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Right-sizing Solar PV and Storage for Household Consumer Using Agent Based Modeling

Ahmed Taimoor[b], Zainab Asif[b], Fahad Javed[ab]

[a]Harvard South Asia Institute, Cambridge, MA, USA
[b]GIFT University, Sialkot Bypass Road, Gujranwala, Pakistan

Abstract

The relatively high upfront cost of solar PV solutions has been the major issue in large scale adaption of solar technology, particularly in the developing world. One of the reasons for higher cost of installation is over provisioning of the solar PV and storage to cater for the variable generation of energy and the propensity of system designers to consider maximal peak load of the household for their calculations. This results in higher capital expense for the customer which in turn limits the population percentage which can participate in solar PV generation. To ameliorate this situation, we propose a solar PV and storage sizing mechanism which builds it's load profile based on an agent model of devices, consumers and events in the house. Instead of focusing on peak load we elicit from consumer, through an online system, their consumption habits and the usage profile for various devices during their daily routine. We construct an agent based model to simulate the usage of devices throughout the day and run Monte Carlo simulations to identify the most likely peak demand at different parts of the day. We integrate this information with solar generation potentials and use hill-climbing algorithm to identify the best solar PV-storage combination which will provide adequate service with the least system size. Our results show that for a typical household we can reduce the capital expenses by 60% without impacting their life style.

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1. Introduction

For the past few years, consistent reduction of solar PV panel prices has improved their cost effectiveness for energy generation from utility scale to household usage. In areas where grid supply is difficult due to terrain or in developing world where brown outs force localized generation of electricity, household solar PV installations provide a very lucrative solutions.

Though this reduction of cost has had positive impact on the solar PV penetration rate, still, the size of the system, including solar PV and batteries, is large enough to be unapproachable for majority of population in developing world. There have been two contrasting ways to improve this situation, one is to manage the demand to fit within the generation capacity and range of DSM systems have been proposed [1]. However, these system require additional investment in terms of controlling hardware. The other aspect has been to increase the efficiency of the generation. Since the problem is the size of the installed system, in this paper we take an orthogonal approach to this problem and look at the way the system is sized.

The traditional model to size a solar PV in the author's country is to calculate the peak load and recommend a system which can provide this peak load in the daylight hours – starting from 7AM till 6 PM during summers in temperate zones. The peak is assumed to be all devices in the house utilizing maximum power at the same time. Similar output was observed from three of the online systems which recommend the size of the system based on consumer data.

We see this assumption of peak load highly unlikely and an unnecessary over-provisioning which can be made leaner and more cost-effective through better modeling of the consumer demands. To achieve this goal we have designed an online requirements elicitation and modeling system which collects from the user data regarding device usage throughout the day. Based on this data an agent model simulates the range of combinations that can occur in the household and provides us with maximum bounds of energy demand [4]. This leaner representation of the system results in 50% savings for the consumer in terms of system design.

Various modeling of household schemes divide the day into events [2][3]. Our system lets the consumer decide the number of events that can occur in a day. The consumer then populate these events with devices that they use in terms of frequency on weekly basis and the duration per use. The agent model uses the frequency and duration to model the probabilities and length of use for each device. The output of each simulation is realized as a graph with the two most likely, two highest consumption profiles provided to the consumer and the solar PV system designer an idea of what type of load is expected from the household.

Based on this simulated output, we calculate the appropriate solar PV and storage that would be sufficient for the system. For the four loads – two most likely and two of the highest consumption profiles, we find the optimal solution using hill climbing algorithm. The algorithm selects from the search space of all the solar PV sizes and battery sizes a combination which suffices the highest consumption profile without having excess energy throughout the day.

Our results show that through this method we can reduce the solar installation cost by up to 60%. Furthermore, we see that demand side management on this system has the potential to further reduce the cost, especially for storage. Discussion of application of DSM in this system is part of our future work.

2. Related Work

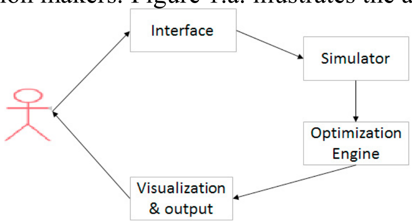
Energy simulation and modeling for household has two distinct flavors based on the proposed usage of the tool. A range of systems predict, forecast or simulate the actual demand of a house, building or space. The most comprehensive tool for simulation of energy demand of a space arguably is EnergyPlus [5]. Developed by U.S. department of Energy, EnergyPlus is very useful in simulating system's performance in a specific environment. For commercial, industrial and household HVAC simulation, this is very appropriate for architects and planners. However, the system is not designed to capture the usage of devices where human interaction plays a role. STMLF proposed by Javed and colleagues was perhaps one of the first instances where accurate forecast for individual household for DSM planning was proposed [6]. Their solution though required collection of data at a regional level which is not applicable for sizing decision of a household solar PV solution. A range of stochastic modeling solutions have been proposed including those by Jaboob [7] and Sancho-Tomás [8] but in all these cases the technique require at least few hundred houses to model the demand appropriately.

Orthogonal to the short term forecasting and rigorous modeling work are bottom-up simulators for regional load forecasting. Models proposed by Capasso et al. [2] and Richardson et al. [3] are considered the benchmark. The techniques divide the daily load into different activities and then model the probability of device usage in each of the categories. These models though are very fine grained and accurate but are designed generate population patterns and are not applicable in simulating for a single household. These models generate hundreds of houses for a period of time whereas we need to simulate a single house for hundreds of days.

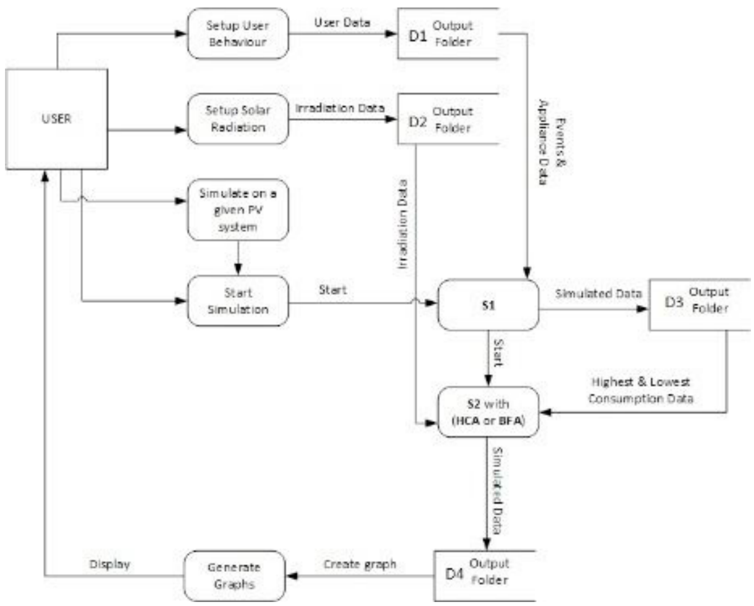
Our strategy essentially is a combination of the bottom-up simulator with the stochastic forecasting model. We divide the day into events and consider events as an agent in itself. Within the event we use stochastic forecasting to simulate the consumption of device.

3. System Design

Our proposed system elicit response from consumer, builds a range of simulations and then provides the optimal combination of storage and solar PV which would be least cost and sufficient for the consumer. To achieve this goal we first collect the data from the consumer. As discussed in previous section, we allow the consumer to define the day in terms of events. These events are regularly occurring activities in the house starting with breakfast all the way to sleep at the end of the day. To collect this data, process it and display the output to the consumer we build a system composed of four components: web interface for user input, Simulation engine, optimization algorithm, and visualization of simulation for decision makers. Figure 1.a. illustrates the architecture of our system.



a.



b.

Fig. 1. (a) System architecture; (b) Level 1 DFD for the system.

3.1. Web Interface

As shown in figure 1.b, the data flow in our system which is used for simulation consists of two intertwined hierarchies. The house is spatially divided into rooms and temporally divided into events. The consumer first defines the rooms in the houses and define the electrical devices in those rooms. There is a provision for floater devices which can be plugged in different rooms such as mobile charging and laptop charging stations. The temporal data is defined within the context of the events. The user is asked to divide the 24 hour period in different events. The user then associate devices with events. For example, the user can associate use of toaster in the breakfast and use of washing machine in the post breakfast event. The user inputs the number of days of a week when the device is usually used and the duration for which it is used. Here we would like to comment on the device usage percentages. The usage percentages for a device are independent in different events. Thus, toaster can be used with probability of 1 in breakfast and again in lunch. We specifically ask users to assign probability to devices which span events and are rather daily activities, such as use of washing machine, such that the probability of use of washing machine is not independent in the entire day. Thus for washing machine the sum of probability of usage throughout the day will be one. We are in the process of implementing a system where the probability of usage will be conditional probabilities based on the use of device previously and also on the use of other devices. For instance, opening of the fridge door (thereby resulting in start of it's compressor) will result in a higher probability for use of toaster and so on. However, our current system does not provide this feature.

The web-interface generates a JSON – JaveScript Open Notation - script which is read by the simulation engine. JSON is a lightweight data interchange format which provides us with the ability to make the simulator interoperable with other interfaces and vice versa.

3.2. Simulation Engine

The simulation engine is responsible for simulating the possible consumption trajectories of devices for a given day. These simulations are saved and the two most common and two of the highest consumption profiles are selected and passed to the optimization engine.

For each simulation run, the probabilities from the interface passed as JSON records is randomly initiated. The events fire according to the timeline defined by the consumers and the devices are selected according to the probability given by the consumer. This is executed in the Java Agent Development Engine (JADE), a platform for agent based computation [4]. The agent model is the core technical component of the system.

Figure 1.b describes the data flow in our system. Each device is represented as an agent which in turn can be situated in a room. The devices can change rooms by changing their association with room agents. From the temporal perspective the devices are contained in events where the events are defined by the consumers with start and end time. For each event the consumer inputs the frequency of the device usage in a week and how long the device would be used.

When a simulation is executed, the simulator runs over the events according to the timeline given through agents by the consumer. The simulator selects for each event the devices that will be used in that day's simulation based on the probability of use. There is an implicit order that we enforce on the devices based on anecdotal evidences (use of water pump before or during the use of washing machine for instance) that we have incorporated in our system. In the future builds we intend to collect this data from consumers as well as this has a very strong impact on the consumption profile.

The output from one day's simulation is saved and it's visualization is created for the consumer. On completion of hundred runs four consumption profiles are selected: 1. with the highest peak load, with the highest aggregate load, 3. with the peak closest to the average peak, 4. with the aggregated load closest to the overall average load of the 100 runs. These four consumption profiles are passed to the optimization engine which plans for the optimal combination of solar PV and storage for the system.

3.3. Optimization Engine

The optimization engine implements hill climbing algorithm. The algorithm initializes with a random <PV size, battery size> combination. It calculates two parameters, unutilized power and unserved load. Unutilized power is energy generation when neither the battery nor the demand can accommodate the generation. Unserved load is the condition when the combination of battery and solar PV is not able to meet the demand. In first case we have a case of over-provisioning and in the second case we have a failure of the system to provide sufficient power to the system. The hill climbing is a local search algorithm. The algorithm starts at a random location and based on the partial derivative of the search space, identifies the next solution set. If the partial derivative is zero, that is no better solution is available in the immediate vicinity, then the algorithm terminates. Hill climbing algorithms are susceptible to local minimas. However, it can be shown that if the prices of solar PV panels and storage are strictly monotonically increasing then the search space is convex and hence a global optimal is possible.

3.4. Visualization

We found the existing technologies which recommend sizing of solar PV solutions very flat. A consumer who is investing a decent amount of money for the solar PV will benefit from seeing how and what adds to the cost of solar PV solution. This has been observed in various studies without solar PV that a visualization of the household energy consumption resulted in reduced energy consumption. Our solution goes a step further and has the capability to show the consumer how her consumption can impact the cost of the system. To achieve this goal we show to the consumer her simulated consumption profile, specifically the profiles which add most to the cost of the system. By showing these profiles we envision a self-enforced DSM without the need for instrumentation of smart plugs. However, we are in the process of collecting this data and present the results in future.

Figure 2.b. shows the visualizations that are available to the consumer. The graph shows the generation, battery and demand of electricity over the day. It also shows the two parameters –unserved load and excess power- for different solutions for the consumer to make an educated decision about the system choice. If the consumer wishes to increase the dependability of the system then she can choose to investigate a solar PV with bigger PV or battery component. As our claim in the start of the study, the decision to over-provision should rest with the system owner. The verity of solutions provide this ability to the consumers.

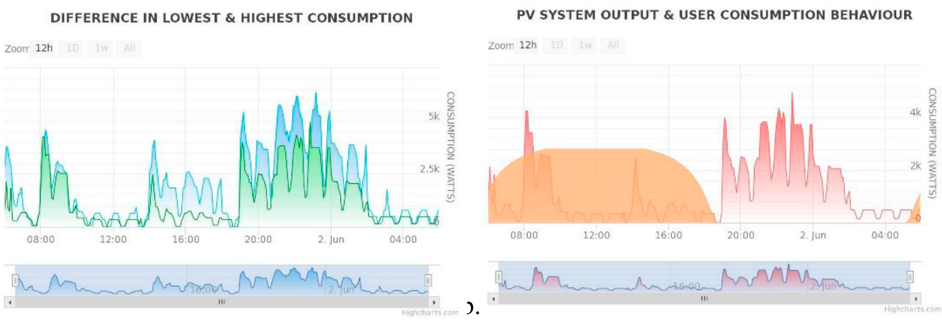
a.  b.

Fig. 2. (a) Difference of lowest and highest demand days; (b) Generation from proposed sizing against the least demand day.

4. Household Data and Results

The goal of our system is to provide a precise sizing of solar PV-battery for a household. Our point of reference in this case are commercially available sizing solutions. We selected three such solutions that were ranked highest according to the page-rank algorithm of Google. Two of these sizing solutions are from USA and one from

Australia. The selected systems allowed consumers to enter their devices and their usage within a day. No online system with more precision was found by the authors.

To compare our results we conducted a pilot study on four households from where we elicited the device and events data. Table 1 shows a sample of the devices spread across five events for one of the houses.

Table 1: Spread of devices across events.

Appliance Name	Usage per week	Breakfast (6am-8am)	Noon (8am-2pm)	Lunch (2pm-4pm)	Dinner (7pm-9pm)	Night (9pm-6am)
Washing Machines	1 day				1hr	
Dryer Machine	1 day				30min	
Irons	7 days			30min		10min

Though are data is split across events, the websites only consider aggregated data for a day. The online system used their own formulation to arrive at the daily generation KWh/day number. Table 2 shows the KWh/day calculated by the three online systems for a system with total load for all the devices combined of 55000 Watts.

Table 2: Sizing of solar PV and batteries by online systems and our system.

Website	Generation Demand (KWh/day)	Storage (amp-hour)	Solar PV
Wholesalesolar.com	48932	0	11000W
solarcalculator.com.au	56200	0	8600W
bimblesolar.com	56221	4824-9684	9032W
Proposed solution	**24000**	**3500**	**4000W**

From the numbers it is apparent that 2 and 3 are considering the possibility that all devices are used every day to the fullest and at the same time whereas though 1 is using some other calculation, it's solar PV installation size is much larger than the other system.

Consumption of devices though is not so straight forward and the demand of electricity vary on daily basis. As shown in figure 2.a. shows the variation in simulated load on two different days. Secondly the consumption is spread across the day meaning we do not require a high demand upfront and may use battery to store energy for later use. This is difficult to calculate with the data collected by the online systems. As shown in figure 2.b. we consider this daily demand curve to size our PV and battery. As can be seen from the results of our proposed solution, the solar PV size is 55% to 60% less than the online system. Even if we consider the battery, the size of the system is smaller than the online sized systems.

5. Discussion and Future Work

In this paper we have presented an agent based simulation system which aids in right sizing the solar PV and storage solution. This solution is built from an analysis of consumer behavior and streamlining of generation and storage resources for a leaner system design. In comparison to the competing solutions, our system provides a 50% saving on capital expenses which may increase the penetration of solar technology in the developing world.

Our work essentially is a work in progress as we are exploring the following streams in this simulator:

First and foremost we are in advanced stages of actual deployment of solar PV solution with instrumentation to measure failure of our system sizing. This will be implemented through measuring when the demand for a household exceeds the solar PV system provided energy. We will also observe if our provisioning even now are beyond the requirements and this will be calculated by measuring available charge at the end of each day.

References

[1] Haider, Haider Tarish, Ong Hang See, and Wilfried Elmenreich. "A review of residential demand response of smart grid." Renewable and Sustainable Energy Reviews 59 (2016): 166-178.
[2] Capasso, A., et al. "A bottom-up approach to residential load modeling." IEEE Transactions on Power Systems 9.2 (1994): 957-964.
[3] Richardson, Ian, et al. "Domestic electricity use: A high-resolution energy demand model." Energy and buildings 42.10 (2010): 1878-1887.
[4] Bellifemine, Fabio, Agostino Poggi, and Giovanni Rimassa. "Developing multi-agent systems with JADE." International Workshop on Agent Theories, Architectures, and Languages. Springer Berlin Heidelberg, 2000.
[5] Crawley, Drury B., et al. "EnergyPlus: creating a new-generation building energy simulation program." Energy and buildings 33.4 (2001): 319-331.
[6] Javed, Fahad, et al. "Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short term multiple loads forecasting." Applied Energy 96 (2012): 150-160.
[7] Jaboob, S., D. Robinson, and O. Beckett. "On the ownership and use of residential electrical appliances." (2015).
[8] Sancho-Tomás, A., M. Sumner, and D. Robinson. "A generalised model of electrical energy demand from small household appliances." Energy and Buildings 135 (2017): 350-366.