Sustainable Cities and Society 21 (2016) 1–11

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Optimal operation of energy systems including energy storage equipment under different connections and electricity prices

Shintaro Ikeda[a,*], Ryozo Ooka[b]

[a] Department of Architecture, The University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo 153-8505, Japan
[b] Institute of Industrial Science, The University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo 153-8505, Japan

ARTICLE INFO

Article history:
Received 26 August 2015
Received in revised form 28 October 2015
Accepted 29 October 2015
Available online 10 November 2015

Keywords:
Thermal energy storage
Battery
Energy system optimization
Metaheuristics
Area rate of prices
Price of purchased and sold electricity
Epsilon constrained differential evolution

ABSTRACT

Thermal energy storage (TES) and batteries have recently become increasingly important for peak-load shifting in energy systems. However, optimizing energy systems is difficult because each machine has multiple combinations of operations, and the objective function contains transformed nonlinear or non-convex characteristics. Therefore, we adopted the epsilon-constrained differential evolution (εDE) in order to minimize operating costs. We demonstrate that the εDE method efficiently solved strict constraint optimization problems on three energy systems: a self-consumption model (Case 1), total amount of a purchased model (Case 2), and a full connection model (Case 3) under 126 case studies. Although 216 decision variables were used under the nonlinear condition, we were able to obtain the optimal solution within a short time period, 16 min on an ordinary PC. Moreover, we proposed a new index "Area rate of prices (ARP)" in order to evaluate the effects of purchased and sold electricity prices on the operating costs. The results showed that when the area rates of purchased price to sold price are higher than 0.2 (ARP > 0.2), Case 1 was superior to Case 2. On the other hand, when the ARP value was less than 0.2, Case 2 was superior to Case 1. Therefore, we can conduct the optimization on everyday practical situations because εDE requires low computational cost. Even if the operators cannot conduct the optimization in practical energy management, they can easily determine the operation strategy by calculation of the ARP value. Therefore, the εDE and ARP methods have substantial advantages for energy system optimization.

1. Introduction

In recent years, the installation of renewable power generators, such as photovoltaic (PV) systems, has increased. As a result, business models for the sale of electricity generated from PVs have spread globally. In addition, batteries have been gradually installed not only to manage the grid's voltage and frequency, but also to minimize operational costs (Toshiba Corporation, 2012; Panasonic, 2015). This is especially true under the dynamic pricing model, in which the price of electricity depends on the estimated electricity consumption. Moreover, thermal energy storage (TES) is a further important system for both individual buildings and districts, as it can minimize operational costs and contribute to business continuity planning (BCP).

However, the optimization of operating schedules is difficult because a substantial number of decision variables and combinations need to be addressed in order to determine an optimal solution. Much research has been devoted to determining these optimal operating schedules. For example, mixed-integer linear programming (MILP) was applied in order to optimize the operating schedules of HVAC systems that include ice-storage systems (Vetterli & Benz, 2012). Further examples are Buoro, Pinamonti, and Reini (2014), Dai and Mesbahi (2013), and Ikegami, Kataoka, Iwafune, and Ogimoto (2012) who used MILP in order to optimize the operation schedule of energy systems. Although MILP is an efficient and powerful method for solving large-scale issues by simplification and linearization, it is not always suitable. The reason is that many practical machines, such as heat source equipment and pumps, have nonlinear characteristics.

Alternatively, Facci, Andreassi, and Ubertini (2014) utilized a dynamic programming method (DP) to optimize the operating schedule of nonlinear energy systems. This method has been used in a number of studies. For example, De and Musgrove (1988) used DP in order to solve a complex issue that included a PV, wind turbine, and battery system. In particular, the wind energy converter was considered as nonlinear modeling. Keefe and Markel (2006) considered a plug-in hybrid electric vehicle (PHEV) energy management system. In addition, Chen, Wang, and Chen (2005) utilized

* Corresponding author.
E-mail address: s-ikeda@iis.u-tokyo.ac.jp (S. Ikeda).

http://dx.doi.org/10.1016/j.scs.2015.10.007
2210-6707/

DP to optimize the operation of an energy system that included ice-storage equipment. DP can derive the theoretical optimal solution under the discrete condition. Thus, it can be said that this method is powerful for solving nonlinear models.

However, its computation time is very long, when many decision variables are included. We have previously pointed out the weakness of DP and proposed new metaheuristic optimization methods (Ikeda & Ooka, 2015). We determined that these methods had the ability to efficiently search the minimum solution by comparing six methods, including DP. Lee, Chen, and Wu (2009) proposed particle swarm optimization (PSO) as a means to optimize the operation of HVAC systems that include ice storage. Bahmani-Firouzi and Azizipanah-Abarghooee (2014) adopted a bat algorithm (BA) in order to optimize battery electric dispatch. Yang and Wang (2012) utilized multi-objective PSO in order to optimize energy consumption and occupants' comfort simultaneously. PSO and BA are considered to be metaheuristics that are able to solve many types of functions, such as nonlinear, discrete, and concave. However, their research did not simultaneously optimize electric and HVAC systems, nor did it consider electricity generated by PVs and batteries that is sold to the grid. In addition, we need to adopt an efficient optimization method that is able to handle a number of constraints in energy systems. Therefore, we conducted an integrated optimization that includes PVs, batteries, TES, and heat source machines using an epsilon-constrained differential evolution (εDE) developed by Takahama and Sakai (2010). This method has been found to efficiently solve constraint optimization problems (Mallipeddi, Jeyadevi, Suganthan, & Baskar, 2012). Moreover, it is important to evaluate the effect of the relationship between the prices of the purchased and the sold electricity, as well as the effect of energy system connections. This is because it is not easy to determine the optimal operating schedule where prices change hour to hour, the so-called dynamic pricing model. There is recent research that handles the dynamic pricing model as a condition of energy system optimization. Dufo-López (2015) considered a dynamic pricing model to optimize the operating schedule of a simple energy system for one year. Murphy, O'Mahony, and Upton (2015) compared various operating strategies of an energy system that includes ice-storage under the dynamic pricing model. Their research showed the effect of various dynamic pricing models for optimal operation.

However, it is not enough to merely evaluate the difference in the dynamic pricing models. The difference between the purchase and sale prices needs to be taken into account. Therefore, we conducted a great deal of optimization of the energy system under the various prices in order to address the results quantitatively. Thus, we applied εDE to three energy systems that had different connections of PVs, batteries and HVAC systems, and 126 cases with varying electricity purchase and sale prices were investigated.

This paper is organized into five sections. Section 2 presents the calculation conditions such as modeling energy systems, load profiles, the price of electricity, and problem formulation. In Section 3, the algorithm of the proposed optimization method is presented. In Section 4, results of the three cases are shown under a fixed price condition of purchased and sold electricity. In Section 5, we verified the relation between the prices of purchased and sold electricity under three different demand curves and prices.

2. Materials

2.1. Modeling energy systems

In this study, we considered an electric system and HVAC system. The electric system is consisted of the electric grid, PV, battery, and electricity demand (D_e). The area of the PV panels and the module conversion rate are fixed at 500 m^2 and 13% (PV EDUCATION.ORG, 2015), respectively. The conversion rate of the power conditioner is 0.97 (Mitsubishi Electric, 2015). The capacity and maximum amount of electric charge to or discharge from the battery is set to 500 kW h and 100 kW, respectively. The charging and discharging efficiency is set to 0.9, so one cycle efficiency is 81% (Ikeda & Ooka, 2015).

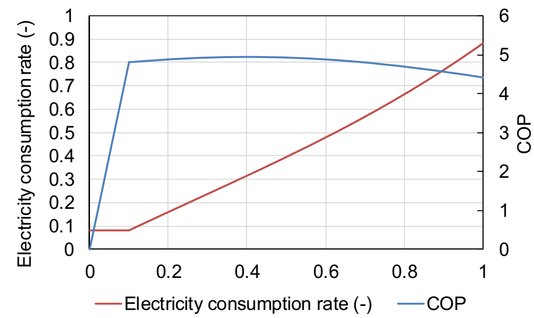

Fig. 1. The characteristics of AHP.

The HVAC system is consisted of air-source heat pump (AHP), TES, and cooling demand (D_c). The battery and grid supply electricity to equipment in HVAC system. The power output of the AHP is dependent on the outdoor temperature, with a maximum of 1000 kW. The inlet/outlet water temperatures of AHP were set to 12 °C and 7 °C. On the other hand, the amount of chilled water changed in order to consider the operation at partial load rate. The AHP has nonlinear relationships between the power output and electricity consumption as shown in Fig. 1. When the AHP generates a cooling load at approximately 40–50% of the operating ratio, its efficiency is the highest. Thus, it is not always true that the rated operation is the best solution.

The TES was water thermal storage with a capacity of 3000 kW h. Its storage and release efficiency was set to 1.0. Further, the self-loss rate was fixed at 5% per day (0.2% per hour) and respective inlet and outlet water temperature were fixed at 12 °C and 7 °C. The AHP and TES pump can vary the amount of chilled water according to the power output of the AHP and the amount of storing and release thermal energy in the TES. Further characteristics of AHP and these pumps can be found in Ikeda and Ooka (2015) and the LCEM tool provided by The Ministry of Land Infrastructure, Transport and Tourism (2014).

We established three energy systems connections to be used as case studies, as illustrated in Fig. 2.where, *XtoY* indicates the electricity or cooling heat flow from *X* to *Y*. In Case 1, PV power generation and battery electrical discharge are provided to the electric demand. The shortage in the provided electricity is compensated by the electric grid. Case 1 indicates a self-consumption model. In Case 2, electricity from these sources is sold to the grid. This process is called the full-amount purchase model because all electricity for electric demand is purchased from the grid, and all electricity generated from PVs and batteries is sold to the grid. In Case 3, we established full connectivity as follows: (1) PV-generated power is distributed to the electric demand, grid, battery, and air-source heat pump (AHP). (2) Electricity discharged from the battery is also distributed to the electric demand, grid, and AHP.

2.2. Load profiles and the price of purchased and sold electricity

We considered an office building in Tokyo with a total floor area of 16,531.1 m^2. The load and electricity demand are determined