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Metaheuristic optimization methods for a comprehensive operating schedule of battery, thermal energy storage, and heat source in a building energy system

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HIGHLIGHTS

- We proposed metaheuristic optimization methods for energy systems.
- The proposed method, m-PSO can calculate the optimal solution quickly and accurately.
- The proposed method can find a solution 62,068 times as fast as previous method.
- The proposed methods can solve nonlinear and non-differentiable problems quickly.

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ABSTRACT

Storage equipment, such as batteries and thermal energy storage (TES), has become increasingly important recently for peak-load shifting in energy systems. Mathematical programming methods, used frequently in previous studies to optimize operating schedules, can always be used to derive a theoretically optimal solution, but are computationally time consuming. Consequently, we use metaheuristics, such as genetic algorithms (GAs), particle swarm optimization (PSO), and cuckoo search (CS), to optimize operating schedules of energy systems that include a battery, TES, and an air-source heat pump. In this paper, we used a GA, differential evolution (DE), our own proposed mutation-PSO (m-PSO), CS, and the self-adaptive learning bat algorithm (SLBA), of which m-PSO was the fastest, and CS was the most accurate. CS obtained the semi-optimal solution 135 times as fast as dynamic programming (DP), a mathematical programming method with 0.22% tolerance. Thus, we showed that metaheuristics, especially m-PSO and CS, have advantages over DP for optimization of the operating schedules of energy systems that include a battery and TES.

1. Introduction

In recent years, renewable power generators, such as wind turbines (WTs) and photovoltaics (PVs), have been increasingly installed in energy grids owing to feed-in tariffs and declining installation costs. The number of installations of renewable power generators is expected to increase [1]. Storage equipment has been installed with WT or PV to avoid electricity grid fluctuation and intermittency [2]. In addition, batteries have a significant role in reducing operating costs in the building sector. Thermal energy storage (TES) with combined heat and power (CHP) and heat pump has a similar role in that sector. Although optimal operation is important in maximizing their roles, it is a complex problem, because there are many things to consider when optimizing their operation, such as outdoor temperature, machine characteristics, and the price of electricity. Therefore, it is important to study energy system optimization.

There have been many previous studies of this topic [3–10]. Omu et al. [3] used mixed-integer linear programming (MILP) to minimize annual investment and operating costs of a distributed energy system. Basu and Chowdhury [4] used the cuckoo search (CS) algorithm to optimize economic dispatch problems of generators on a microgrid. Chandrasekaran and Simon [5] used CS to solve the unit commitment problem (UCP) and economic dispatch problem (EDP) using a fuzzy algorithm. Fazlollahi and Marechal [6] proposed a hybrid method with an evolutionary algorithm and MILP

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Nomenclature

acd^t	amount of charging/discharging of electricity at tth time interval (kW)
acr^t	amount of storing/releasing of thermal energy at tth time interval (kW)
c_1	coefficient of returning to the past personal best position of PSO
c_2	coefficient of moving to the best position in all individuals of PSO
C_b	capacity of a battery (kW h)
C_{TES}	capacity of TES (kW h)
D_{max}	maximum demand in all time horizons (kW)
D_e^t	electricity demand at tth time interval (kW)
D_c^t	cooling demand at tth time interval (kW)
ec_{AHP}^t	electricity consumption for operating an AHP at tth time interval (kW)
ec_{Pump1}^t	electricity consumption for operating Pump 1 at tth time interval (kW)
ec_{Pump2}^t	electricity consumption for operating Pump 2 at tth time interval (kW)
$ecoe^t$	electricity consumption for operating a battery and meeting electricity demand at tth time interval (kW)
ef_b	efficiency of charging/discharging of electricity (–)
ef_{TES}	efficiency of storing/releasing of thermal energy (–)
ep^t	price of electricity per kW h at tth time interval (yen/kW h)
$epoe^t$	price of electricity for operating a battery and meeting electricity demand at tth time interval (yen/h)
$epes^t$	price of electricity for operating an AHP and TES and meeting cooling demand at tth time interval (yen/h)
f_i^t	frequency of ith individual at tth time interval
f_{min}	minimum value of frequency (=0.0)
f_{max}	maximum value of frequency (=2.0)
$loss_{TES}$	loss of energy of TES per an hour (–)
$macd$	maximum amount of charging/discharging of electricity (kW)
$macr^t$	maximum amount of storing/releasing of thermal energy at tth time interval (kW)
$max\_P_{AHP}^t$	maximum power output of an AHP at tth time interval (kW)
$\overrightarrow{Mean^t}$	position vector of mean individual at tth time interval
n	population size
nd	number of dimensions
nc	number of children
P_{AHP}^t	power output of an AHP at tth time interval (kW)
pe	assumed SCOP based on primary energy (=0.77)
r_1, r_2	random number with uniformly distribution
R_b^t	rate of charging/discharging of electricity at tth time interval (–)
R_{TES}^t	rate of storing/releasing of thermal energy at tth time interval (–)
S_b^t	state of charge at tth time interval (kW h)
S_{TES}^t	Stored thermal energy at tth time interval (kW h)
t	time interval (=1 h)
$time$	time horizon in each calculation period (=30 h)
$\overrightarrow{v_i^t}$	ith velocity vector at tth time interval
w	coefficient of inertia of PSO
$\overrightarrow{x_i^t}$	position vector of ith individual at tth time interval of PSO and SLBA
$\overrightarrow{x_p^t}$	position vector of parent of DE
$\overrightarrow{x_i^{pare}}$	position vector of ith parent of GA
$\overrightarrow{x^{pare\_g}}$	position vector of all parents' center of gravity of GA
$\overrightarrow{x_i^{child}}$	position vector of ith child individual of GA
$\overrightarrow{xPbest_i^t}$	vector of the best position found by ith individual at tth time interval of PSO and SLBA
$\overrightarrow{xGbest^t}$	vector of the best position in all individuals at tth time interval of PSO and SLBA
$\overrightarrow{x_{d1}^t}, \overrightarrow{x_{d2}^t}$	position vector of differentiable individuals of DE
$\overrightarrow{x_{new}^{t+1}}$	position vector of a new individual of DE
$\overrightarrow{xWorst^t}$	vector of the worst position in all individuals at tth time interval of SLBA
ζ_i	random number of a uniformly distribution with mean 0 and variance $\sigma_\zeta^2 = 1/(nd+k)$

to solve a multi-objective problem of energy systems that include biomass energy. Fong et al. [7] applied a non-revisiting strategy to a genetic algorithm (GA) and particle swarm optimization (PSO) to minimize life cycle costs in centralized air-conditioning systems. Lee and Kung [8] used PSO to minimize life cycle costs by optimizing the capacity and volume of melted ice of the ice storage in an air-conditioning system. Moradi et al. [9] applied a hybrid method combining PSO with fuzzy linear programming to optimize heat production and electricity dispatch of CHP. Wang et al. [10] used a GA to optimize the capacity and operation of combined cooling, heating, and power (CCHP) in comparison to a separation production system.

Although these previous studies provided effective optimization methods, they dealt with energy systems without storage equipment. On the other hand, the number of studies that have considered storage equipment has increased in recent years [11–33]. Although there are many optimization methods, we can divide them into two categories, mathematical programming, such as MILP and dynamic programming (DP), and metaheuristic optimization or metaheuristics. MILP [11–20] and DP [21–23] are often used in previous studies, because those methods can always derive a theoretically optimal solution. However, their computation time is very long, when many decision variables and discrete points are included. In contrast, metaheuristics, such as neural networks [24], the bat algorithm (BA) [25], GAs [26], PSO [26–31], CS [32], and simulated annealing (SA) [33], first determine all variables at once, and then change each decision variable using a specific method to minimize (or maximize) an objective function. Thus, an optimal solution can be obtained fast, even if the problem is complex. Additionally, there are no limitations on the use of metaheuristics, in contrast to mathematical programming, which has such limitations as linearity, non-linearity, convexity, differentiability, and continuity. Therefore, metaheuristics have substantial versatility for optimizing nearly all functions. In this paper, we apply five metaheuristics to optimize an operating schedule of energy systems and compare the results with those obtained using DP. The metaheuristics used are GA, differential evolution (DE), CS, mutation-PSO (m-PSO), developed by the authors to improve the original PSO, and the self-adaptive learning bat algorithm (SLBA) because of their efficiency.

2. Materials and methods

2.1. Energy system and load profiles

2.1.1. Modeling energy systems

We considered a simple energy system consisting of a battery, an air-source heat pump (AHP), and TES, as shown in Fig. 1.