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Optimal scheduling of buildings with energy generation and thermal energy storage under dynamic electricity pricing using mixed-integer nonlinear programming

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HIGHLIGHTS

- Optimal scheduling strategy for building energy systems is developed.
- Mixed-integer nonlinear programming approach is used for the optimal scheduling.
- Four scenarios are investigated to evaluate the optimal scheduling strategy.
- Case studies are conducted on the Hong Kong Zero Carbon Building.

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ABSTRACT

The increasing complexity of building energy systems integrated with renewable energy systems requires essentially more intelligent scheduling strategy. The energy systems often have strong non-linear characteristics and have discrete working ranges. The mixed-integer nonlinear programming approach is used to solve their optimal scheduling problems of energy systems in building integrated with energy generation and thermal energy storage in this study. The optimal scheduling strategy minimizes the overall operation cost day-ahead, including operation energy cost and cost concerning the plant on/off penalty. A case study is conducted to validate the proposed strategy based on the Hong Kong Zero Carbon Building. Four scenarios are investigated and compared to exam the performance of the optimal scheduling. Results show that the strategy can reduce operation energy cost greatly (about 25%) compared with a rule-based strategy and the reduction is even increased to about 47% when a thermal energy storage system is used. The strategy can also reduce the on/off frequency of chillers significantly.

1. Introduction

The use of renewable energy resources has been recognized as a solution to the energy problems in future for low carbon society construction and sustainable development [1,2]. A wide range of technologies including photovoltaic system (PV) [3], wind turbine (WT) [4], combined cooling, heating and power system (CCHP) [5], thermal energy storage (TES) [6] and other renewable energy systems [7] have been employed in various types of buildings. These energy systems integrated in buildings can be considered as a kind of small distributed energy systems. Such distributed energy systems should be more intelligent so as to respond to the dynamic or time-sensitive electricity price under micro/smart grids. Facing these challenges, optimal scheduling of building energy systems is important to achieve operation cost saving and to contribute to improving the reliability of grids.

However, the integration of renewable energy systems and energy storage systems in buildings results in more complex energy systems, which poses the complexity and great challenge for the optimal control of these integrated energy systems. Energy generations of some renewable energy systems (e.g. PV system and wind turbines) are depending on passive renewable energy resources, which are difficult to be controlled according to the demanded load during operation. Other energy systems (e.g. CCHP, CHP, CCP and TES) could be controlled effectively to alleviate the peak load on power grid and improve the efficiency of energy conversion [8,9]. In CCHP systems, "following the thermal load" (FTL) and "following the electric load" (FEL) are

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the two basic control strategies in applications [10,11]. However the mismatch problems of the thermal and electric loads are still difficult to be solved by both two strategies. Thermal energy storage (TES) systems can be installed in buildings to shift energy demands from peak periods to off-peak periods, and an optimal control strategy for thermal energy system could contribute significant peak electricity load reduction [12].

Nearly all the energy systems have the scheduling problem [13,14]. There have been already considerable studies conducted on scheduling problems of cogeneration/thermal energy storage systems [15–25]. Mathematic programming techniques, such as linear programming algorithms [15,16], mixed-integer linear programming algorithms (MILP) [17–19], nonlinear programming (NLP) algorithms [8,22,26], and even mixed-integer nonlinear programming (MINLP) algorithm [23,25], were widely used to address the scheduling problems. Ren and Gao [18] formulated the optimal control scheduling of industrial CHP plants under time-sensitive electricity prices as a mixed-integer programming problem which considering different operating modes for each plant. Chandan et al. [8] employed the NLP solver in MATLAB to address a model-based, look-ahead optimization strategy for a campus CCHP plant with TES. Ozoe et al. [17] formulated the problem of the power scheduling for a smart house as a mixed-integer programming problem to seek the optimal power schedule at the least operation cost. They formulated the uncertainty problem of electricity demand, heat demand and PV generation as a stochastic programming problem. Ma et al. [22] presented a study on the application of model-based predictive control on the operation of thermal energy storage in building cooling systems. As the problem of MINLP is complex for real time application, they then simplified it to a nonlinear program (NLP) problem by fixing the tank operation mode. Kitagawa et al. [23] proposed "particle swarm optimization" for optimal operational planning of a cogeneration system which was formulated as a mixed integer nonlinear optimization problem. They mainly focused on the analysis of optimization method. Wu et al. [24] presented an optimal operation strategy for micro-CCHP system based on MINLP model. Two objective functions including energy saving ratio and cost saving ratio were considered hierarchically.

However, very limited studies have been conducted on the optimal scheduling of the building energy systems using passive renewable energy resources (e.g. solar irradiation and wind), active energy resources (e.g. bio-diesel, the grid electricity) and thermal storage under dynamic/time-sensitive electricity pricing. Our previous study proposed a model predictive control method using NLP algorithm to optimize the scheduling of the building energy systems [26]. But, the NLP algorithm cannot handle the discrete working ranges of the energy system which often occur in actual operation. Furthermore, the on/off frequencies of the active energy devices (i.e. CCP and chillers) have a negative influence on the lifetime of the devices, but it is not considered properly in existing studies on the scheduling problems.

This paper therefore presents a new optimal scheduling strategy, which is based on MINLP considering both the nonlinear input–output characteristics and the discrete working ranges of the active energy systems, for buildings with active/passive generations and thermal energy storage to minimize the daily operation cost. A cost penalty is introduced to consider the on/off number of the active energy systems and therefore reduce their on/off switching frequencies. Section 2 gives an outline on the optimization approach. Section 3 describes the MINLP approach used in the optimal scheduling strategy. The simplified physical models are built for the energy systems and presented in Section 4. In Section 5, a case study is presented and the system performance under different scenarios are analyzed and compared. Conclusion is given in Section 6.

2. Outline of optimization approach

Fig. 1 illustrates the general approach of scheduling the building energy systems based on forecasted weather (e.g. outside air temperature, solar radiation) and electricity price given by the grid. The optimization objective is to serve the building electric load and cooling load in the control trajectories with least electricity cost. The values of day-ahead building cooling load (Q^t_{cl}), electricity consumption of the building ($P^t_{others} + P^t_{HVAC'}$) and PV power generation (P^t_{PV}) in the interval of one hour are the input variables for the proposed scheduling strategy. The strategy minimizes daily operation cost comprising of the electricity bills from grid $\left(c^t_{elec} \times P^t_{grid}\right)$, the oil consumed by CCP ($C^t_{oil} \times V^t_{oil}$) and cost penalty $\left(C^t_{seq} \times N^t_{seq}\right)$ considering the on/off number of the electric chillers and CCP. The oil usage by the CCP (V^t_{oil}) and the cooling provided by the electric chillers (Q^t_{EC}) are the two input control variables. The prediction horizon considered in this study is 24 h. Therefore, there are 48 values (2×24) of the two input control variables. Finally, 96 values (4×24) of four control variables (cooling charged/discharged by TES (Q^t_{TES}), the oil usage by CCP (V^t_{oil}), the cooling provided by electric chillers (Q^t_{EC}), and electricity received/delivered from/to the grid $\left(P^t_{grid}\right)$) in the next 24 h are determined by the strategy. In this study, the electricity price is formed based on the day-ahead pricing profile in New York in 2013, which has the average converted to the average electricity price in Hong Kong [26]. It is also assumed that the selling electricity price is the same as the buying price.

The proposed optimal scheduling strategy is based on predictive models. The main steps are as follows. At the current time k, the optimal control variables are obtained on a fixed horizon for the next term, say $[k, k+N]$. Among the optimal controls on the fixed horizon $[k, k+N]$, only the first one $k+1$ is

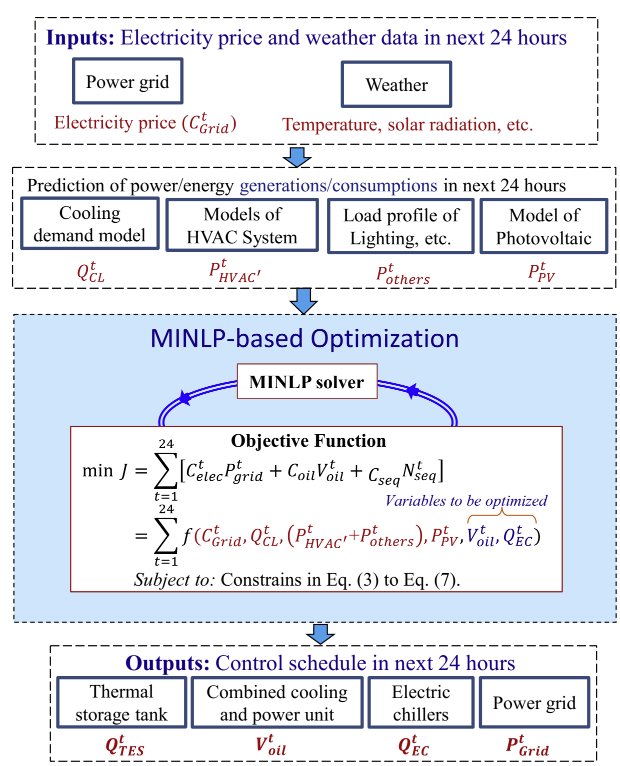

Fig. 1. Optimal scheduling based on predicted loads/generations of building energy systems and electricity price.