6, and 7 show images of the GUI in various modes. The main menu allows the consumer to select which appliance they would like to model, and it also houses a general overview of the total energy and money spent for each appliance separately or combined along with the amount saved. Other appliances like the EWH and the charging station can be separately controlled with the user interface. There is also a menu allowing for graphs to be shown one at a time according to what the user wishes to see.

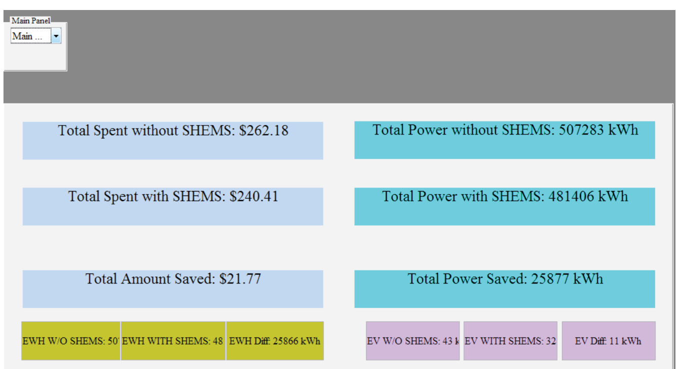

Fig. 5:Combined GUI's Main Menu

The combined GUI functions in a similar manner to the prototype EWH GUI. The user begins by selecting which appliance is to be modeled first. Then, on the respective load's menu, the user selects the RTP price from a specific date. Next, the user inputs specific parameters unique to the appliance that is currently being modeled. Once that is done, the appliance is activated, and the user can select from specific graphs produced by the SHEMS to be displayed.

The menu for the electric water heater functions the same as the previous prototype, while the page for the charging station has flexibility to account for the choices that the user can take. The user can specify two charging periods while adjusting for another electric vehicle based on the battery capacity and station's charging rate as well as the population size and the number of generations for the optimization equation. Through this method, the SHEMS is presented in a simplified form.

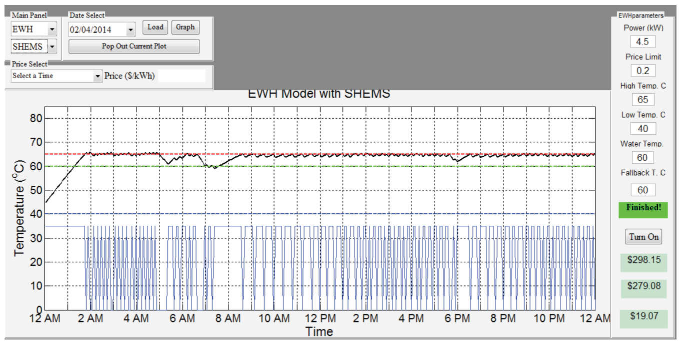

Fig. 6: Combined GUI's EWH Page

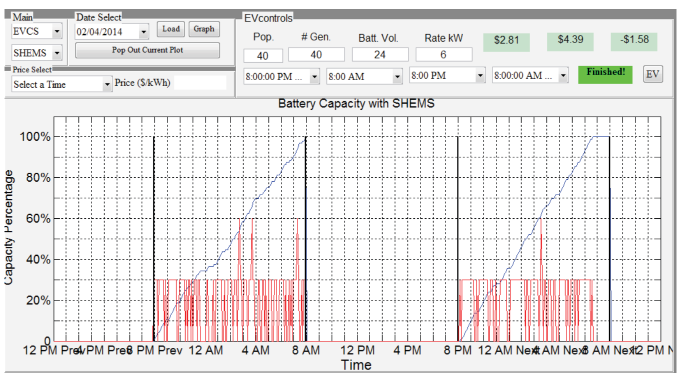

Fig. 7: Combined GUI's EV Page

Results

Testing of the EWH was done using the prototype GUI. As a part of the test, multiple simulations were carried out using different dates with the same parameters for the EWH. The parameters for the electric water heater are shown in Table III.

TABLE III: EWH GUI Test Parameters

Power of the Charging Station	Approx. 6 kW
Price Limit	$0.01/kWh
High Temperature Setting	80 °C
Low Temperature Setting	40 °C
Demand Temperature Setting	60 °C
High Price Temperature Setting	60 °C

Figure 8 shows an example of one of the real-time pricing array that was used in testing. The data for each array was filtered for accuracy before being used in the model. Each RTP array consists of 288 points that make up the number of five-minute intervals in a 24-hour period. This is used as the basis for all subsequent SHEMS EWH models.

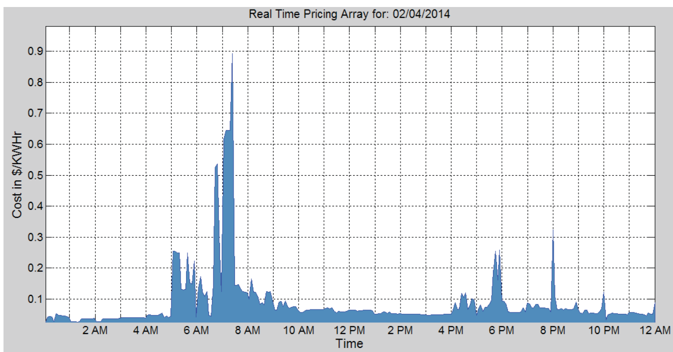

Fig. 8: Real-Time Pricing Array Plot

Below, Figure 9 shows the typical electric water heater temperature curve without SHEMS implementation. The red, blue, and green dotted lines represent the high temperature limit, the low temperature limit, and the default temperature, respectively. The black line represents the temperature of the EWH, while the blue solid line represents the status of the EWH. The normal EWH model follows the behavior specified in the previous description for the entire day.

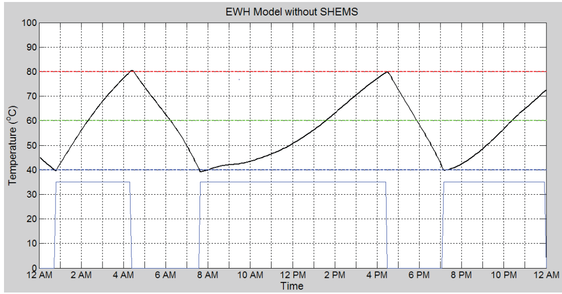

Fig. 9: EWH Temperature Curve without SHEMS

Figure 10 shows an example of an electric water heater temperature curve with SHEMS. It follows the description mentioned above in the design of the EWH SHEMS model, heating up only when the price is low enough and otherwise remaining constant at the temperature specified by the user.

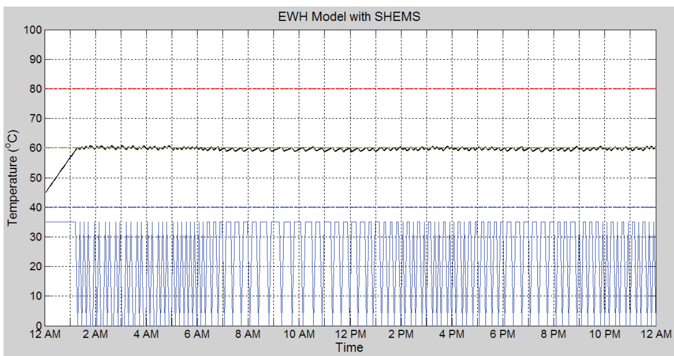

Fig. 10: EWH Temperature Curve with SHEMS

Using the GUI, the EWH model was tested with various price data from different dates. The prices with and without the SHEMS along with the savings were calculated and recorded. Table IV below shows the test results for the EWH based on the parameters that it was subjected to. Based on the results, the consumer saves an average of approximately $1.47.

TABLE IV: EWH GUI Test Results

Date	Cost w/o SHEMS	Cost with SHEMS	Savings
7-11-2013	$7.04	$6.34	$0.70
7-12-2013	$5.87	$4.93	$0.94
7-13-2013	$5.90	$4.96	$0.94
7-14-2013	$10.48	$9.95	$0.53
7-15-2013	$18.89	$15.81	$3.08
7-16-2013	$16.22	$14.10	$2.12
7-17-2013	$15.15	$13.15	$2.00

The electric vehicle charging station was also modeled with MATLAB. As stated before, the MATLAB simulation was based on the parameters along with the condition that the electric vehicle had to be charged fully to 100 percent. Figure 11 shows a model of a charging station without SHEMS while Figure 12 shows an example of a charging station under the influence of SHEMS.

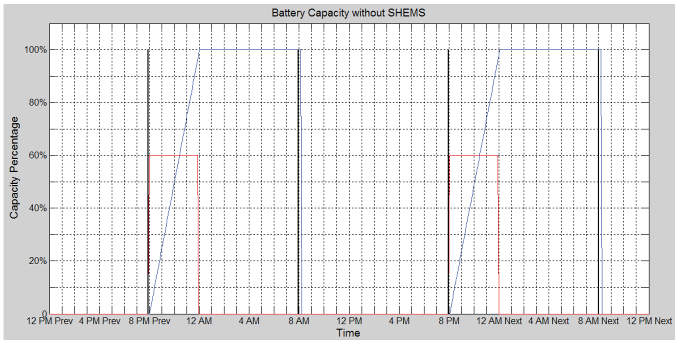

Fig. 11: Electric Vehicle Battery Capacity without SHEMS

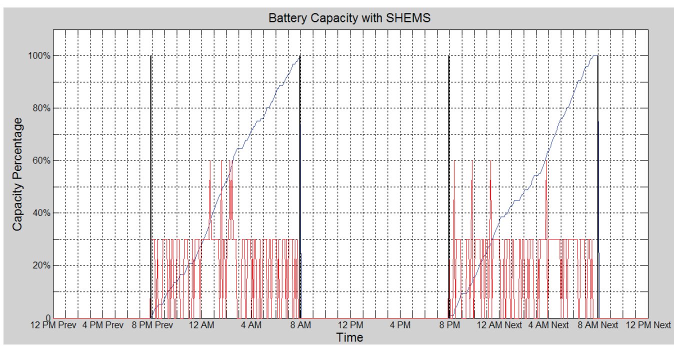

Fig. 12: Electric Vehicle Battery Capacity with SHEMS

The time frame for the electric charging station spans 48 hours, starting from the afternoon of one day and continuing to the early morning of the third day. The black vertical lines in the figures represent charging intervals at which the electric vehicle can be charged. The battery of the electric vehicle charges immediately at the beginning of the intervals. From there, it charges at a constant rate until 100 percent capacity. Once it reaches full capacity, the charging station stops charging the car.

Several tests were run on the electric vehicle charging station to test the optimization equation and the generic algorithm for accuracy based on the number of generations used. Results are shown in Table V. Based on these results, the consumer saved an average of $0.23 as a whole.

TABLE V: Electric Vehicle Charging Station Test Results

a_f=100, a_e=100

Generations	**Price w/o SHEMS**	**Price with SHEMS**	**Savings**
2	$1.28	$1.28	$0.00
20	$1.28	$1.00	$0.28
50	$1.28	$0.98	$0.30
100	$1.28	$1.09	$0.19
200	$1.28	$1.08	$0.20
500	$1.28	$0.99	$0.29
1000	$1.28	$0.90	$0.38

Conclusion

The proposed model of the SHEMS in the previous paper focused on data collecting, processing, and load controlling. In this paper, MATLAB was utilized to simulate the SHEMS on household loads, such as the electric water heater, and a charging station for an electric vehicle. Overall, the goal was to demonstrate that the SHEMS could reduce the peak load while saving money for consumers. The results of the electric water heater show that implementation of a SHEMS reduces the cost of operation for the heater by a significant amount. Likewise, simulation of the electric vehicle charging station showed adequate savings when compared to the amount without SHEMS. Future work to be done on the simulation includes adjusting the optimization equation for efficiency, as well as including simulations on other household loads. In the future, other loads, such as the refrigerator or an HVAC system, will be assessed. Ultimately, the authors hope that these results can be used as a tool to help raise public awareness of the SHEMS system by demonstrating its easy integration into households.

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