HomeSim: Comprehensive, Smart, Residential Electrical Energy Simulation and Scheduling

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Abstract— **Residential energy constitutes 38% of the total energy consumption in the United States [1]. Although a number of building simulators have been proposed, there are no residential electrical energy simulators capable of modeling complex scenarios and exploring the tradeoffs in home energy management. We propose HomeSim, a residential electrical energy simulation platform that enables investigating the impact of technologies such as renewable energy and different battery types. Additionally, HomeSim allows us to simulate different scenarios including centralized vs. distributed in-home energy storage, intelligent appliance rescheduling, and outage management. Using measured residential data, HomeSim quantifies different benefits for different technologies and scenarios, including up to 50% reduction in grid energy through a combination of distributed batteries and reschedulable appliances.**

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

I. Introduction & Related Work

The focus of building energy consumption research has been on commercial and industrial sectors, as they constitute a majority of energy consumption. However, the residential domain contributes to 38% of total energy consumption in the United States and directly affects hundreds of millions of individuals [1].

There have been several published studies that instrument homes to get detailed energy use, but only a few concerned with electricity. One work analyzed records of two years of home electricity usage and simulates tradeoffs between utility pricing and energy storage using batteries [2]. A second study also considered photovoltaics [3]. The largest study recently published [4] provides the first freely available data set of detailed power usage information from several homes, with a disaggregation of the component appliance contributions. The algorithm developed based on this data can isolate appliance power non-intrusively using a learning model with 82% accuracy. Instrumenting homes involves a considerable overhead in data collection and physical testing. It does not enable easy comparison of various options, or studies of how residential energy management system should be architected. This is one of the key motivations behind the design of simulators for residential and industrial energy usage.

Building electricity simulation involves modeling loads and sources with a schedule to aggregate each element's provision or consumption [4]. The simulators in [3] & [5] study the tradeoffs between renewable generation and grid pricing, but only for the homes and neighborhoods where their study was deployed. This precludes the possibility of verifying their results with different usage and residence configurations. The Department of Energy's NZERTF home simulator [6] provides an open interface for user models, allowing comparison of energy consumption based on user behavior patterns. However, usage patterns are tested on a single, instrumented house, with no ability to specify a different home configuration, thus limiting its scope.

Commercial and open-source energy simulators provide the complex interactions found between elements in the energy grid. However, the granularity of the interactions is not extended to the residential domain. GridLAB-D, a comprehensive grid simulation platform, provides nominal residence and appliance modeling [7], but the simple load model is not able to convey the various scenarios explored in Section III, though some attempts have been made towards extending GridLAB-D in this direction [8]. Similarly, OpenDSS [9] provides the ability to model complex distribution networks at different levels of the grid, but this does not extend to individual end-use elements, which can only be specified as generic loads or sources.

The technology of residential electricity consumption has been evolving. The emergence of energy storage, smart appliances, and automated control [3] [5] has blurred the distinction between loads and sources. Storage elements such as batteries can consume grid or renewable power for charging or be used as energy sources. Consequently, scheduling must evolve to a distributed system of interactions among elements. The related work demonstrates that existing residential electrical energy simulators lack the sophistication to handle emerging technologies and quantitatively compare the impact of different home energy management policies.

To address these issues, we develop HomeSim, a simulator for evaluating residential electrical energy usage, storage, and generation. It is capable of modeling energy consumption of the typical sources and loads, including utility power, generators, and household appliances, as well as energy storage, renewables, fuel cells [5], and "smart" appliances. HomeSim's model enables many configurations of end-use elements. Similarly, while the majority of existing simulators use a monolithic event-driven scheduler, HomeSim provides a highly extensible scheduling algorithm that can simulate more complex interactions among nodes and subsets of nodes, uniquely providing the ability to test new scenarios.

With the added capabilities of HomeSim, we are able to explore the impact of home energy scenarios that were previously impossible without actual implementation and instrumentation. We consider lithium-iron phosphate batteries, an emerging technology considered to be an alternative to traditional lead-acid batteries due to better performance characteristics. Through HomeSim, we can quantify their benefit within different house configurations and compare to their theoretical benefit. We also implement two energy-saving improvements suggested in the related work: distributed, appliance-specific batteries [10] and dynamic rescheduling of appliances [3]. By modifying the scheduling algorithm and the configuration of energy elements in the home, we can test both scenarios in HomeSim, demonstrating 36% reduction in grid energy using distributed batteries, and 25% reduction using distributed batteries. In addition, we investigate the impact of outage management, taking into account the appliance limitations/restrictions that must be imposed and the scheduling policies that would improve battery consumption, demonstrating high green energy efficiency. The ability to quantitatively validate residential energy management policies exemplifies the benefit of our simulator vs. the previous work.

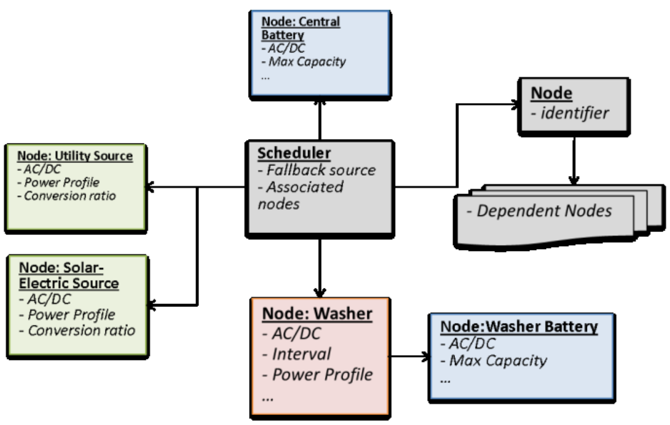

Fig. 1. HomeSim System Model with dependent node interfaces

II. HOMESIM DESIGN

An electrical energy simulation platform can be broken down into two key components: the end-use elements (i.e. loads, sources) and the scheduler. Fig. 1 depicts the general model of HomeSim, including the event-driven *scheduler* and the constituent *nodes* which represent energy sources, loads, storage, and hybrid components of a home energy management system. The scheduler determines which nodes are active at a particular iteration, and executes the consumption computation for them. While the core of the scheduler is straightforward and representative of a bottom-up home energy model [11], the actual computation at each step is configurable. While the merits of a central vs. distributed scheduler are debatable, for residential energy, the centralized approach is particularly useful when modeling complex interactions between loads and sources. One example is the growing popularity of "smart" appliances, which can modify their own power profiles or schedules as a function of the control input. HomeSim's modular computation facilitates the adaptive behavior of such emerging technologies.

Nodes provide an easy way to define all the relevant parameters for energy sources, loads, storage, and hybrid elements of a residential system. They also contain *power profile* functions, which provide a time-indexed mapping of node power. This provides the flexibility to model complex devices using a single data structure by changing the behavior of power profile function. Additionally, each node can be associated with a list of *dependent nodes*. This list creates a direct connection between nodes that affect each other. The result is a tree of dependent nodes under the scheduler that inherently captures interactions among elements that is lacking in other simulators. Dependency lists enable load, source, and storage interactions previously unavailable in home energy simulation. The next subsections explore these components and the scenarios they enable in greater detail.

A. Nodes

A *node* is the abstract data structure that encompasses the end-use elements of a home. This data structure has an *identifier*, which classifies the device as a *source*, *load*, or *hybrid*. Complex elements such as batteries fall into the latter category, as they are both producers and consumers. Each node has a list of *dependent_nodes*, which informs the scheduler of node-to-node interactions. In Fig. 1, the "Node: Washer" illustrates this idea, with the dependent "Washer Battery" modeling an appliance-specific battery whose capacity is only available to the connected node. Here, the washer and the battery behave differently, with the washer able to use the additional energy stored in its battery. This approach allows modeling more complex scenarios, like a backup generator, or virtually partitioning the hierarchy of nodes by the physical circuits in the home.

TABLE I. LOAD PARAMETERS

Parameter	Description
AC/DC	AC or DC power
Interval	The time until the next event instance
Offset	The daily time offset to begin the event
Power Profile	Power consumption profile function
AC/DC Duration	The length of a periodic event interval
Continuous	Continuous or periodic appliance
Conversion factor	Transmission/conversion loss factors

Loads represent the sinks in our energy model, consuming power whenever active. From the energy traces [12] [13], we can further classify loads as either periodic or continuous, where periodic loads (i.e. dishwashers, dryers) have fixed intervals and frequencies, and continuous appliances (e.g. HVAC) have functional usage patterns over time. The actual energy for each load is defined by a dynamic *power profile* mapped against a fixed interval or a time-dependent function. An appliance can also be characterized as operating on AC or DC power. Depending on the state of the incoming energy, appropriate conversion efficiency losses are used. Table 1 summarizes the parameters used for loads.

Sources refer to nodes that are purely generators. The typical residential energy source is utility power. Others include solar, wind, and fuel cells [3]. Consequently, HomeSim maintains a completely open model, with a binary *AC/DC* specification, a *power profile* function over time, and appropriate *conversion factors*. This allows for fine-grained modification of source energy data. For example, utility power can be a constant power function with very high magnitude, since utility production far exceeds residential consumption. The parameters for each source are provided in Table 2.

TABLE II. SOURCE PARAMETERS

Parameter	***Description***
AC/DC	AC or DC power delivery
Power Profile	Power generation profile function
Conversion factor	Transmission/conversion loss factors

Hybrid sources such as batteries, flywheels, and plug-in electric vehicles (PEVs), are becoming more prominent in the residential domain [2]. Their ability to both supply and consume energy requires a separate interface. In addition to having a fixed capacity, these sources can also have specific parameters, which are outlined in Table 3.

TABLE III. HYBRID NODE PARAMETERS

Parameter	***Description***
AC/DC	AC or DC power supply
Max Capacity	The maximum stored capacity in Ah
Current Capacity	The current capacity of the node, in Ah
Nominal Voltage	The device line voltage
Charge/Discharge cutoff voltage	The maximum charge/discharge voltage
Lower current limit	The minimum device operational current
Upper Charge/ Discharge current	The maximum charge or discharge current limit, respectively
Conversion factor	Transmission/conversion loss factors

Batteries are a special case of hybrid nodes, and require a more sophisticated model to capture additional parameters. Four additional parameters are modeled for batteries: the *Peukert exponent*, *depth of discharge (DoD)*, *state of health (SoH)*, and *state of charge (SoC)*. The parameters are described in Table 4**Error! Reference source not found.**. The *State of Charge (SoC)* tracks the current level of discharge. *Depth of discharge (DoD)* is a function of battery technology, and specifies the minimum level of charge that should remain in the battery for correct operation. 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 [14] whose main benefit is simplicity, as it only needs measurements of voltage and current. The battery's discharge current, $I_{discharge}$, is:

$$C_{released} = \Delta t * I_{discharge} \tag{1}$$

$$DoD_{curr} = \frac{C_{released}}{C_{maximum}} * 100\% \tag{2}$$

The current depth of discharge can be calculated using Equation (2) where $C_{maximum}$ refers to the maximum capacity of the battery. We can then express the *effective* charge of the battery:

$$C_{eff} = C_{maximum} * \left(\frac{C_{maximum}}{I_{discharge} * H}\right)^{k-1} * \frac{SoH_{old}}{100} \tag{3}$$

where H is the rated discharge time, k is the Peukert's exponent, and SoH_{old} is the *previous* SoH (initialized at 100). Using this value and a manufacturer-provided Depth of Discharge (DoD), we can calculate the current SoC and SoH:

$$SoC = DoD - DoD_{curr} \tag{4}$$

$$SoH_{new} = SoH_{old} - (100 - SoH_{dead}) * \frac{C_{maximum}}{Cycles_{DoD_{final}} * C_{eff}} \tag{5}$$

where DoD_{final} is the final discharge point after the current cycle through Equation (2), extended for the duration since the last SoH update, SoH_{dead} is the point at which the battery is effectively dead (technology-dependent), and $Cycles_{DoD\_final}$ is the number of cycles over the lifetime of the system where the final discharge point is DoD_{final}.

TABLE IV. BATTERY PARAMETERS

Parameter	**Description**
Peukert Exponent	The storage efficiency of a battery
Depth of Discharge (DoD)	The max. fractional depth of discharge
State of Health (SoH)	The fractional available battery capacity
State of Charge (SoC)	The current fractional battery capacity

B. Scheduling Algorithms

The standard scheduler for HomeSim is an event-driven scheduler over a time-ordered list of nodes, similar to other simulation platforms. It is the computation at each step, called the *execute* step, that distinguishes HomeSim from the previous home simulations. The *execute* step operates on the list of active nodes, allocating energy to each as necessary and determining the net consumption or generation. The implementation of this step can vary to handle different configurations of nodes and scheduling goals. In essence, the *execute* step provides an open scheduling platform. The following subsections investigate the different scheduling algorithms implemented within the *execute* step.

1) Default Scheduler

The simplest 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 reverts to battery energy when there is not enough green energy. Finally, if the battery capacity is exhausted, the node uses grid energy. This is a relatively naïve scenario, and the next two subsections illustrate two more sophisticated cases of scheduling that are made possible by the flexibility of HomeSim's infrastructure.

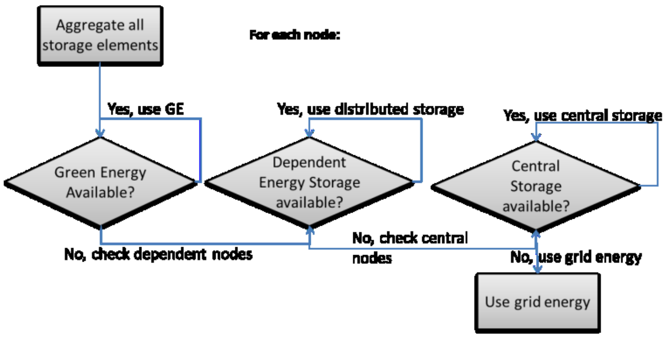

Fig. 2. Schedule to prioritize distributed batteries

2) Distributed Battery Scheduler

The incorporation of green energy has made energy storage a necessity. The state of the art is a large, centralized battery, although the concept of appliance-specific batteries has been mentioned in [10]. Such distributed batteries offer the flexibility to allocate energy for the largest consumers, mitigating the stress on a centralized battery and preventing interference from other appliances. They can also be implemented by custom repartitioning and management of central batteries in a distributed manner. Fig. 2 illustrates how a distributed battery model can be run by the scheduler's *execute* step. When the appliance is active, it will greedily seek out its own battery before attempting to use the central battery. Conversely, other appliances will not be able to access the node-specific battery.

3) Smart Appliance Scheduling with Green Energy Prediction

Smart appliances refer to the ability develop learned or automated behavior in appliances. A popular example is NEST thermostat [15], which learns temperature patterns in the home and automatically sets appropriate temperatures. Similarly, we envision adaptable appliances, a concept presented in [3], which set flexible deadlines for loads such as dishwashers, as their execution is typically open to rescheduling. While the *execute* phase in this case remains the same as in the previous section, the ability to reschedule appliances requires modifications of the event queue. The general approach is to predict the appliance usage and either use instantaneous or predicted green energy data to determine the best schedule for flexible appliances.

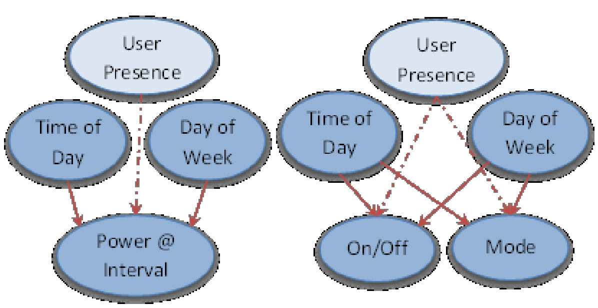

Fig. 3. Cont. & Discrete BNs for Appliance Prediction

Based on precedent from previous work [11] [12] [16], in this example we choose to perform appliance prediction using a learning model. With a few input variables, techniques such as Support Vector Machines (SVM) or Artificial Neural Networks (ANN) are error-prone, while Bayesian networks and their derivative Hidden Markov Models are more appropriate. We use the more versatile Bayesian network, as in [16], where the random variables can easily be adapted to match the training set. Based on our input data from MIT's REDD database [12], we develop the Bayesian networks shown in Fig. 33 for each home appliance. Bayesian network probability variables can be obtained by counting. Equation (6) represents all the instances that a random variable matched the expected outcome over all training samples. The scheduler utilizes the data provided by the predictor to schedule appliances in an energy-efficient manner.

$$\boldsymbol{p}(\boldsymbol{X_i} = \boldsymbol{x_j}) = \boldsymbol{T^{-1}} * \boldsymbol{count}(\boldsymbol{x^{(t)}} = \boldsymbol{x_j}) \text{ for all } \boldsymbol{t} = \boldsymbol{1} \ldots \boldsymbol{T} \quad (6)$$

1. The expected available energy at each timeslot, *power[],* is determined by the predicted green energy availability, *predicted_renewable_schedule[]*.
2. The energy consumption of all non-reschedulable appliances, *inflex_app[]*, is deducted from the potential energy available to determine how much energy is actually free for use.
3. Based on the results in step 2, we can now schedule all reschedulable appliances, represented by the array *flexible_intervals[]*. It is important to sort them by the highest maximum energy consumption first, to match the largest consumers to the highest green energy slots.
4. Iteratively, the algorithm schedules each successive appliance and recalculates free energy for each timeslot.
5. The ultimate result is the scheduled slots for each reschedulable appliance in the variable *flexible_intervals[]*. This is then provided to the scheduler for execution.

The algorithm determines the energy available at each interval based on predicted solar energy. Depending on the prediction horizon, different predictors can be used. This energy is reduced by the predicted schedule of appliances which do not have flexible deadlines, resulting in the expected unused solar energy at each interval. The scheduler then allocates each flexible-deadline appliance based on the highest green energy available in the 24-hour period. The scheduler iterates this process until all flexible appliances are allocated, and provides this schedule to the simulator.

III. CASE STUDIES

Our goal with HomeSim is to create a versatile, configurable residential energy simulation platform capable of quantifying the impact of current and future technology improvements. In the following case studies, we test our simulator in these scenarios: We test the efficacy of the new lithium-iron phosphate batteries and compare against their theoretical benefits (i.e. 5x battery life). 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. With the functionality of HomeSim, we are not only able to determine the improvement over a base case, but compare the benefit of one approach to another. We also investigate the scenario of grid outage management and its impact on appliance usage in the home.

A. Input Data

All of our case studies use measured data from MIT's REDD project [12] for residential energy consumption. The dataset contains low-frequency (1Hz) readings of power consumption from the major appliances in 6 houses over two weeks. We use several datasets, representative of a typical home, with data for major appliances: stove, microwave, washer/dryer, refrigerator, dishwasher, and HVAC; and other, more minor energy loads: kitchen outlets, lighting, electronics, etc. These readings are composed into a schedule for each *load*, and are also used for appliance prediction.

TABLE V. 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

Our renewable energy data is obtained from the UCSD Microgrid photovoltaics at 15-minute intervals, and normalized to match 35% of the residence's average consumption for a more appropriate solar capacity [17]. We incorporate lead-acid (LA) and lithium-iron phosphate (LFP) batteries into our analysis. Battery characteristics are described in Table 5.TABLE V. The use of solar data from the southwest United States, with energy consumption data from the homes in northeast may seem contradictory, but both characteristics are similar to areas such as Denver, Colorado, whose annual sunlight is similar to San Diego [18], while the weather is comparable to that of Boston in the winter [19].

B. Smart Appliances

The smart appliance scheduling algorithm (Section II.B.3)) requires reschedulable appliances and predicted green energy. We use the washer, dryer and dishwasher as smart appliances with flexible schedules ([3]) with the parameters in Table 6. We set a threshold for the confidence level at which appliance prediction is considered valid, so that the predicted appliance can be scheduled. We derive this value empirically, varying the threshold over our training data in intervals of 0.1, and selected the minimum error (0.7, with mean error of 0.31).

TABLE VI. 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

C. Renewable Prediction

Smart appliance scheduling can also leverage predicted green energy, which, for our experimental setup, is solar. Referencing a quantitative comparison of several time-series prediction algorithms [17], we take advantage of the reasonable accuracy (<10% error) and low overhead of the extended Exponential Weighted Moving Average (eEWMA) prediction algorithm, which predicts 24 hours in advance:

$$\boldsymbol{X(i+1) = \alpha x(i) * (1+\varepsilon_1) + (1-\alpha) * x(i-1) * (1+\varepsilon_2)} \tag{7}$$

where $X(i+1)$ is the prediction for the next day based on a linear combination of the *measured* data from the current & previous days $x(i)$ & $x(i-1)$, weighted by α and the error of the previous predictions ε_1 & ε_2. We empirically determine the value α with lowest prediction error at α = 0.45 for the UCSD's PV dataset. This predictor is used to estimate solar energy availability for the 18h window we used for appliances listed in Table 6.

D. Simulation Engine Validation

Our validation is based on the mean absolute error (MAE) of each individual model, as well as the MAE of the overall simulation. We calculated MAE as the average of the absolute error for each result obtained as compared to the actual measured values. The results provided in Table 7 show that our simulator very accurately estimates the appliance power consumption at the appropriate granularity, though the error increases to 10% when simulated with input models that are discretized to 1min. This is not unexpected, as at such granularity simulation of very short-duration appliances loses accuracy. The higher error in HomeSim compared to the total energy provided by the grid is caused by the non-ideality of transmission and conversion. While HomeSim models these losses (see *Conversion Factor* in Table 2-3), their nonlinearity inevitably introduces some noise in total simulation accuracy.

TABLE VII. MODEL VALIDATION ERROR

Model	*Mean Absolute Error*
State of Health (SoH)	8%
Avg appliance power per interval	0.2%
HomeSim (Total Energy Consumption)	7%

E. Case 1: Battery Technologies:

Related research discusses the use of batteries and the advantages they provide, whether to improve the efficiency of renewable sources [3] or to reduce the energy costs via TOU pricing. These works assume lead-acid (LA) batteries, the most popular option. However, recent work motivates the use of lithium-iron-phosphate (LFP) batteries over LA for residences, citing 2.7x increase in energy density and 5x improvement in cycle life [18]. Neither work can compare or quantify the difference between the two scenarios. The simulator in [3] does not take into account a sophisticated battery model, opting to use a linear model instead, while work presented in [2] requires physical measurements to test the results, severely limiting its applicability In contrast, HomeSim can easily model and test both types of batteries and quantify the differences.

We compared a lead-acid (LA) battery with an equal-volume lithium iron-phosphate (LFP) battery. We show the differences in the various power characteristics in Table 8, where Green Energy Efficiency (GEE) refers to the fraction of green energy used for useful work (running loads or charging batteries) compared to the total available renewable energy in the system. By taking into account the state of health, we can estimate the lifetime of each battery in the given scenario.

The results do not match the theoretical 5x improvement due to the complex interaction between batteries, the solar source, and the different loads. While we see both a reduction in total grid energy and improvement in green energy efficiency, the latter is due to additional energy spent charging the larger LFP battery. Due to the larger capacity and slower overall recharge time, the LFP battery spends a majority of time in low SoC, accrues a higher number of total charge/discharge cycles, and reduces the LFP lifetime from a theoretical 5x to under 3x. So, while there is an improvement with the LFP battery, HomeSim demonstrates that it is tempered by the particular configuration of the system.

TABLE VIII. BATTERY TECHNOLOGY RESULTS

Characteristics	*LA battery*	*LFP Battery*
Total Grid Energy (kWh)	78.5	63.8
Green Energy Eff. (%)	20.4	23.1
Average SoC	0.47	0.49
Estimated Lifetime (yrs)	2.3	6.08

F. *Case 2: Reschedulable Appliances:*

With HomeSim, we can explore the possibility of rescheduling appliances with flexible deadlines using the parameters outlined in [3] and the algorithm in Section II.B.3):

TABLE IX. PREDICTION MODEL VALIDATION

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

Table 9 summarizes the accuracy of the predictors used for this case. The error for appliance prediction is due to the discretization of a more continuous sample. These errors are aggregated when energy consumption is calculated. The appliance prediction incurs 31% mean error. However, as the last row demonstrates, appliance prediction is significantly improved when verifying appliance prediction within +/- 2 timeslots. In the reduced granularity of the predictor, appliances that execute across a timeslot boundary may be predicted to execute in either slot. Qualitatively, however, predicting an interval early or late does not make a significant impact on the efficacy of rescheduling, as solar energy values are comparable for adjacent intervals.

TABLE X. 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

The results in Table 10 demonstrate that rescheduling appliances has a positive impact on the total grid energy and on green energy efficiency (GEE), with a reduction of total grid energy by nearly 25%. GEE was improved, as seen in Fig. 4 (right), where a rescheduled dishwasher at 9:00 AM consumes all available green energy. However, this improvement is limited by the fact that battery usage was slightly reduced, resulting in more intervals of surplus green energy and fully charged batteries. This case is displayed in Fig. 4 (left), where only a constant 600W is needed to run an appliance, with the rest of the green energy unused. In a grid-connected residence, the unused energy can be sold back to the grid, shown independently from net energy in Table 10.

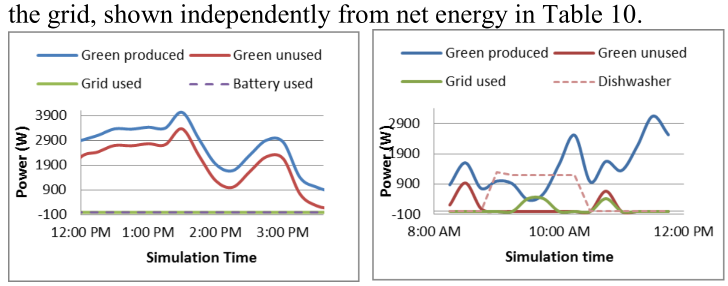

Fig. 4. Low GEE (left) and (right) high GEE

G. *Case 3: Distributed Batteries:*

The distributed battery example stems from recent research into associating batteries with appliances [10]. In the case of a centralized battery, the battery experiences a sustained drain on its energy from the combination of loads, forcing a more frequent fallback to grid energy. Load-proportioned distributed batteries are more appropriately drained. In testing distributed batteries, we apportioned distributed batteries to the large appliances based on a ratio of their power consumption, normalized against the total capacity (18.6kWh) of the single centralized battery.

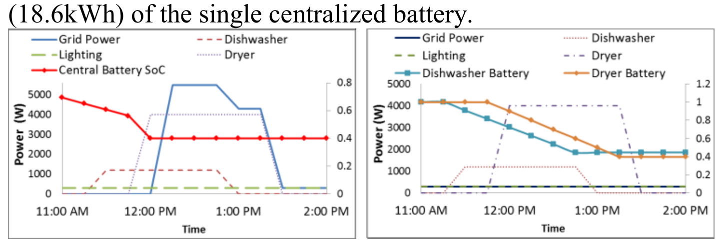

Fig. 5. Centralized (left) vs. Distributed (right) batteries

The results in Table 11show that the total grid energy consumption drops by a factor of 1.5x, while battery consumption and green energy efficiency increase. By comparing the traces, as in Fig. 55, we can see 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 batteries store sufficient amount of energy for the connected appliances, delivering enough to prevent reliance on the grid, even when there is not enough instantaneous renewable energy available. The improvement in green energy efficiency comes from the fact that distributed batteries can be charged in an ad-hoc manner, providing a level of parallelism to charging that was not previously possible.

TABLE XI. 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

H. *Case 4: Power Outage Management*

Another scenario prevalent in modern smart grids is intelligent power outage management, which has been studied in related work on the domain of distribution to end-use loads [19]. However, outage management of individual houses has been largely neglected, with focus instead on the grid behavior. This case study focuses on the tradeoffs that must be made in the home during power outages. It explores how residences typically respond to outages or intermittent power availability, and applies these principles to a residence with local renewable energy and storage. While the presence of renewables and battery storage provides compensation for lack of utility power, appropriate management and prioritization of appliances must be integrated.

Outage management represents an extension of reschedulable appliances: a scenario when appliance usage should be flexible, but limited whenever possible (e.g. only a subset of lighting is used) and the hard deadline of reschedulable appliances needs to be relaxed, since it may not be possible to use the appliances at all. With these scenarios in mind, appliance use has been modified to a *tiered* approach, with each tier having different characteristics:

TABLE XII. RESCHEDULABLE APPLIANCE PRIORITIZATION

Tier	*Appliance*	*Modification*
	Kitchen Outlets (main)	
	Stove	
	Bathroom	
	Refrigerator	
	Unknown Outlets (main)	
	Electric Heat	(reduce by 0.5)
	Lighting	(reduce by 0.25)
Tier 1	Air conditioning (main)	(reduce by 0.5)
	Kitchen Outlets (secondary)	
	Electronics	
	Washer	
Tier 2	Dryer	
	Unknown Outlets (secondary)	
	Dishwasher	
	Air conditioning (secondary)	
Tier 3	Air conditioning (tertiary)	

Tier 1: Prioritized Appliances. Tier 1 appliances are prioritized, as they serve necessary functions. These appliances have the highest priority.
Tier 2: Deferrable Appliances. Tier 2 appliances are deferred, in that they can be rescheduled until there is enough energy to execute them. However, unlike the reschedulable appliances in Case Study 2, they no longer have hard deadlines.
Tier 3: Forced-off Appliances. Tier 3 appliances will be forced off whenever there is not enough energy to run an instance.

Table 12 summarizes the appliance tiers, along with the modifications made to the output of the appliance. The appliances are sourced from REDD's database 6 of an instrumented house. While different residences may schedule slightly differently, we devised a schedule based on prioritized necessities: food and climate control, lighting, facilities, and kitchen elements, similar to what would be done. Of the repeated appliances (unknown outlets, air conditioning, kitchen outlets), the primary instances are prioritized, while the backup or supplementary instances are deferred.

The implementation of the algorithm required a reprioritization of the reschedulable appliance scheduler in Section II.B.3). Instead of reverting to the grid, green energy consumption is organized as follows: any scheduled Tier 1 appliances greedily consume available energy, followed by the central battery, which provides storage for all appliances. The prioritization then falls to distributed batteries, which provide storage for the deferred appliances, and finally the deferred appliances themselves. All Tier 1 and Tier 2 appliances that cannot be scheduled are added to a list of deferred appliances, ordered first by tier, and second by the scheduled time.

The outage management algorithm is tested against the *default* case (no outage) to provide nominal consumption. The experimental scenarios are *outage management + centralized battery* and *outage management + distributed battery*, which test the algorithm with equal-sized centralized and distributed batteries, as described in Table 5. Finally, as an upper bound, the algorithms are compared to the *ideal* case, where all appliance consumption data is known ahead of time rather than predicted. The results are summarized in Table 13.

TABLE XIII. OUTAGE MANAGEMENT COMPARISON

	Normal	Outage + Centralized	Outage + Distributed	Ideal
Avg. Daily Ener. (kWh)	28.2	12.3	13.4	15.8
Tier 2 Appl. Instances	28	5	9	14
Green Energy Effy. (%)	56%	87%	86%	87%

As shown in Table 13, the outage management algorithm enables a schedule that allows Tier 1 appliances to execute while limiting Tier 2 and Tier 3 appliances. We also establish a comparison against a theoretical ideal by maximizing the energy consumption. However, Green Energy Efficiency (GEE) improved to 87%, which is nearly ideal when taking into account conversion and transmission losses. The distributed algorithm maintains this GEE, while improving the number of Tier 2 appliance instances by 44%. The majority of

Tier 2 appliances rely on distributed batteries, which are slowly charged until they contain enough capacity to run their associated appliances. In the centralized case, other appliances ebb the battery's charge, preventing the Tier 2 appliances from executing. Both cases demonstrate near-ideal GEE because batteries are almost always in a partial state of discharge, providing a consistent sink for renewable energy. The most significant results are the comparisons to the *ideal* case: the green energy efficiency is identical and only 5 more appliances can be scheduled in the ideal case.

The experiments in this section cover both the cutting edge of technology and scenarios faced in the residential domain. While other building energy simulators focus on node consumption [8] [4], specific scenarios [2] [5], or the grid distribution network [9], HomeSim enables comparing different scenarios for residential end-users. We quantify actual vs. theoretical benefits of different battery technologies, demonstrating only 60% of the theoretical battery capabilities in real scenarios. We also investigate the impact of home automation enabled by renewable appliances, which can be a means to more efficiently use the energy available [3]. HomeSim evaluates such claims, demonstrating a 25% reduction in grid energy by taking advantage of automation. We demonstrate the impact of using distributed, node-specific batteries for large energy consumers, proposed in [10], to guarantee energy delivery for specific appliances. This theory, proposed but not validated, is confirmed in our tests, as we can reduce grid energy use by 50%. Finally, we investigate the impact of utility outage in a residence with local renewables, allowing a subset of prioritized appliances to continue functioning at the cost of low-priority appliances. We allow all prioritized appliances to execute, taking advantage of both rescheduling to accommodate for available green energy and judicious use of batteries. This allows actual homes to test and compare different technologies and scenarios to identify suitable ones for energy savings. While the focus of this paper has been on energy, we will consider the tradeoffs involved with both capital and operational costs in separate work.

IV. CONCLUSION

In this work, we present HomeSim, a versatile simulator for the growing field of home energy management. HomeSim provides a configurable environment to quantify and compare present and future improvements in residential energy consumption. We further test HomeSim by validating battery technologies; by incorporating distributed batteries and renewable sources; by predicting appliance use and green energy availability; and by investigating algorithms that intelligently account for outage management. We plan to release HomeSim as an open-source tool that can facilitate energy research, provide insights into residential energy usage, and even help provide cost/benefits and evaluations for end users who are considering investing in energy improvements for real homes. Further extensions include modeling the thermal properties of homes, cost-modeling, grid-tied vs. merged and off-grid houses, and occupancy levels in order to better estimate and control HVAC.

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