Household power consumption monitoring and modeling

47096815 Li Meng
Supervisor: Prof. Okamoto

As electronics continuously come to our daily life in an ever increasing number, and their usage become an indispensable part of our working and life experience, the demand for a reliable, and capacious energy supply is being paid more and more attention. Smart grid technologies are introduced to build a flexible and robust next generation power grid. However, for an accurate simulation of power consumption in the grid, the experiential model is not competent to adapt to the changes that are never seen before. A new power consumption simulation system is needed to anticipate the impacts of new appliances as well as new policies and strategies in the future smart grid.

In this research, we proposed a multi-agent system approach in obtaining more realistic simulation data based on practical data captured by a power monitoring system. And as an example of utilizing the system, we discussed the advantage of bringing about micro-scale controlling in balancing the grid power usage.

Keywords: Smart grid, Power consumption modeling, Multi-agent system simulation, Micro-scale controlling

1. Background & Objective:

In building a traditional simulation system of a power grid, behaviors of individual appliances and human users are usually not taken into consideration。 However, when designing a smart grid, it is necessary to examine the changes happen in micro scale, so as to anticipate their impacts on the whole grid.

Therefore, we need a more accurate and flexible load simulation system, to aid future power grid design as well as verifying the effectiveness of new features such as floating price and micro scale controlling.

2. Methodology:

We proposed a multi-agent system approach in building the simulation environment (SE) for generating power consumption data, based on the practical power data captured by a power monitoring system (PMS).

By using the SE, we discuss about strategy making for consumers and policy design for the power supplier with simulation results. The process is shown in the figure below:

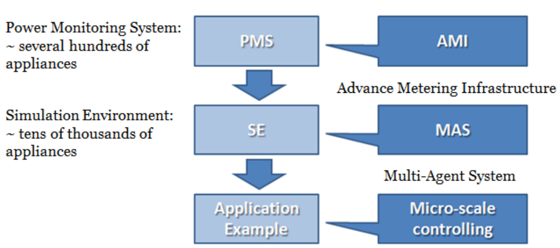

Fig.1. Overall experiment process

2.1. Building of power monitoring system:

We use ready-made smart metering system, which consists of a number of smart meters and one raw data gathering server. Power usage of appliances which are plugged on to the smart meters can be measured and the power data is sent to the raw data gatherer wirelessly. Based on this smart metering system, we built up the power monitoring system (PMS) for sorted storage and better accessibility to historical data.

The setup of the system is shown in figure 2. We use DB server to retrieve raw XML records from raw data gatherer automatically, and update the power database with sorted data format. The power data is stored for later inquiries from either local or intranet. Figure 3 shows an example visualization result of practical power data, captured by the PMS.

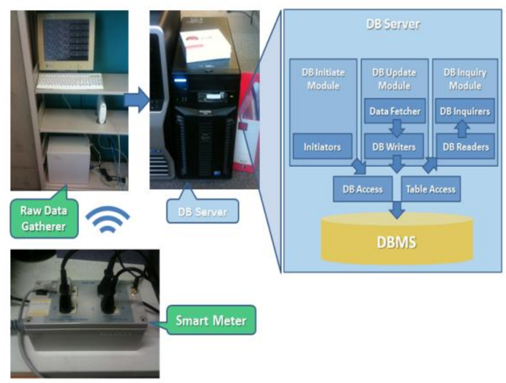

Fig.2. Power monitoring system. Smart metering device send power measures to raw data gatherer via wireless network, DB server periodically fetch raw data and update it into database. The data is stored for later inquiries.

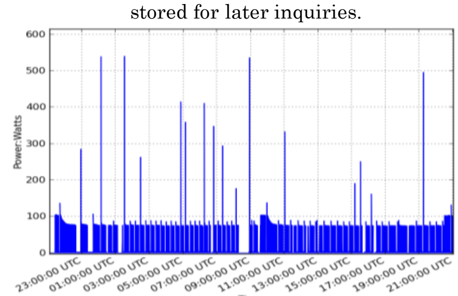

Fig.3. Practical power consumption data of fridge

2.2. Building of simulation environment:

In a practical power consuming environment, such as a community, the cell is the basic unit of power consumption that contains human users and appliances as shown in below:

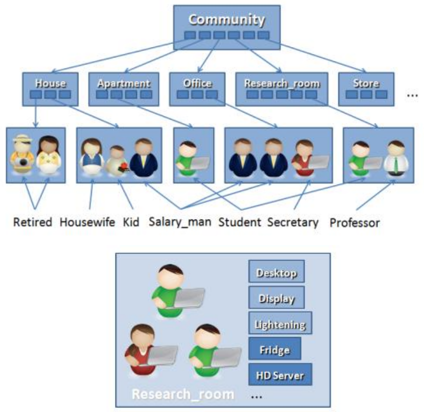

Fig.4. Power consumption environment of a community consists of cells (Upper), and the composition of a cell (Lower)

The community usually consists of different classes of cells with a different quantity of instances in each class. Within each cell, there may be a number of human users as well as some appliances, which may be of different classes. The class of a cell is decided by its composition: what kind of human users and appliances are in the cell at what quantities of each class.

All the components are model in our SE: For human users, we introduce agent that act their behaviors in the system. The agent behaviors can be modeled as a set of layered structures based on the observation that people are more likely to conduct certain procedures around specific times during a day. For appliances, we model them as finite state machines based on the observation that electronics usually possess a number of working phases. The power consumption can be viewed as a function of internal timer under current state and environment parameters usually.

2.2.1. Agent modeling

The class of an agent is decided by the procedures it can execute. Different agents usually have different types of procedures to execute and/or different time parameters on execution. Figure 5 shows an example: student class agent's procedures.

Procedures can be further divided into two types: status and activities: a status is the procedure that does not involve appliance (power) usage directly, whereas an activity involves usage of certain appliance (power) directly.

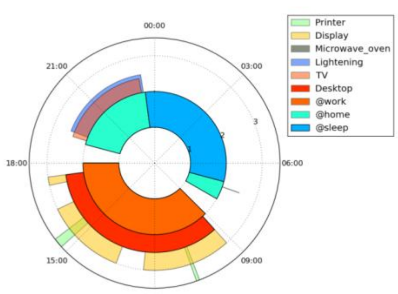

Fig.5. Depending structures of student class procedures.

2.2.2. Appliance modeling

In modeling the appliances as state machines, the class of appliance is decided by the working states it possesses and the transitions between these states. Appliances of same class possess same states and transitions in between; Appearances of different models are presented in different time and power parameters. The following figure shows the modeling process of an air conditioner.

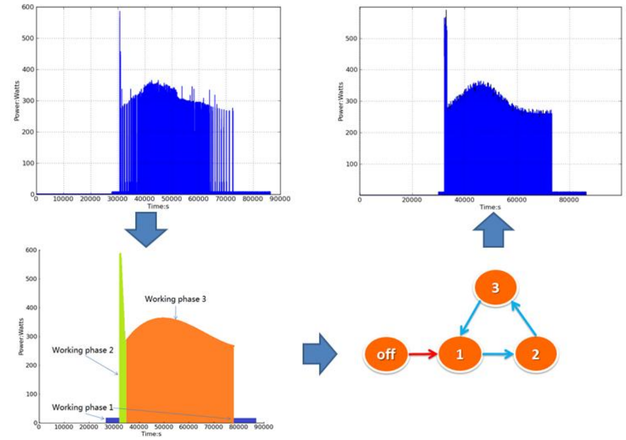

Fig.6. Making of profiles for air conditioner class appliance: 1.Capturing of practical power data using PMS (upper left), 2.Deciding abstracted working phases (lower left), 3.Making transition chart (lower right), 4.Comparing the simulation data.

2.2.3. System configuration

Whole system setup of simulation environment is shown in the following figure 7. The system takes template profiles of cells, agents and appliances as input. The quantities of agents and appliances within each cell type is specified in cell profiles, the agent profiles contain information about procedures the class of agent may conduct, and time parameter are specified in the profile. In appliance profiles, possible transitions of the state machine are specified, time and power parameters are also specified in this file.

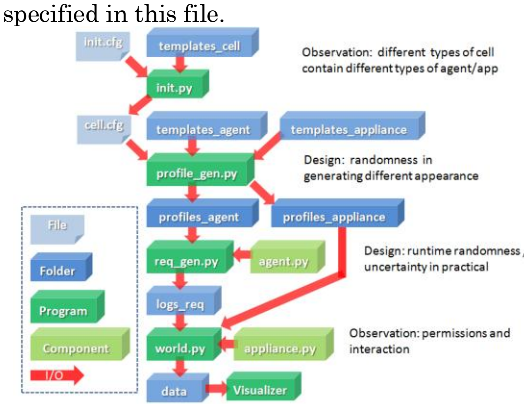

Fig.7. System setup of the simulation environment (SE)

With statistic assumptions, profile generator generates concrete profiles for each agent and appliance with randomness according to cell templates and initial parameters such as length of time, classes and quantities of cells. This is for emulating the different appearances of human users' behavior and power appliances' model in the practical. Request generator generates runtime requests using agent profiles, and then the world simulator use them to make interactions with virtual appliances made according to appliance profiles. World simulator reads the request log and enables interactions with interactive appliances with considering permissions.

Interactions between agents are implemented via competitive usage of mutual exclusive appliances here. Power phase delays are considered for non-interactive appliances in at this stage. Power logs for each appliance in all cells are generated and they can be visualized later for analysis purpose.

2.2.4. Result:

In a simulation of 100 research rooms during 10 days, the power-time chart is shown in the figure below:

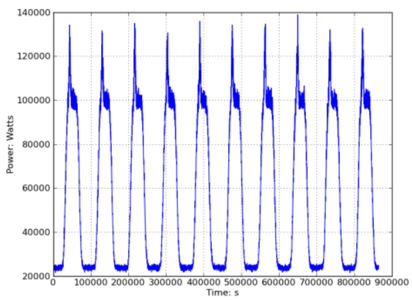

Fig.8. Totaled power simulation result visualization in 100 research rooms

Analytical power consumption modeling enables a detailed visualization of power usage of different appliances within one cell. Figure 9 shows the visualization example of compositional power consumption in one research room during a day:

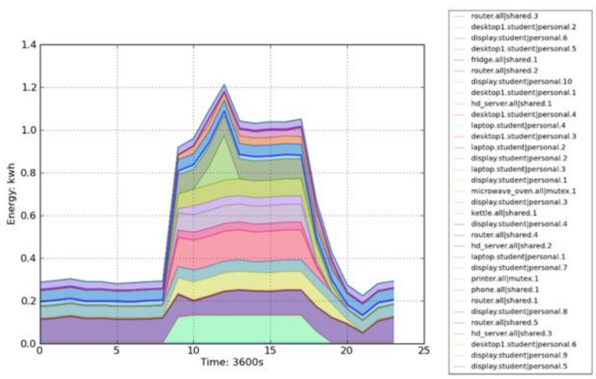

Fig.9. Energy composition of one research room in 24 hours

3. Discussion:

As an application of our simulation environment, we discuss the effectiveness of floating pricing and a simple design of corresponding consumer end strategy.

The objective of the floating pricing is to achieve a balanced usage by encouraging non-peak hour usage using power price. Consider in an environment of the setup shown in figure 10:

Power supplier applies a pricing function F to the usage vector (which contains the usage for each hour) of previous day $U=(u_0,u_1...u_{23})$, to generate the price vector $P=(p_0,p_1...p_{23})$: $P_{i+1}=F(U_i)$, in which F is a linear transform F: $P=kU$, k is the pricing rate for unit power consumption.

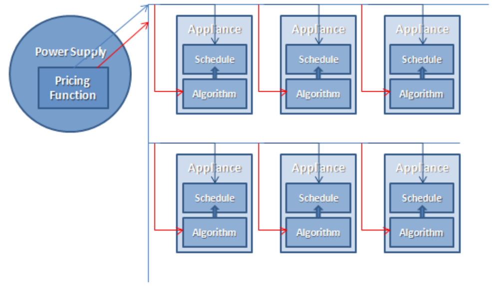

Fig.10. Power consuming environment with price broadcasting and task scheduling. Blue line: power line. Red line: price information channel

On the consumer end, appliances receive and utilize such information to schedule their tasks. The basic idea is that: when a non-emergent task usage is scheduled from the peak hour to idling time, the total usage would be balanced as shown example in figure 11.

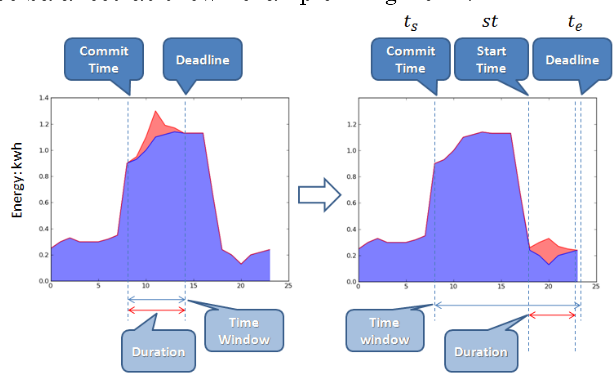

Fig.11. Energy composition of one research room in 24 hours

For these schedulable usages, we define a time window of execution, and the objective of the micro-scale controlling mechanism is to set the start time according to received price information so as to avoid peak hour usage in the background and to avoid time crash usage from other appliances.

To achieve the first objective, we schedule tasks following the guiding information provided by the usage-related price vector. However, if all tasks are scheduled for the most optimized cost, their usage would crash in time and another peak usage would be created in the following day. To avoid this social disaster, which is also to achieve the second objective, we use a moderate random algorithm to set the practical start time of a task within a time window:

1. Get the price vector and find the greatest component p_m in the price vector: $p_m=\max(p_1,p_2...p_{23})$
2. Get the probability weight vector. Its components are the complementary of price vector's components to p_m : $PW=(p_m-p_0,p_m-p_1...p_m-p_{23})$
3. When a non-emergent task incomes, with the task start time st schedulable on a time window $[t_s,t_e]$ (as shown in figure 11), get normalized cumulative distribution function by integrating the probability weight function on time window $[t_s,t_e]$:

$$cdf(st) = \frac{\int_{t_s}^{st} PW(t) \cdot dt}{\int_{t_s}^{t_e} PW(t) \cdot dt}, \quad st \in [t_s, t_e]: \text{task start time.}$$

4. Uniformly distributed random variable a is used to decide st in practical: $a = cdf(st)$

$$\int_{t_s}^{st} PW(t) \cdot dt = a \cdot \int_{t_s}^{t_e} PW(t) \cdot dt$$

Since the right side is a constant when a is given, and the left side is the cumulative density function of *st*, which is monotonically increasing. The value of *st* can be uniquely decided on time window.

In a simulation test of 1000 cells during 20 days, there is a background usage power in each room, which represents the usage of non-interactive appliances and usage of non-schedulable emergent tasks. There is also a schedulable non-emergent task in each room. The environment settings are shown in figure 12.

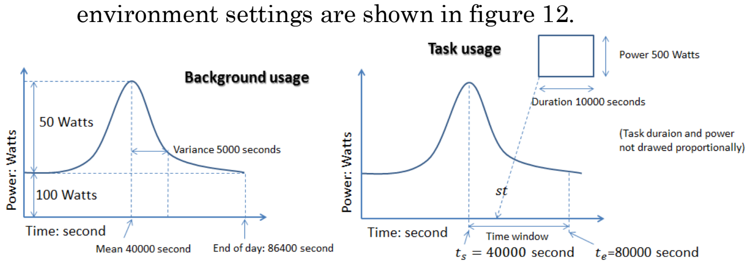

Fig.12. Parameters of background and task usage

With a scheduling mechanism under a floating pricing policy as discussed, we expect to see the usage balancing effect: peaks of power usage go lower in height gradually, as more and more non-emergent tasks become schedulable, the simulation result is shown in figure 13.

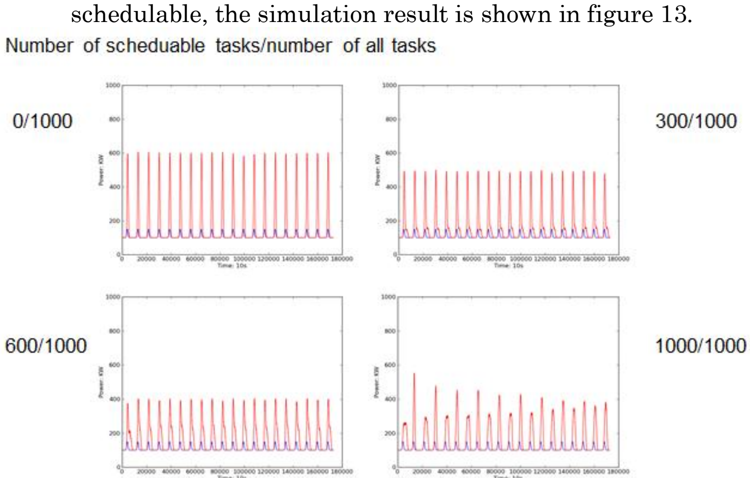

Fig.13. Power curves with different number of schedulable tasks, the number beside is the portion of schedulable tasks in non-emergent tasks

In the result, we confirm the effectiveness of the micro-scale controlling: when more non-emergent tasks become schedulable using the scheduling algorithm built in the smart appliances, the height of peak power can be reduced.

When all the tasks become schedulable, the peak power height goes fluctuate. However, stabilizing effect can be seen with the time passage. When applying the usage-related pricing policy, the power price will be predictable, which is crucial for consumers to budget their energy usage cost.

4. Conclusion:

We developed a power monitoring system based on the advanced metering devices. Using existing software component, we designed a real time power data capturing and storing mechanism. It is shown that this method to be applicable in building a database system for a power grid.

Multi-agent system is a useful approach for building a flexible and expansible power consumption simulation system in a large scale. With appropriate profiling, the system is able to perform power consuming simulation at a resolution of individual appliances.

Using the simulation environment built this way, we confirmed the effectiveness of floating pricing policy and corresponding scheduling mechanism in balancing grid power usage. We may design, and test quantitively the advanced features of future smart grid, such as grid pricing policy and appliance end strategy. Multi-agent system approach is suitable not only in building a power forecasting system but also a policy/strategy testing platform as well.

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