Optimal Energy Management in Nanogrids

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***Abstract*—Home energy management is not efficient for a number of reasons. In this paper, we discuss a home energy management scheme which uses a nanogrid that introduces peak load shifting for energy control using the location patterns of the user. Sensors in the home can monitor the locations of residents and adjust the power consumption of the home in real time. This allows the system to estimate the behaviors of occupants in various situations to reduce the amount of power used. Major ideas and experimental systems are expected to be applied not only to green buildings but also to a large number of existing buildings to reduce the level of power consumption without sacrificing human comfort or convenience.**

Keywords*—*energy management; joint control; nanogrid; peak load shifting; person location pattern; multi-objective optimization

I. Introduction

The existing power infrastructure in homes and buildings faces a number of challenges that are difficult to solve. The conventional power distribution method causes large power losses and reduces the efficiency of the power grid. Moreover, grids are susceptible to costly outages due to environmental events (e.g., heavy rain or wind) as well as non-environmental events (e.g., age-related equipment failures). A nanogrid can be used for one building, while a microgrid can serve an island of 15000 consumers. Typically, a nanogrid is technically smaller than a microgrid [1] [2].

Control strategies for buildings to operate heating and cooling, lighting, and ventilation are important to the living standards and health of the residents. Heating, ventilation and cooling (HVAC) is the single largest contributor to a home energy component and accounts for 33% of residential power consumption in the US [3]. Thermal comfort, visible comfort and the indoor air quality are considered to be the three main factors that affect the quality of life of residents in a building environment [4] [5]. Occupant presence and behavior in building have been shown to have large impacts on space heating, ventilation and cooling demand, power consumption by lighting and space appliances, and building control strategies [6].

With regard to energy management, minimizing the energy cost, maximizing the overall efficiency, and the efficient control of peak demand loads are important factors [7] [8]. In addition, maximizing the lifetimes of the energy storage system (ESS) and the generator as well as reliability and security of the power provision are of great importance. To minimize the peak load, the emphasis has been on allocating appliance operation over time scales where there will be a leveling of the peak demand load over the given range of time [9]. The proposed demand-side management strategy achieves substantial savings while reducing the peak load demand on the smart grid using heuristic optimization [10]. These efforts range from improving the energy efficiency by using better materials to smart energy tariffs with incentives for certain consumption patterns and to sophisticated real-time control of distributed energy resources [11]. The development and application of load-shifting control strategies have been discussed in the literature [12].

In this study, an experimental system which optimizes power consumption and human convenience using the positions of people in a nanogrid is presented [13]. In the experiments done to test the system, user location patterns serve to realize optimal control of user locations through a hidden Markov model (HMM) which is calibrated using time-use data collected from the Korea Power Exchange (KPX) Institute. Multi-objective optimization methods are implemented in the system to find Pareto-optimal solutions. The total power consumption and the overall comfort level are considered as the two contrasting goals of building energy management and comfort management [14] [15].

This paper is organized as follows. In Section 2, the HMM for the occupant patterns is explained. The operational characteristics of the house energy management scheme are expressed in terms of the relationships between power consumption and human location patterns. Section 3 provides details of the optimal energy management scheme. Section 4 presents the experimental results. Section 5 concludes this paper with a summary.

II. Occupant Behavior Modeling

A. Korea Time Use Survey (KTUS)

Korea Time Use Survey (KTUS) creates a resident behavior model for the average individual in Korea.

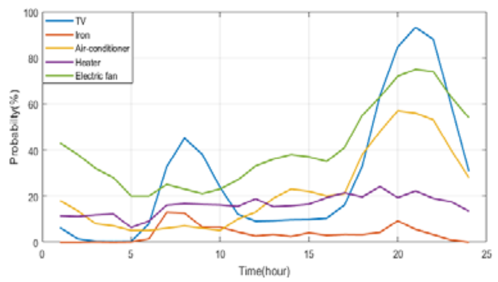

Fig. 1. Profile of merged activity types people are at home: patterns for the TV, iron, air-conditioner, heater, and electric fan

KPX measures the amount of time people spend engaged in various activities, such as washing, watching TV, or cooking. The information collected by KPX includes the start and end times (hours) of each activity. The KTUS data collected in 2013 were used here to create a statistically driven occupant behavior model. An analysis of the KTUS data provides an outline of pattern information related to the respondents' activities. This is shown in Figure 1. We use a sample size of 500 houses, a sample time interval of 1 hour, and a power consumption interval of 60kWh ~ 1000kWh.

B. Hidden Markov Model (HMM)

An HMM was used to model the behavior of home residents [16]. The HMM is used to model the likelihood of transitioning to the next state from the current state. This transition probability is entirely dependent on the current state and does not depend on the state sequence preceding the previous state [17]. A visual representation of the HMM is shown in Figure 2. Resident behavior can be modeled by a hidden state that represents complex behavior that affects the observation and the observed behavior [18] [19]. The HMM is a probabilistic model consisting of the transition and emission probabilities. The emission probability refers to symbols that can be emitted by models related to actions performed by occupants, such as a shutdown of the air conditioning system or a change of the thermostat level.

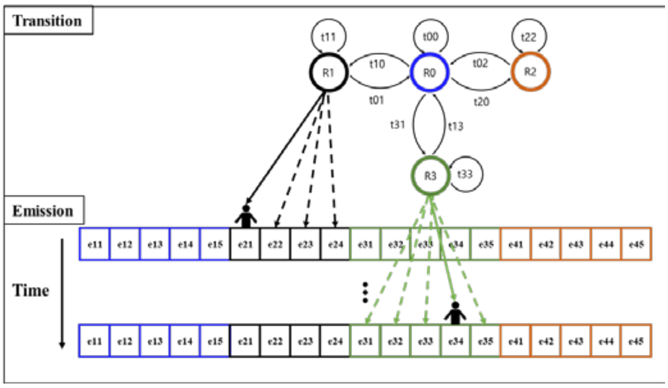

Fig. 2. Block diagram illustrating occupant behavior using a hidden Markov model

The ten activities, including laundry, food preparation, washing machine usage, watching TV, and computer usage were chosen because they incur the largest and the most common power consumption loads in the residential sector. (These appliances are the washing machine, heater, electric fan, iron, microwave, vacuum cleaner, rice cooker, air-conditioner, television, and computer.)

III. OCCUPANT-LOCATION-DEPENDENT OPTIMAL CONTROL SCHEME

Multi-objective optimization involves selectively minimizing or maximizing multiple objective functions that are dependent on a set of constraints. The goal is to solve complex optimization problems by simultaneously considering potential conflicting goals.

With this scheme, we consider a system with n modules and set the power of the *i*th module to $P_i\ (t)$ watts when it operates in the usual manner prior to energy management. The switching on/off status of the *i*th module in the proposed energy management scheme can be represented by the following switching function,

$$\min_{u_i(t)} \sum_{i=1}^{N} P_i(t)u_i(t) \tag{1}$$

$$\max_{u_i(t)} \sum_{i=1}^{N} \frac{u_i(t)}{D_i(t)} \tag{2}$$

subject to

$$CO_{2,inner}(u_i(t)) - CO_{2,inner,\max} \le 0 \tag{3}$$

$$T_{inner}(u_i(t)) - T_{inner,\max} \le 0 \tag{4}$$

where $u_i(t)$ is the switching on/off status of the *i*th module, $D_i(t)$ is the appliance distance relative to the position of the human, $CO_{2,inner}(u_i(t))$ is the inner CO_2 concentration, $CO_{2,inner,\max}$ is the maximum allowed inner CO_2 concentration, $T_{inner}(u_i(t))$ is the inner temperature, and $T_{inner,\max}$ is the maximum allowed inner temperature.

IV. EXPERIMENTAL RESULTS

A. Experimental setup

In the experiment, the outdoor temperature is determined using temperature information from the meteorological office and the outdoor CO_2 concentration is set to 490 ppm. The $CO_{2,inner,\max}$ level is 470 ppm and $T_{inner,\max}$ is 23℃.

TABLE I. INDEXES OF ELECTRIC APPLIANCES FOR THE APPLIANCE SET

Index	Type	Power	Index	Type	Power
1	Air conditioner	2.07kW	6	Washing machine	242W
2	Fan	60W	7	Vacuum cleaner	1.07kW
3	Heater	1.16kW	8	Computer	255W
4	Iron	1.23kW	9	Microwave	1.04kW
5	TV	130W	10	Rice cooker	1.03kW

Table 1 shows the amounts of power used by household appliances. In this experiment, ten appliances and four rooms are considered.

B. Experiment

The experiment compares power consumption patterns with respect to the location, which is based on the user's location with priority distances of 5m and 10m. Figure 3 shows that optimizing the use of a device depends on the person's location, leading to less power use. The blue line represents the optimizations of independent user locations. In every room, an air conditioner and an electronic fan are used to maintain the target temperature and CO_2 level. It can be confirmed that the priority distance of 5m, as optimized according to the location of a person in the building, is useful in terms of power consumption.

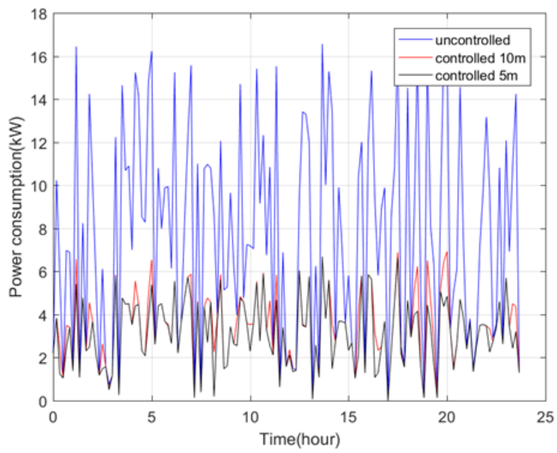

Fig. 3. Experimental results of multi-objective optimization depending on the user location and not depending on the user location (priority: depending on the user location - 5m and 10m, and then independent of the user location)

As a result, when considering this distance, the peak power can be reduced. The capital and operating costs can be reduced.

V. Conclusion

This paper discusses home energy management of a nanogrid with shifting of the peak load according to the location patterns of residents. Sensors in the building can monitor residential location patterns. This allows residents with diverse roles to participate in energy efficiency efforts using a HMM to determine the occupant pattern. Major ideas and experimental systems are expected to be applied not only to green buildings but also to a range of existing buildings in order to reduce power usage without sacrificing human comfort or convenience. Human comfort is linked to the maximum number of devices without scheduling. The operational characteristics of the house energy management scheme here are expressed according to the relationships between power consumption and human location patterns. Experimental results indicate that the reduction of power consumption based on the resident location optimization scheme is superior to that independent of resident locations. End users of this system can save electricity and continue to feel comfortable.

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