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Building-group-level performance evaluations of net zero energy buildings with non-collaborative controls

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HIGHLIGHTS

- Investigate performance limitations of conventional/non-collaborative controls at building-group-level.
- Analyze NZEB performance improvement potentials with collaborations enabled.
- Demonstrate the significance of NZEB collaborations in building-group-level performance optimizations.

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ABSTRACT

Net zero energy building (NZEB) is widely considered an effective solution to the increasing energy and environmental problems. Focusing on performance optimizations at single-building-level, conventional control strategies have not considered collaborations among NZEBs (such as renewable energy sharing) and thus optimal results may not be able to be achieved at a higher level, i.e. building-group-level. Few studies have evaluated the building-group-level performance of NZEBs using non-collaborative controls and researchers are still unclear about the performance improvement potentials if collaborative controls are implemented. Considering economic cost, load matching and grid interaction, this study aims to evaluate the performance of a group of NZEBs in which conventional controls are used. Meanwhile, associated performance improvement potentials are analyzed at building-group-level. The study results show that significant performance improvement potentials exist if NZEB collaborations are enabled. The study results also analyze the benefits of the NZEB collaborations in the three different aspects. To improve NZEB performance at building-group-level, new collaborative controls need to be developed to replace the conventional ones.

1. Introduction

Energy and environmental problems have become increasingly challenging worldwide due to the growing population and improved living standards. As a major energy user, building plays a key role in energy conservation and environmental protection. Utilizing on-site renewable energy, net-zero energy buildings (NZEBs) have been considered an effective solution to the increasing energy and environmental problems [1]. To promote the NZEB practical applications, various countries/organizations have established clear legislative targets [1–3].

A typical NZEB contains renewable energy supply system, energy-consuming system (e.g., HVAC-heating, ventilation and air-conditioning) and energy storage system. Control strategies have been developed to manage the energy flows among these systems and with the grid for achieving expected/optimal performance in the aspects of economic cost, load matching and grid interaction. Economic cost mainly refers to system operation cost in NZEBs. Although a NZEB produces the amount of renewable energy equivalent to its energy use, system operation cost still exists, such as biomass fuel purchase cost for CCHP (combined cooling, heating and power system) and electricity bill caused by the buy-back electricity price differences. Load matching measures the degree of overlap between on-site renewable energy generation and building energy use (e.g. percentage of load covered by on-site renewable energy); while grid interaction refers to energy exchange between a NZEB and the grid, e.g. peak powers delivered to the grid [4,5]. Salom et al. provided a systematic analysis of existing indicators used to evaluate load matching and grid interaction

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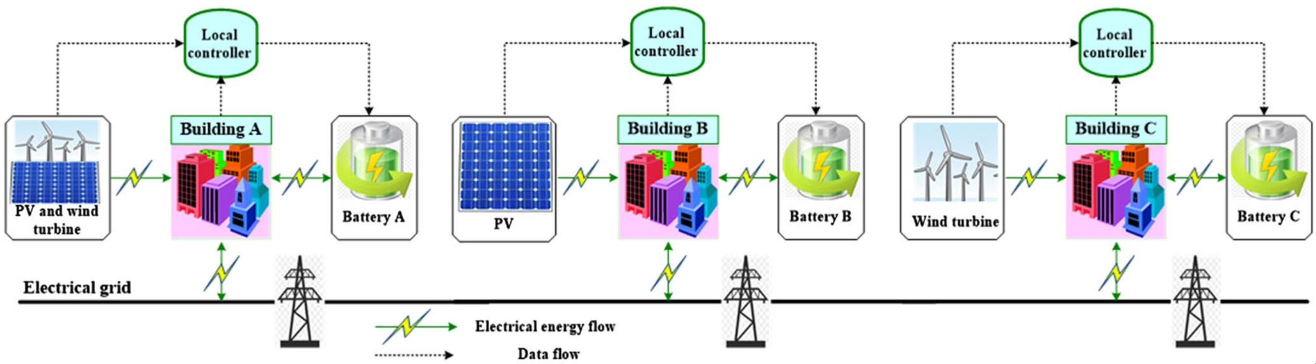

Fig. 1. Conventional non-collaborative control using independent local controllers.

performance of NZEBs [6].

Regarding economic cost, both simple rule-based control and complex model predictive control were developed. Two rule-based control strategies were developed to manage the CCHP operations in NZEBs, i.e. electric load following and thermal load following strategies [7]. It was found that the thermal load following strategy consumed less primary energy and consequently caused less operation cost than the electric load following strategy [8]. Meanwhile, Zhao et al. [9] and Lu et al. [10] adopted a model predictive control to optimize the operation of integrated energy systems in low/zero energy buildings under day-ahead electricity price. The study results proved that the proposed strategies can achieve significant reductions of operation cost, primary energy use and CO_2 emissions. Similarly, a hybrid model predictive control was proposed to manage the thermal and electrical subsystems of a smart house with the objective of minimizing the expense of the grid energy purchase [11]. The effectiveness of the proposed control was also experimentally validated. In addition, Milo et al. [12] proposed an adaptive control strategy to consider the prediction errors of renewable energy generation. Using the proposed adaptive control, the operations of different equipment were optimized together and the overall operation cost was minimized considering the entire life of the facility.

Regarding load matching, control strategies often took renewable energy self-consumption or related CO_2 emission as objective functions. For instance, Vieira et al. [13] proposed a rule-based control to maximize the self-consumption of the on-site renewable energy. The rule was simply injecting renewable energy into the grid if it cannot be consumed or stored. Allison [14] developed a robust multi-input multi-output controller which was applicable to the control of hybrid renewable microgeneration systems. The study results proved the control strategy was effective in maximizing the utilization of the on-site renewable energy. In another study [15], a differential evolution-based algorithm was proposed for the multi-objective optimization of a hybrid energy system. The optimization was to simultaneously minimize the unmet load, fuel emission and system cost considering the uncertainties associated with renewable energy sources. Similarly, considering various conflicting objective functions, a multi-objective optimization model was proposed to solve the emission-cost problem of a battery/PV/fuel-cell hybrid system in the presence of demand response program [16].

Regarding grid interaction, a few control strategies were developed to optimize energy exchanges with grid and thus minimize associated grid stress caused by the building-grid energy exchanges [17,18]. For instance, Al-Ali et al. [19] developed an energy management strategy to control the energy flow of a smart home. The strategy depended on scheduling the energy flow during on-peak and off-peak periods. According to the study results, the peak energy exchange with the grid was effectively reduced. Another peak shaving strategy was developed for a hybrid energy system in Ref. [20]. In the strategy, the renewable systems mainly operated to meet the load and the excess part was used to charge the battery. As the renewable systems and the back-up generator cannot meet the increasing energy demand, the battery was discharged to limit the large energy imports from the grid. Meanwhile, Palma-Behnke et al. [21] developed a neural network based energy management strategy for a micro-grid system. The strategy was able to minimize not only the operation cost but also the peak energy interactions with the grid.

However, the existing strategies merely focus on single-building-level performance optimizations, and collaborations between NZEBs (e.g. renewable energy sharing) have not been considered. For this reason, the conventional/non-collaborative controls may not be able to achieve the optimal results at a higher level, i.e. building-group-level, in the aspects affecting NZEB practical applications. Very few systematic studies have been conducted to evaluate the building-group-level performance of NZEBs, and researchers are still unclear about the performance improvement potentials for NZEBs if collaborative controls are implemented. Therefore, this study aims to evaluate the building-group-level performance of NZEBs using non-collaborative controls and investigate associated performance improvement potentials in the aspects affecting NZEB practical applications.

2. Non-collaborative control and building-group-level performance evaluation

2.1. Basic idea of conventional non-collaborative control

Fig. 1 shows the basic idea of the conventional non-collaborative controls in NZEBs. In the conventional controls, each local controller operates independently to optimize NZEB performance at single-building-level. Little communication or collaboration is allowed/performed between these individual local controllers, and thus overall performance at building-group-level may not be optimized. For instance, as economic cost considered as the objective function, a local controller will try to minimize the single-building-level electricity bill by optimizing the charging controls of associated battery. Due to little collaboration, NZEBs generating insufficient renewable energy cannot share and use the surplus renewable energy from other NZEBs, and thus unnecessary high-priced electrical energy has to be imported from grid. Consequently, the total electricity cost at building-group-level is not optimized.

Fig. 2 shows the schematic diagram of a local controller used to search for the optimal battery charging rate u for an established objective. Regarding optimal search, many technologies are available (e.g. simulated annealing, extremal optimization and genetic algorithm-GA). GA is a search heuristic that mimics the process of natural selection. Due to its powerful search capability and easy application, GA is selected in the study to optimize the battery charging rate u.

In each GA trial computation, the hourly battery charging rates of jth building (i.e. $[u_1^j, u_2^j, ..., u_{24}^j]$) are sent to the fitness function estimator. Using the provided hourly weather data, the fitness function estimator