Residential Energy Simulation and Scheduling: A Case Study Approach

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***Abstract*— Residential energy contributes to 38% of the total energy consumption of the United States [1]. Current research aims to reduce consumption through time-of-use (TOU) pricing or by providing energy information to consumers. Industrial innovations are focused on energy efficiency and automated control of appliances. However, to date, quantifying the benefits of current and future technology improvements in residential energy management is difficult. This work presents HomeSim, a simulation platform aimed at residential energy modeling that can compare and quantify these results. The subsequent case studies leverage HomeSim to explore current and future technologies, including distributed batteries, renewable sources, smart appliances, cost-aware scheduling, and peak power reduction.**

Keywords- Smart grids, green energy, residential energy management, smart scheduling

I. INTRODUCTION

Building energy consumption has been well-researched, but the focus has been on commercial and industrial domains, which constitute a majority of global energy consumption [1]. However, the residential domain contributes over a third of the total energy consumption in the United States. Moreover, the residential domain is important because of the significantly higher number of end users impacted–in the United States alone, residential energy consumption impacts hundreds of millions of homes and other residences. As such, recent research has turned to improving residential energy use. Some works focus on reducing a single aspect of consumption [1] [2], while others seek to provide more granular energy information to end-users in order to facilitate user-driven improvements [1]. While these works are indeed beneficial, they require considerable overhead in data collection and testing, and results cannot be quantitatively compared.

Home energy simulators have been developed as part of other research endeavors [3] [1] [2], but they are either specific to the residence or scenario being investigated, or particular to one aspect of energy consumption. For example, the Department of Energy's NZERTF project [4] has established a user-model centric energy simulation, but the results are determined by actually emulating the user models on a real house, prohibiting widespread use. To counter the lack of testing and comparison of energy improvements, we have developed HomeSim, a simulation platform capable of modeling the energy consumption of the typical loads and sources of a home. The platform is designed in an extendable way, to be able to simulate cutting-edge and future technologies. Leveraging the capabilities of HomeSim, we investigate case studies presented in research an industry.

Residential energy research has been motivated in part by the number of people it affects and the ubiquitous nature of home energy consumption [5]. A majority of work has focused on characterizing green energy consumption within the home, with appliances accounting for 74% of total energy, as shown in Figure 1. Consequently, much of the related work has been aimed at providing more granular appliance data or improving appliance energy usage.

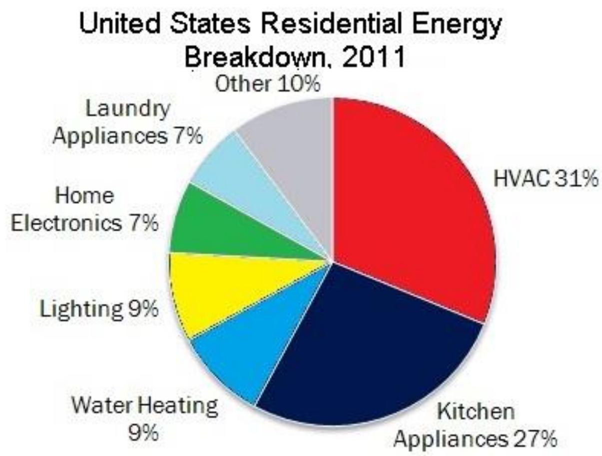

Figure 1. 2011 US Residential Energy Consumption Breakdown [6]

The work in [1] focuses on non-intrusive load monitoring, with the ultimate goal of presenting very granular power consumption for each appliance to enable users to make smarter decisions. The significant contribution is the ability to isolate appliance power data non-intrusively using a learning model, with 82% accuracy. However, the work does not strive to automate the process, choosing instead to leave power management decisions in the hands of users. [3] presents automated energy efficiency improvement in homes that are partially powered by green energy with storage. The work proposes an energy management system that provides early warnings, and suggests task rescheduling for maximizing energy. However, again, decisions are left to the user, with automation addressed as a feasibility study. In the wake of smart appliance and home automation research, we choose to investigate the impact of automation in reducing grid consumption.

A more related work [7] automates battery charging and discharging in a green home based on predicted solar energy and battery state-of-charge. The work reduces grid energy by an impressive 3.9x. However, the paper only improves one aspect of energy consumption–battery charge–while making several assumptions that limit the widespread benefit, including a reliance of time-of-use (TOU) pricing; depleting batteries completely instead of a specific depth-of-discharge; and dependence on a variety of forecast data.

The ability to correctly model energy consumption in a home is important for scheduling and determining load use, and is helpful for implementing the complex scheduling behavior explored in our case studies. The work in [5] provides a comprehensive review of residential energy, detailing both top-down and bottom-up simulation, which involves the modeling individual buildings, similar to our goals, and leveraging the models into classifications (single-family residences, apartments, etc), as appropriate to a region, and simulating the result. A second work [8] compares the use of different learning techniques such as Bayesian Networks and Artifical Neural Networks (ANNs) to predict residential water use, and develops an integrated ANN to predict demand with average relative error of 30%. Similarly, [9] uses Bayesian Networks to predict user behavior, which in turn is used to determine appliance usage, and ultimately, energy needs for 24 hours ahead. Using time, energy, and duration as the input random variables, the paper predicts appliance usage based on a real dataset. Finally, MIT's REDD project [1] utilizes the Factorial Hidden Markov Model to disaggregate overall energy data from residences, and predict which appliances are active over a given timeframe in a non-intrusive manner. They train their predictor using supervised approaches, providing as granular circuit-level information as possible, and are able to determine the appliance with 82% accuracy.

The rest of this work is organized as follows: Section 2 introduces the major components of HomeSim and the means of extending the system. Section 3 describes a set of case studies and results that are enabled by HomeSim, and Section 4 concludes the paper.

II. HomeSim System Design

HomeSim cam be broken down into two key components: the end-use elements (loads, sources, etc.), and the scheduler. Collectively, the end-use elements are described by the generic *node* data structure. The event-driven *scheduler* is an open interface for extensibility for different test cases. The following subsections describe these components in detail.

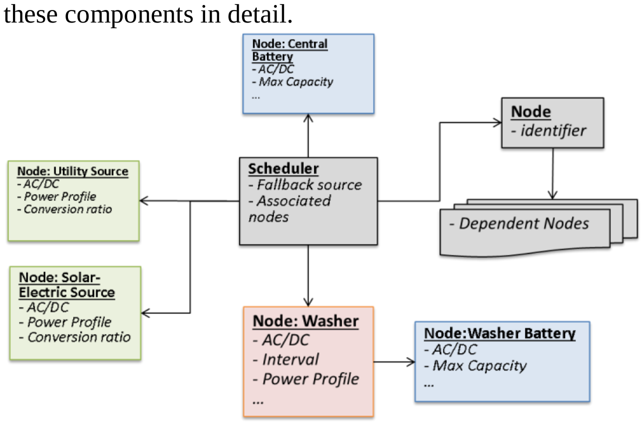

Figure 2. HomeSim System Model

A. Nodes

A *node* is an abstract data type that represents end-use elements of a home, including *loads*, *sources*, and *hybrid* elements. An *identifier* differentiates each of the classes. Two such examples are the *Node: Washer* in Figure 3, which is a load (only consumes energy), and *Node: Washer Battery*, which represents a hybrid (both consumes and produces energy). Each node contains a list of *dependent nodes*, which identifies other nodes that are directly interact with it. These interactions are identified and captured by the scheduler, described in Section III.B. Figure 3 also illustrates the concept of a dependent node, as *Node: Washer Battery* is a dependent node of *Node: Washer*. Each node contains a set of *conversion factors*, which defines the transmission and conversion losses for AC and DC power. The appropriate factors are used by the scheduling algorithm depending on the source of energy at each intervals. The key to versatility of the sources is the use of a function, the *power profile* funtion, to model any real device accurately.

Loads are the consumers within a simulation, consuming power when active. By examining the loads within a home from traces [1] [10], we can break down a load into either continuous or periodic. We can further define loads as AC/DC, the interval of occurrence for periodic applications, the daily offset of the event, and the duration of each event.

Sources represent the pure producers for the home. These are predominantly the utility grid, but can also extend to solar-electric, wind, or even fuel cells. The appropriate source is simulated by appropriately adjusting the *power profile* function. For example, the utility grid can be represented by a constant high AC voltage at 120VA.

Hybrids: are sources that can both produce and consume, such as batteries, flywheels, and plug-in electric vehicles [7]. In addition to having a fixed *capacity*, these sources can also have different *charge/discharge rates* and additional parameters: the *Peukert exponent*; *depth of discharge (DoD)*, a metric for batteries to denote the minimum level of charge that should remain in the battery for correct operation; *state of health (SoH)*, and *state of charge (SoC)*, which represents the current level of discharge. Battery lifetime is dependent on the *State of Health (SoH)*, which decreases with the number of charge/discharge cycles. HomeSim uses the Coulomb Counting method to estimate these parameters [11] whose main benefit is simplicity, as it only needs measurements of voltage and current.

B. Scheduling

HomeSim's execution is based on event-driven scheduling of a time-ordered list of nodes. Other building simulators demonstrate the effectiveness of this approach [1] [2]. The computation at each step, called the *execute* step, distinguishes HomeSim. The *execute* step calculates the effect of the interaction between active nodes, allocating energy to each as necessary and determining the net consumption or generation. However, this step is also open to modification/extension, to handle different configurations of nodes and scheduling goals. Additionally, the *execute* step can uniquely handle the interaction between *dependent nodes*, to provide an open scheduling platform.

The base scheduling implementation is representative of the state of the art in renewable-enabled homes today. At each step, each node uses the green energy greedily, and then reverts to battery energy when there is not enough green energy remaining. Finally, if the battery capacity is also exhausted, the node uses grid energy.

III. Case Studies

To demonstrate the effectiveness of HomeSim, we present a series of case studies exemplifying its usefulness in modeling and quantifying the impact of several proposed residential energy management technologies: We simulate the new lithium-iron phosphate batteries and compare them against their theoretical benefits. We implement and execute experiments that were proposed without validation in related work: rescheduling appliances for better energy efficiency [3] and replacing centralized batteries with distributed, appliance-specific batteries. By integrating cost models to the scheduler, we are also able to demonstrate the cost-benefit of local green energy generation and storage. Finally, we investigate reconfiguring the system in the presence of utility service degradation or outage conditions.

A. Input Parameters

Residential appliance data is obtained from the MIT REDD database [1], which instruments houses and provides granular energy consumption for loads. The dataset contains low-frequency (1Hz) readings of power consumption from the home appliances over two weeks. We use several constituent datasets, which contain information for different house configurations. These readings are composed into a load schedule and are also used for appliance prediction.

Table 1. Experimental battery specifications

Specification	*LFP spec*	*LA spec*
Capacity (kWh)	18.6	18.6
Nominal voltage (V)	12	12
Charge/Discharge cutoff (V)	14/10	14/10
Depth-of-Discharge limit	0.6	0.6
Lower/Upper current limits (A)	300/400	150/250
Peukert ratio	1.05	1.15

Renewable energy data is obtained from the UCSD Microgrid's photovoltaics at 15-minute intervals, normalized to match 35% of the residence's average consumption: a more appropriate solar capacity for the loads [12]. Green energy cost information is obtained from [13]. We incorporate lead-acid (LA) and lithium-iron phosphate (LFP) batteries into our analysis, with the characteristics shown in Table 1. Battery pricing is obtained from [14]. For cost models, utility pricing is obtained from previous work: wholesale energy prices from the California ISO, normalized to match retail SDGE pricing [15].

B. Case Study 1: Smart Appliance Scheduling

Smart appliances have the ability to learn or automate behavior in appliances. An example is NEST thermostat [16], which learns temperature patterns in the home and automatically sets appropriate temperatures. We envision similarly adaptable appliances, a concept presented in [3]. Periodic appliances such as dishwashers or washing machines are typically open to rescheduling, as their timing is flexible by nature. In this implementation, rather than modifying the *execute* phase, we extend the functionality of the event queue. The general approach is to predict appliance usage, and use instantaneous or predicted green energy to determine the best flexible appliance schedule.

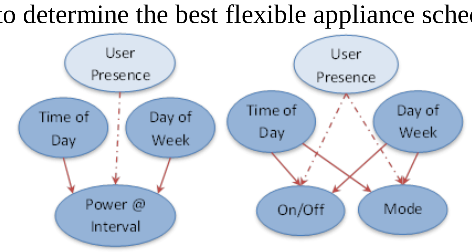

Figure 3. Cont. & Discrete BNs for Appliance Prediction

Based on precedent from previous work [5] [1] [9], in this example we choose to perform appliance prediction using a learning model. With only a few input variables, techniques like Support Vector Machines (SVM) or Artificial Neural Networks (ANN) are error-prone. Bayesian networks and their derivative Hidden Markov Models are more appropriate. We use Bayesian networks, as in [9], where random variables can easily be adapted to match the training set. Based on our input data from [1], we develop the Bayesian networks shown in Figure 3 for each home appliance. The probabilities of the random variables can be obtained by counting from training data. The scheduler utilizes the data provided by the predictor to schedule appliances in an energy-efficient manner.

The algorithm determines energy availability at each interval based on the predicted solar energy using the low-overhead Extended Exponential Weighted Moving Average (eEWMA) prediction algorithm, with a prediction horizon of 24 hours [17]. The expected energy availability is reduced by the predicted schedule of fixed-deadline appliances. The result of this operation is the *unused* solar energy at each interval. The scheduler then allocates each flexible-deadline appliance based on the highest green energy available in the prediction horizon. The scheduler iterates this process until all flexible appliances are allocated, and provides this schedule to the simulator.

In this case study, we use the washer, dryer and dishwasher as our smart appliances, from precedent set in [3]. The scheduling parameters are provided in Table 2. We set a threshold for the confidence level at which appliance prediction is considered valid. We derive this value empirically, varying the threshold over our training data and selected the minimum error (0.7, with mean error of 0.31).

Table 2. Flexible Appliance Scheduling

Appliance	*Flexible Schedule*
Washer	Up to 12 h before predicted deadline
Dryer	Up to 12 h before, within 2h of washer
Dishwasher	Within 6 h after predicted deadline

Table 3. Prediction Model Validation

Prediction	*Mean Absolute Error*
Solar Energy Prediction	9%
Appliance Prediction	31%
Appliance Prediction (+/- 2 timeslots)	14%

Table 3 summarizes the accuracy of appliance prediction. The error for appliance prediction is due to the discretization of a continuous sample, which is compounded when energy consumption is calculated. Although exact prediction incurs 31% error, as the last row indicates, the prediction is mostly off by only one or two timeslots. As appliances are discretized to execution intervals, those that execute at the boundary of two intervals may be predicted to execute in either slot. When a larger prediction window is provided, appliance prediction is significantly improved, with only 14% error. Qualitatively, an interval early or late does not make a significant impact on the efficacy of rescheduling, as solar availability is comparable in adjacent intervals.

Table 4. Rescheduling Appliance Results

	Fixed	*Reschedulable*
Total Grid Energy (kWh)	83.0	61.6
Green Energy Efficiency (%)	41.5	47.7
Green Energy Sold to Grid (kWh)	53.7	48.0
Grid Energy Cost ($)	21.1	15.65

Table 4 summarizes the results of rescheduling appliances with the total energy consumed and green energy efficiency (GEE), the percentage of available green energy that is consumed for useful work. Rescheduling reduces the total grid energy by nearly 25% and improves GEE by over 6%. However, this efficiency improvement is limited by the reduction in battery usage, resulting in more intervals where there was surplus green energy and all batteries were fully charged. This unused energy is a net surplus, and in a grid-connected residence, can be sold back to the grid, identified separatetly from total gird energy. The cost of grid consumption also presented, with 26% in cost savings.

C. Case Study 2: Distributed Batteries

Distributed batteries have been proposed in industrial research and development as a viable alternative to a single, centralized battery, in which smaller batteries are associating with high-energy appliances [18]. In this case, an appliance first uses its own battery before reverting to other sources. The rationale is that a centralized battery experiences a sustained drain from a combination of loads, forcing a more frequent fallback to grid energy, but load-proportioned distributed batteries provide better usage. We allocated capacities to large appliances based on a ratio of their power consumption, normalized against the total capacity (18.6kWh) of the single centralized battery.

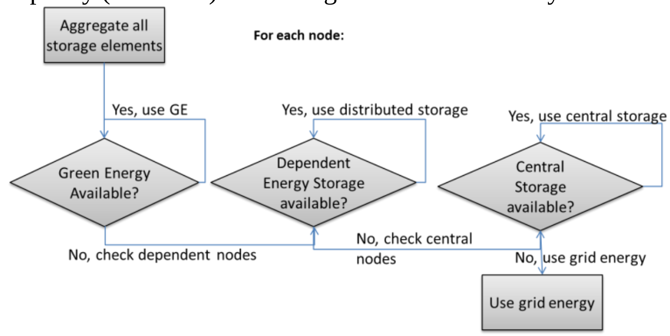

Figure 4. Schedule to prioritize distributed batteries

We also require a more complex scheduling algorithm, which takes advantage of *dependent node* interactions in HomeSim. Figure 4 illustrates how a distributed battery model can be run by the scheduler's *execute* step. In this case the dependent node lists for each appliance establish a storage element as a distributed, appliance-specific battery (see "Node:Washer", "Node:Washer_Battery" in Figure 1). When the appliance is active, it will consume its own battery before using other sources. Conversely, other appliances will not have access to node-specific batteries.

Table 5. Centralized (Fixed) vs. Distributed Battery Results

	Centralized	*Distributed*
Total Grid Energy (kWh)	130.6	83.0
Total Battery Energy (kWh)	25.3	35.6
Green Energy Efficiency (%)	23.1	41.5
Grid Energy Cost ($)	33.2	21.1

Table 5 demonstrates the HomeSim results comparing centralized and distributed battery models. The total grid energy consumption is reduced a factor of 1.5x, while battery consumption and GEE increase. By investigating the output traces, we observe that large appliances that have a built-in battery are less susceptible to requiring grid energy, especially at times when the net load is high. The improvement in green energy efficiency is a result of distributed batteries that are charged in an ad-hoc manner, providing a level of parallelism to charging that was not previously possible. Finally, by calculating the operational costs of each method, we demonstrate 36% improvement when leveraging distributed batteries over centralized.

D. Case Study 3: Cost Savings

By integrating cost calculations to the scheduler, HomeSim can evaluate the cost-benefit of centralized batteries, distributed batteries, and rescheduling appliances, as well as provide a comparison among the three for the same test case. Using the operational costs outlined in Section III.A, we execute HomeSim for the same residence configuration, alternately using the three cases above for comparison. For rescheduled appliances, we extended the distributed battery case to determine additional benefit over the most financially viable case.

Table 6. Operational Costs of Centralized, Distributed, and Rescheduled Appliance cases

	Default	*Central Battery*	*Distrib. Batteries*	*Resched. Appliances*
Avg. Monthly Cost ($)	89.2	73.14	69.81	62.96

Table 6 demonstrates the operational costs of each of the cases compared against the base case of no energy management. Incorporating any energy storage provides a cost reduction of 18%, which is further improved with distributed batteries. In this configuration, it is important to note that the savings with distributed batteries is only 5%, much less than the 36% improvement in Table 5, demonstrating that the technologies have variable impacts in different homes. Rescheduling further improves energy savings, with a net monthly energy reduction by 30%.

Similarly, we can incorporate capital costs into HomeSim, and extend the scheduler to calculate the recoupment of the cost of batteries and local solar generation. Using the capital cost numbers from Section III.A, HomeSim calculates the net energy savings weighed against the capital costs. Because our input data only lasts 2 weeks, we cycle the data until the savings exceed the costs. We compare the central and distributed battery cases as well as the case of distributed+rescheduled appliances. Finally, we also investigate the *mixed case*, including an additional 18.6 kWh central battery to the appliance-specific distributed batteries and rescheduling. This final case provides insight into how savings scale with battery size.

Table 7. Recoupment Time (in years) for Centralized, Distributed, Rescheduled Appliance, and Mixed cases

	Central Battery	*Distributed Batteries*	*Rescheduled Appliances*	*Mixed*
Recoupment time (yrs)	22.6	20.2	16.6	11.9

Table 7 compares these results, demonstrating very large recoupment time, over 22 years, in the centralized battery case. This scenario is the current state of the art, but is shown to have an unreasonably low cost-benefit. The distributed batteries case, while an improvement, has a similar duration. Rescheduled appliances, however, reduce the net-even time by 20%, and the introduction of an additional reduces the recoupment time to almost 50%. Since solar costs represent a large majority of the capital, increasing total battery capacity demonstrates good scaling in the time to net-zero. It is important to note that these experiments do not consider selling energy back to the grid, which is a further increase in savings, and also that after the recoupment time, all energy savings result in a net profit.

E. *Case 4: Cost-aware Scheduling*

Time-of-use (TOU) pricing is prevalent in European energy provision, and the concept is growing in relevance in the United States [7]. Integrating pricing information into the scheduler requires extending the algorithm in Figure 4 to further sort intervals by the lowest energy cost when grid energy is needed. Our comparison is between the reschedulable appliances scheduling algorithm in Section III.B to the algorithm with the inclusion of cost awareness. We compare the cost savings of two cases by maintaining the same building and battery configurations.

Table 8. Reschedulable Appliance Scheduling vs. Cost-Aware Scheduling

	Rescheduled Appliances (RA)	*RA+Cost*
Avg. Weekly Grid Energy (kWh)	62.96	61.02
Avg. Weekly Green Energy Eff. (%)	49.8	49.8

Table 8 compares reschedulable appliance scheduling to the cost-aware scheduling. The results indicate that cost-awareness has almost negligible impact on energy savings, and no impact on green efficiency. Analyzing the output traces demonstrates the reason: the net benefit of a small amount of freely available green energy is still cheaper overall than an interval with lower cost. Therefore, it is more feasible to greedily use green energy than to rely on a cheaper grid interval. In total, 10 jobs were rescheduled due to cost savings, resulting in a marginal reduction in grid energy, and almost no impact on green energy efficiency.

F. *Case 5: Peak Energy Shaving*

Utility energy providers such as SDGE are providing net-metering and metered pricing options for residences with local renewable generation [19]. One particular case is peak-energy pricing (2x normal energy costs) for residences that exceed a power threshold. We simulate this scenario by enforcing peak pricing when consumption exceeds 212.5 kWh, 25% of average monthly consumption, and charging the referenced 2x for consumption above this limit. We develop a peak-power shaving algorithm to limit this cost:

1. Allocate a peak-energy threshold for grid energy of 7.1 kWh per day (from the total energy limit over 30 days).
2. Reschedule appliances based on predicted green energy availability to achieve highest green energy efficiency.
3. Prevent the use of non-essential appliances in the dataset (“Unknown Outlets”, “Air Conditioner 2”, etc.), and add deferrable appliances (“Kitchen Outlets B”, “Electronics”, “Washer-Dryer”) to the reschedulable queue when the daily power threshold is exceeded.

The algorithm emulates the tradeoffs made in an actual home to accommodate the benefits and variability of renewable sources. By removing the deadline restrictions of deferred appliances, we ensure that they will eventually be executed, if at all possible

Table 9 shows the results of the peak-energy shaving algorithm. Using only rescheduling, the residence is unable to remaing below the peak-power limit, exceeding the threshold by an average of almost 8 kWh. However, with the peak-power shaving algorithm incorporated, the residence remains well below the threshold, and results in only 3 appliance instances not being able to be scheduled due to peak-power restrictions. Overall, the algorithm demonstrates 31.9% weekly energy cost savings.

Table 9. Peak power shaving cost analysis

	No improvment	***Reschedulable Appliances (RA) only***	***RA + Peak-power shaving***
Avg. Wk. Grid Energy (kWh)	74.5	57.4	44.3
Avg. Weekly Utility Cost ($)	24.35	16.53	11.25
Unschedulable Instances	--	--	3

IV. Conclusion

In this paper, we note the lack of a residential building energy simulator capable of quantifying and comparing existing and future technologies in residential energy management. We introduce HomeSim, a simulator that responds to this need with an open, highly versatile platform. We investigate emerging technologies in residential energy management by performing a series of case studies targeting the proposed improvements: the current state-of-the-art centralized battery, distributed batteries, reschedulable smart appliances, and cost-aware scheduling using real data from instrumented houses. We further demonstrate the cost savings of each case by integrating capital and operational costs and determine the recoupment time. We plan to release HomeSim as an open-source platform that can facilitate energy research, provide insight into residential energy usage, and even provide cost/benefit and evaluations for end users considering investing in energy improvements for real homes.

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