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A Highly Configurable Simulator for Assessing Energy Usage

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Abstract

Smart grids provide newer ways of energy production, transmission, and distribution. In a smart grid finer control of electrical devices in household and buildings are implemented to better manage energy demand and supply. However, this finer control commonly known as demand side management (DSM) requires extensive simulation at various levels before a DSM algorithm may actually be deployed in a real building or neighborhood. Since forecasting the energy usage behavior of myriad number of electrical devices is a difficult exercise, simulations are done to assess the effectiveness of a DSM algorithm. The problem with the state-of-the-art simulators is that each is designed for simulating electrical devices' behavior under specific and limited settings. To this end, we present a highly configurable and extensible smart grid simulator (SGS) that is capable of simulating per-minute granularity of energy usage under numerous settings. Moreover, SGS is able to simulate behavior at four levels: electrical devices, households and buildings, neighborhoods and cities. Given different scenarios SGS can simulate relativistic behavior of energy usage at all four levels.

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Keyword: Smart gird simulator, energy consumtpion behavior, load profiling, relativistic simulator

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1. Introduction

Energy crisis is impending. One of the reasons behind this energy crisis is the growing use of energy especially in the residential sector. In the period between 1990 and 2009, energy usage in this sector has increased by 24% in the European Union[b]. Similarly in the housing energy fact file 2011 of Great Britain shows that the energy use in the residential sector has risen by 17% from 1970 to 2009 [c].

One of the solutions to the better management of energy in residential sector is demand side management (DSM). DSM systems focus on efficient planning and forecasting of energy usage. Based on efficient planning the goal of a DSM system is to shift the peak usage of energy to off-peak hours. This requires an advanced metering infrastructure and time-driven economically incentivized tariff rates for the consumers.

The major use of energy in households is through electrical devices or appliances. Therefore, knowing their energy behavior is crucial in implementing DSM systems. However, the energy profile data and usage data of electrical devices is not easily available. One of the ways in which this energy usage data can be collected is by field measurements. However, field measurements are very difficult if the number of houses and electrical devices are large. Also because of the manual work this method of data collection is expensive and time-consuming. Moreover, various kinds of errors are possible in collecting field data like sampling errors, reading errors, etc. Additionally a lot of human involvement is necessary for collecting data from a large number of houses and electrical devices. Furthermore, field measurement is also problematic due to privacy concerns of individual consumers.

The solution to the unavailability of consumption data can be solved by simulations of electric appliances. Traditionally, a simulation is an important tool in finding the solutions to various problems where actual data is scarce. There has been quite some work in simulation of data of electrical appliances as discussed later in section 2.

Compared to other simulators and simulation models the simulator presented in this paper has a few distinct features. First and foremost feature of this simulator is that it can work with minimal inputs from the user with an option the modify any simulator generated scenario. The second feature of this simulator is that it can generate per minute energy consumption information for a myriad number of electrical appliances. This per minute consumption of various appliances may be combined in many interesting ways to simulate the behavior of electrical devices, a house, a neighborhood or even a city. Thirdly, the simulator presented here is configurable and extensible so that one can configure the simulator to his or her needs and can add more features, if required. Fourthly, the state of the art simulators like EnergyPlus and IDA ICE provides absolute values of energy consumption of electrical devices. This is very different from our simulator which simulates relativistic energy consumption behavior. Through its high configurability one can develop scenarios that simulate changes in energy usage patterns when a new tariff rate is introduced, for instance.

The simulation models and simulators available today cannot readily be used for certain simulations mainly because of the following reasons:

1. None of the ‘open source’ state-of-the-art simulation models work on per-minute level. This means that if a device consumes more power at startup and less power later then such information will not be captured accurately in an hourly-based simulation. Since many decisions in DSM are to be taken on a minute basis, models that do not work on per-minute basis cannot be used to analyze per-minute behavior of DSM algorithms.

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[b]. http://www.eea.europa.eu/data-and-maps/indicators/energy-efficiency-and-energy-consumption-5/assessment

[c]. http://www.decc.gov.uk/assets/decc/11/stats/climate-change/3224-great-britains-housing-energy-fact-file-2011.pdf

2. Most simulation models are highly restrictive for the settings they are tailored for. For example, a simulator may only be capable of device-level usage simulations; another may simulate house-level simulations but cannot simulate device level usage. Similarly, some simulations use surveys as inputs which again require a lot of manual work before the simulation can take place.
3. Finally, the simulators are not very configurable and extensible. This means that other than a few scenarios and devices the simulator cannot be extended for a new type of electrical device or for new environmental conditions. Virtually source code of none of the simulator is available for public use.

2. Related Work

Before discussing our simulator model we present related simulator models.

2.1. Bottom Up Simulation

The ARGOS simulation model follows a "bottom-up" approach that demonstrates the load profile of individual household appliances. ARGOS constructs the energy load shape using socioeconomic and demographic characteristics. This model basically combines the psychological factors and behavioral factors of household using Montecarlo extraction. ARGOS simulates the consumption data over 15-minute interval of power demands by individual appliance [1]. This model used by Paatero et al. [2] for generating realistic domestic electricity consumption data on an hourly basis for a myriad number of households. They conducted three case studies on simulated data and presented some opportunities for appliance level demand side management (DSM). Moreover, they calculated the statistics using DSM techniques like reduction of 7.2% in daily peak loads, 42% reduction in yearly peak loads and 61% mean load reduction.

Yao and Steemers [3] used a bottom-up approach for a simple method of formulating load profile (SMLP) for UK domestic buildings. They used varieties of physical and behavioral factors to determine energy demand load profile. Stokes [4] proposed a fine-grained load model using bottom up approach to support low voltage network performance analysis in UK urban areas. This approach is also used by Armstrong et al. [5] for Annex 42 of the IEA Energy Conservation in Buildings and Community Systems Programme (IEA/ECBCS) and generating Canadian household electrical demand profiles from available inputs including a detailed appliance set, annual consumption targets, and occupancy patterns.

2.2. Agent-Based Simulation

Agent-based simulation approach has been used for office building electricity consumption [16]. In this model each appliance and user behaves like an agent and they have states like on, off and standby. This approach integrates four important elements including: organizational energy management policies and regulations, energy management technologies, electric appliances and equipment, and human behavior. These four elements when combined provide solution for office electricity consumption problems by testing and verifying different scenarios.

2.3. High-Resolution Simulation

A high-resolution simulation model uses a survey and time-of-use data to calculate consumption data for UK households at ten minute granularity while considering weekdays and weekends and the number of occupants in each & every household. Occupants are considered active when they are present within a house at a given particular time and using some appliances while using occupancy. This model is only applied to UK households so far [6]. In another paper by the same authors a high-resolution model is used with the combination of patterns of active occupancy and user daily activity profiles. This work recorded data from 22 dwellings in the East Midlands, UK over a one year period for the validation of this model [7].

2.4. Temperature-sensitive Simulations

Electricity DSM strategies and policy options for providing robust technology for energy efficiency and load reduction for Shandong, China has been proposed by conducting different surveys and calculating the consumption data at hourly load, and temperature impacts on electricity demand. The proposed model and the policy options and recommendations are only applied to the scenarios for China especially Shandong. This model simulates temperature-sensitive load simulation hourly electricity demand by the end users which takes into account time-of-use patterns, life style and behavioral factors. The main goal of this research is focused on the provision of DSM techniques that will result in reduction in peak load and total electricity consumption in Shangdong, China [8].

2.5. Markov-chain model Simulations

In a Markov-chain simulation model the household electricity load profiles are generated by using a non-homogeneous Markov-chain model with the combination of probabilistic and bottom-up models. In this method all the household activities are connected to a set of appliances. This model, proposed by Widen, uses large-scale survey by the Swedish Energy Agency (SEA) for realistic probability distribution of each appliance in household [9]. Widen also used a combined Markov-chain Model and bottom-up approach to model the domestic lighting demand [10]. This model is also used by Ardakanian for fine-grained measurements of electricity consumption for four months in twenty homes [11].

2.6. Statistical Simulations

This method is used for UK domestic buildings to generate realistic electricity load profile data based on a conducted survey. The input to this survey is based on daily basis probabilistic record of electrical appliances [12].

In view of the aforementioned problems we have designed a Smart Grid Simulator (SGS). SGS is capable of simulating energy usage behavior at different levels in the residential sector. It is able to work in a hierarchical manner which means that based on user needs and inputs it can simulate behavior of devices, households, neighborhoods and cities.

3. Simulator Approach and Methodology

SGS is capable of generating per-minute level energy behavior that can be aggregated to assess the energy usage at hourly, daily, monthly or seasonal energy usage. Additionally, energy usage simulations are required at the level of devices, buildings, neighborhoods and cities. SGS is designed to provide interfaces to its users to simulate at any of the aforementioned level. For each level a very simple interface is developed that requires a minimum set of inputs from the users to simulate a desired scenario.

Before delving into the details of the simulation approach and discussing each level of simulations there are certain inputs that are required in the simulator at all levels. These required inputs include minimum and maximum temperatures of the day as well as the sunrise and sunset timings of the locale.

The minimum and maximum temperature values are used to calculate the hourly temperature during the day. We use the temperature variation model as proposed by Cheng [8].

$$(M-m)(2.1185\times10^{-5}T^{4}-0.0018T^{3}+0.0409T^{2}-0.2462T)+0.4402M+0.5598m$$

where M = *maximum daily temperature*
m = *minimum daily temperature*
T = *hour of a day*

Given a minimum temperature of 26 C and a maximum temperature of 36 C the temperature variations are produced by Cheng's model as shown in Fig 1. We assume that in each hour the temperature is constant for generating per-minute energy usage behavior. Temperature values have a strong correlation on the usage of energy at all levels. Therefore, temperature values are a necessary input. Moreover, average temperature values are easily available for almost any locale in the world[d].

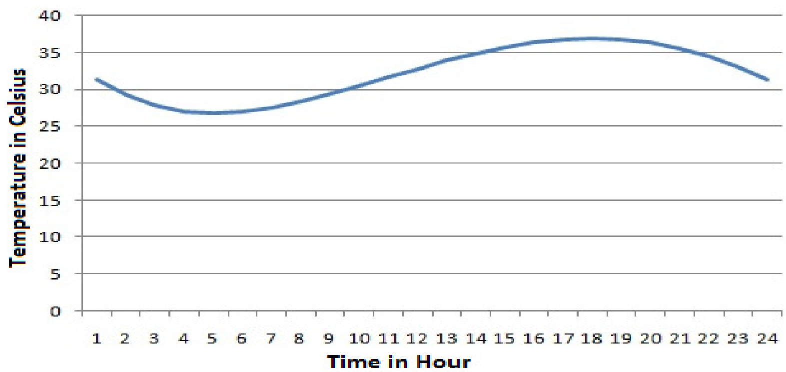

Fig. 1. Temperature variation for a 24 hour period. Time vs. Temperature of the day

The second set of input vales are the sunrise and sunset timings of the locale for which the simulation is taking place. The sunrise and sunset timings are again necessary because of many reasons. For example, the lighting usage is directly dependent in these timings. Moreover, the usage of high powered electrical appliances such as air conditioners or heaters is also dependent on the daylight timings and temperature.

As shown in Fig 2 the SGS can work at four different levels. For generating energy usage behavior at any level the temperature, daylight timings and at what granularity the energy data is to be generated are required to be specified by the user. Additionally at each level certain other inputs are required to generate a complete energy behavior simulation. Let's discuss the inputs required at each of the four levels in SGS.

3.1. Device Simulation

Other than the aforementioned necessary inputs a device energy behaviour simulation requires three other inputs. These include the device type, power rating, and usage probability of a device for each hour for a 24 hour period.

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[d] http://www1.ncdc.noaa.gov/pub/data/ghcn/daily/

Table 1. Households Appliances

Category	Appliance
Cooking Appliances	Electric hob, Electric oven, Microwave Oven
Cold Appliances	Refrigerator, Freezer
Brown Goods	Television, LCD, CD player
Wet Appliances	Dishwasher ,Washing Machine, Tumble Driers
Miscellaneous	Electric Kettle, Computers/Laptops, Iron & Others (Vacuum Cleaner etc.)
Seasonal Appliances	Air Condition, Fan, Heater
Lighting	Bulb, Tube Lights

The first input ‘device type’ puts the device into one of the categories as shown in Table 1.This categorization is used to determine the frequency of usage of a device. For example, some appliances, like most lighting devices, have constant load at all times. One other hand some appliances have varying loads at different times, for example, heating or cooling appliances are controlled by a thermostat so a fridge draws 150 watts more when its compressor is on. Similarly the devices can have a start-up load and a stand-by load. Some appliances have different startup load when the appliance is turned on for the first time that stabilizes after a period of time, for example, if an electric oven is set at 180°C then it will draw 2400 watts initially which reduces when the oven reaches its desired temperature.

The second input ‘power rating’ of a device is an average power that a device consumes. Based on the temperature variations and the type of device this power usage can increase or decrease. We have developed customized algorithms to show this behavior in our simulator. The details of these algorithms will be discussed in another paper.

The third input ‘usage probability’ of a device refers to the probability of a device being used in each hour of a twenty four hour period. This probability is necessary because most devices are dependent on the presence of people in the house. Since occupancy behavior can vary, a realistic simulation can only if the usage probabilities are know.

Given these variables the simulator generates the energy usage of the appliance for the time granularity required by the user.

3.2. Household Simulation

Often times it is necessary to simulate the energy behavior of a building or household. It is often very difficult to specify each and every device that a household use. Therefore, to generate a household level simulation the necessary inputs are the occupancy information and household income.

The occupancy information includes the number of people residing in the household. Similarly occupancy characteristics like ages of the occupants as well as if the adults are employed, school going children etc is required from the user.

The household income is used by the simulator to estimate the number of devices present in the household. We use Yao et al. [3] device penetration rate to estimate the number and types of appliances used in a given household.

When these inputs are provides to the simulator it generates a set of devices based on the household income. The probabilities of usage of these devices can vary and depends on the occupancy information and their characteristics. Again the algorithms to determine this correlation will be discussed elsewhere.

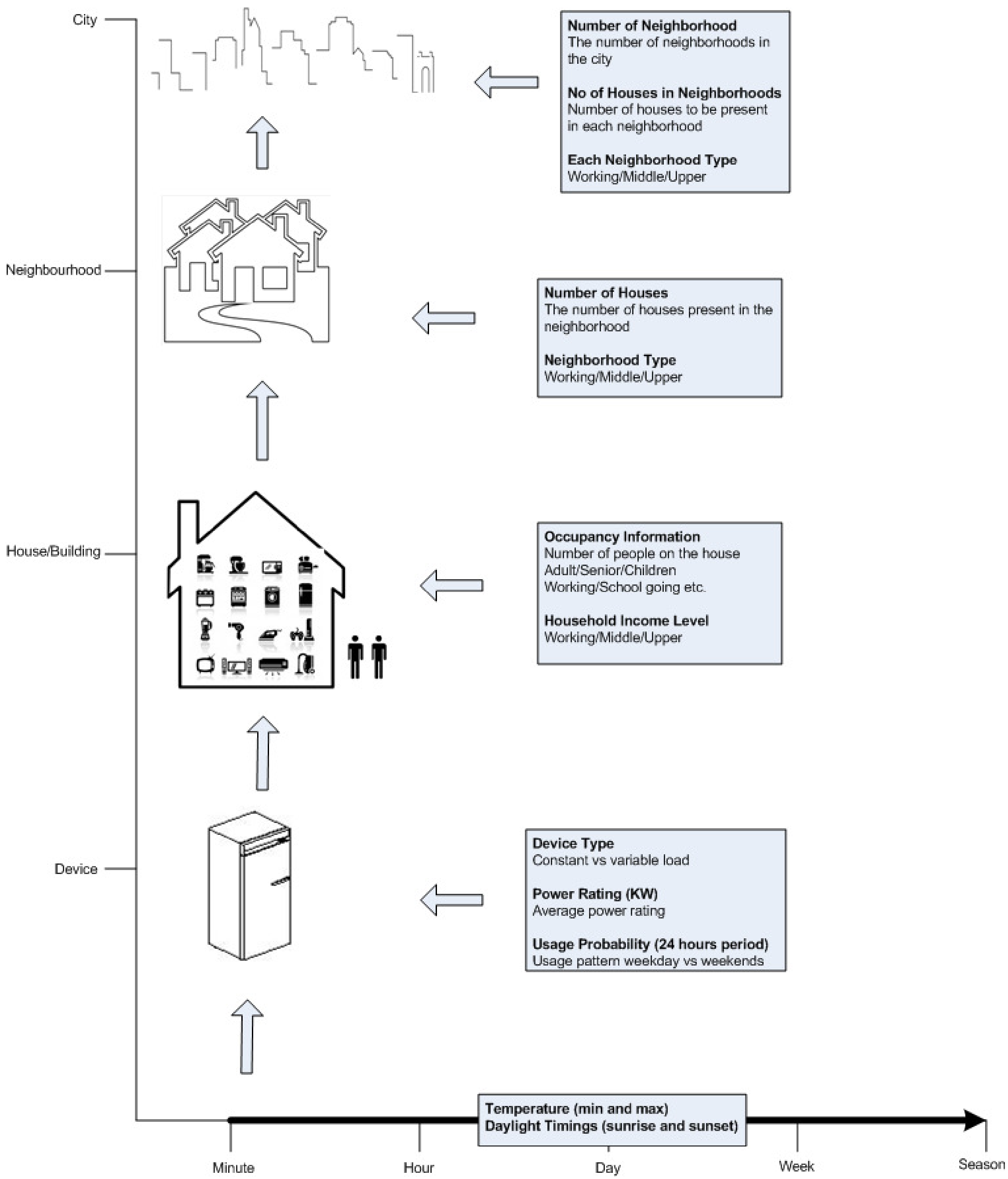

Fig. 2. SGS Simulation-levels, time granularity and inputs

3.3. Neighborhood Simulation

A group of houses or a building with multiple apartments/condominiums is considered in our simulator as a neighborhood. In a neighborhood-level simulation the required input parameters are the number of houses and the neighborhood type.

Our simulator generates houses along with random number of devices based on these inputs. The neighborhood type determines the device penetration in the households.

It is pertinent to mention that while generating the occupancy level of the houses and the device penetration are determined through pseudo-random probabilities that we have already built into the simulator. Therefore, all the houses and their device mix will be different.

3.4. City Simulation

A city is a collection of neighborhoods. Therefore, the energy behavior of a city is the aggregate behavior of the neighborhood it contains. Also, the city energy behavior simulation is lot like the neighborhood-level simulation because at this time we do not consider commercial or industrial buildings or neighborhoods in our simulator.

For generating energy behavior in a city the number of neighborhoods are specified. Additionally, the types and number of houses of each neighborhood are also specified. Given these inputs the city-level energy usage simulation is generated.

An important feature of the simulator is that at any level the user can manually adjust the values of automatically generated. Be it the neighborhoods, or households or devices, users can modify these automatically generated entities as per his or her requirements.

4. Case Study

Our simulator generates per-minute behaviour of energy usage in each of the aforementioned levels of simulations. Depending on the users' needs the simulator could output hourly, weekly, monthly or seasonal energy usage. Following we describe a household simulation and its generated output as a demonstration of our simulator.

We generated a household simulation where we specify two adult occupancy-level for a household. Both the occupants are working adults and the household income level is working class. The simulator takes this information and generated a set of five devices. Based on default usage probabilities already coded in the simulator generated the hourly energy behavior of this household as shown in Fig 3.

As shown in Fig 3 the simulator generated five devices: iron, refrigerator, television, computer, and lighting. We use one lighting parameter for all the light sources in the house. The refrigerator is a device that is turned on almost every hour for about 20-30 minutes. The computer, television, and lighting are only used in the evening since the adult occupants of this household are employed and are supposed to be working elsewhere during day time. The iron is used for a short time in the evening but since the energy usage of the iron is high it spiked the energy usage in that hour.

Similarly other simulations at all the four levels can be generated by our simulator. The device usage is similar to the device usage behaviour in Fig 3. Although for device usage behaviour the hourly probabilities can vary the energy usage of the devices.

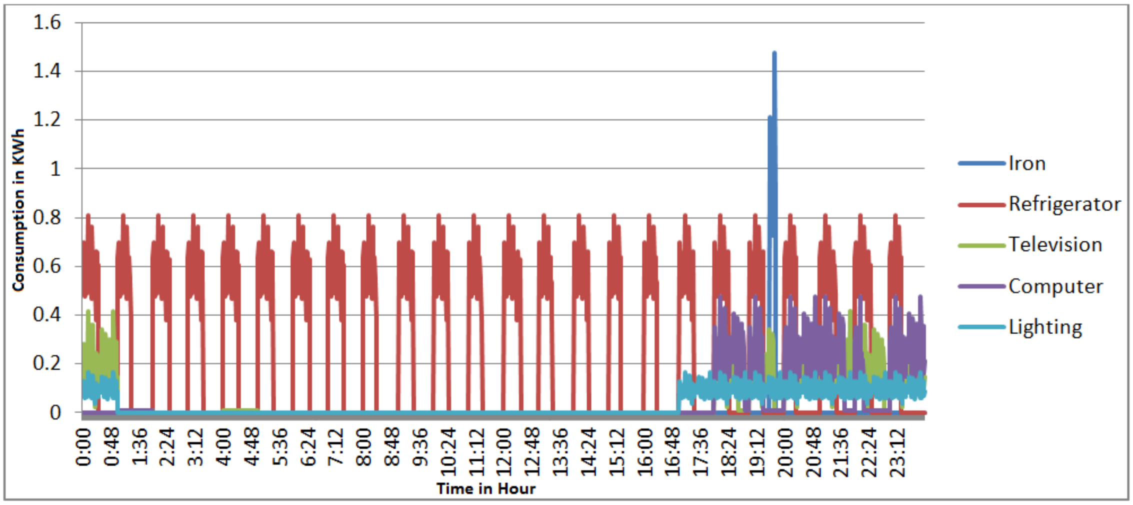

Fig. 3. House Energy Usage Simulation. Hour vs. KWh

5. Conclusion and Future Work

The simulator presented in this paper may be used for virtually generating any kind of demand scenario of electricity. This capability of the simulator can be very useful for city planners and utility companies. Since the simulator is extensible more features can be added to the simulator. For example, SGS can be extended so that the temperatures and daylight hours can be calculated automatically. Also, at this time we are not taking into account the architectural and structural features of the buildings such as north facing or south facing buildings, material used in the building construction, type and size of windows etc. It will be an interesting add-on to put all these features in the simulator as well. Moreover, at the city-level simulations the simulator does not take into account any commercial or industrial energy usage simulations. It will be interesting to add behaviour of commercial or industrial energy usage to get a more accurate city-level energy simulation. Furthermore, we are planning to develop the simulator into a web service where any user can use the simulator and generates the required simulation data. Finally, SGS only looks at the demand-side aspects of smart grid. It can be potentially enhanced to look into the supply side of energy also. In this way the economic dispatch and demand-side management could be integrated at one place.

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