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Multi-objective cost-load optimization for demand side management of a residential area in smart grids

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ABSTRACT

Demand side management (DSM) is one of the most interesting areas in smart grids, and presents households with numerous opportunities to lower their electricity bills. There are many recent works on DSM and smart homes discussing how to keep control on electricity consumption. However, systems that consider minimization of peak load and cost simultaneously for a residential area with multiple households have not received sufficient attention. This study, therefore, proposes an intelligent energy management framework that can be used to minimize both electrical peak load and electricity cost. Constraints, including daily energy requirements and consumer preferences are considered in the framework and the proposed model is a multi-objective mixed integer linear programming (MOMILP). Simulation results for different scenarios with different objectives verified the effectiveness of the proposed model in significantly reducing the electricity cost and the electrical peak load.

1. Introduction

Increasing population, urbanization, industrialization and technological developments throughout the world have increased energy consumption intensively. Increase in energy use has caused problems including depleting energy sources and creating pollution due to energy production process. For the solution of these basic energy issues, traditional grids are being transformed into smart grids (SG), which could be defined as the grid infrastructure that optimizes the energy efficiency while lowering both the energy sources' installation expenses and pollution effects on the environment (Ozkan, 2016). A research area that has been very popular within SGs is demand side management (DSM), as shown by the increasing number of publications over the recent years (Galvan-Lopez et al., 2014); More than 2000 scientific papers have been published in this area since the 1980s, with more than half in the recent decade (Galvan-Lopez et al., 2015).

DSM technique mainly relies on matching present generation values with demand by controlling the energy consumption of appliances and optimizing their operation at the user side (for instance, by shifting appliances such as dishwashers, washing machines and dryers from peak time to off-peak time).

The importance of energy usage optimization in a smart house can be inferred from the statistical information, which indicates that the electricity consumption in the residential sector represents over 27% of the global energy consumption in 2014 (Ministry of Energy of Iran, 2016). Therefore, a large number of research efforts have been devoted to the application of DSMs in the residential sector (Tascikaraoglu et al., 2014). For example, a mixed integer linear programming (MILP) model was formulated by Sou et al. (2011) to minimize the total electricity cost for operating the appliances. The cost calculation was based on a given 24-hour ahead electricity tariff. Tascikaraoglu et al. (2014) put forward a scheduling approach of operation and energy consumption of various electrical appliances in a grid-connected smart home system, which utilized wind and solar power predictions, electricity tariff information, states of storage systems and load priorities for deciding the optimal operation times of appliances. It was aimed to minimize the monetary expenses with autonomous decisions while avoiding to buy electricity at high-price times by shifting the deferrable loads to the times with higher renewable energy potential and/or with cheaper electricity price. Gottwalt et al. (2011) introduced an algorithm that simulated residential load shifting under time of use (TOU) regimes using previously generated profile data to model realistic demand response behavior. Different groups of household appliances were included into the model with their technical and practical usage patterns and operation constraints. Giorgio and Pimpinella (2012) addressed the design of a smart home controller strategy providing

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Nomenclature

Sets

A	Set of appliances
H	Set of hours (24 hour in a day)
T	Set of electricity tariffs
C^h	Set of c^hs
$TSAs$	Set of time-shiftable appliances
$PSAs$	Set of power-shiftable appliances
$NSAs$	Set of non-shiftable appliances

Indices

h	Time interval index
a	Household appliances' index
s	Start time index
e	End time index
n	Number of appliances

Functions

f_1	Electrical peak load function
f_2	Electricity cost function

Variables

EPL	Electrical peak load
c_a^h	Energy consumption of appliance a in a particular hour h
c^h	Total energy consumption in hour h
u_a^h	Binary variable: if time-shiftable appliance a operates in hour h, ; otherwise,
U_a	Binary integer vector of

Parameters

DR_a	Daily requirements of energy for appliance a
h_a^s	Operation start time of appliance a
h_a^e	Operation end time of appliance a
p_a^*	Fixed hourly energy consumption of non-shiftable appliance a
$\underline{p_a}$	Minimum energy consumption of power-shiftable appliance a
$\overline{p_a}$	Maximum energy consumption of power-shiftable appliance a
p_a^h	Fixed energy consumption of appliance a in hour h
P_a	Fixed energy consumption pattern of time-shiftable appliance a
P_a^{total}	A matrix of shifted pattern for a time-shiftable appliance a
t^h	Electricity tariff for hour h

efficient management of electric energy in a domestic environment. The problem was formalized as an event driven binary linear programming problem, the output of which specified the best time to run smart household appliances under a virtual power threshold constraint, taking into account the real power threshold and the forecast of consumption from non-plannable loads. Ma et al. (2016) proposed an optimization power scheduling scheme to implement demand response in a residential unit when the electricity price was announced in advance. Adika and Wang (2014) presented appliance scheduling and smart charging techniques for household electricity management. They proposed an intelligent energy management framework that can be used to implement both energy storage and appliance scheduling schemes. Two variants of evolutionary algorithms were used by Galvan-Lopez et al. (2014) to search for efficient charging schedules for fleets of electric vehicles (EVs); they achieved good results in terms of reducing peak demand and consumers' electricity costs, while maintaining a high overall state of charge of EVs' batteries. Chavali et al. (2014) described a distributed framework for demand response based on cost minimization. Each user in the system could find an optimal start time and operating mode for the appliances in response to the varying electricity prices. Galvan-Lopez et al. (2014) surveyed the use of Monte Carlo tree search in SG technologies with the ultimate goal of learning the optimal times to switch electric devices on or off to minimize electricity cost by learning and predicting the electricity price based on a pricing history in a dynamic price environment. An MILP model was put forward by Steen et al. (2016) to schedule the load demand for residential customers with the objective being minimization of their electricity cost. Bae et al. (2014) focused on a system architecture and an algorithm for DSM using information and communications technology (ICT). As the first step, the objective function was based on electricity bill, and the usage pattern was formulated. Then the electricity bill was minimized, and the usage similarity was maximized. In the second step, a load balancing algorithm was applied to avoid blackout and to minimize rebound peak. Mesaric and Krajcar (2015) developed a mixed-integer program to reach maximum amount of renewable energy sources, scheduling optimal power and operation time for EVs and appliances. Muralitharan et al. (2016) presented a multi-objective evolutionary algorithm, which resulted in the cost reduction for energy usage and minimizing the waiting time for appliance execution. Pallotti et al. (2013) discussed the use of genetic algorithm (GA) to find the optimal planning of energy consumption inside 246 smart homes in a neighborhood. For this purpose, a multi-objective optimization problem was formulated aiming at reducing the peak load as well as minimizing the energy cost and its impact on the users' satisfaction. An appliance control algorithm, called appliance-based rolling wave planning, was developed by Ozkan (2016) with the aim of reducing electricity cost and improving energy efficiency while maintaining user comfort. Vardakas et al. (2014) presented and analyzed four power-demand scheduling scenarios that aimed to reduce the peak demand in a smart grid infrastructure. Caprino et al. (2015) addressed an approach to the peak shaving problem that leveraged the real-time scheduling discipline to coordinate the activation/deactivation of a set of loads. A multi-objective mixed integer nonlinear programming (MOMINLP) model was developed by Anvari-Moghaddam and Rahimi-Kian (2015) for optimal energy use in a smart home, considering energy saving and a comfortable lifestyle. Elma and Selamogullari (2015) introduced a home energy management algorithm for smart home environments to reduce peak demand and increase the energy efficiency. A system that produced a real time solution to reduce the electricity cost and to avoid the high peak demand problem for a smart home which, was equipped with smart electrical appliances, power units, a communication network and a main controller was proposed by Ozkan (2015). Bradac et al. (2015) focused on an optimal scheduling of domestic appliances by using MILP. The aim of the proposed scheduling was to minimize the total energy price paid by the consumer. Missaoui et al. (2014) developed a global model based on anticipative building energy management system in order to optimize a compromise between user comfort and energy cost by taking into account occupant expectations and physical constraints like energy price and power limitations. A mixed-integer nonlinear programming (MINLP) approach was used by Lu et al. (2015) to solve the optimal scheduling problems of energy systems in the buildings integrated with energy generation and thermal energy storage. The optimal scheduling strategy minimized the overall operation cost day-ahead, including the cost of operation energy and the cost concerning the plant on/off penalty. Zhang et al. (2015) proposed an MILP model to schedule the energy consumption within smart homes by coupling the environmental and economic sustainability in a multi-objective optimization with ε-constraint