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An augmented multi-objective particle swarm optimizer for building cluster operation decisions

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ABSTRACT

It is envisioned that other than the grid-building communication, the smart buildings could potentially treat connected neighborhood buildings as a local buffer thus forming a local area energy network through the smart grid. As the hardware technology is in place, what is needed is an intelligent algorithm that coordinates a cluster of buildings to obtain Pareto decisions on short time scale operations. Research has proposed a memetic algorithm (MA) based framework for building cluster operation decisions and it demonstrated the framework is capable of deriving the Pareto solutions on an 8-h operation horizon and reducing overall energy costs. While successful, the memetic algorithm is computational expensive which limits its application to building operation decisions on an hourly time scale. To address this challenge, we propose a particle swarm framework, termed augmented multi-objective particle swarm optimization (AMOPSO). The performance of the proposed AMOPSO in terms of solution quality and convergence speed is improved via the fusion of multiple search methods. Extensive experiments are conducted to compare the proposed AMOPSO with nine multi-objective PSO algorithms (MOPSOs) and multi-objective evolutionary algorithms (MOEAs) collected from the literature. Results demonstrate that AMOPSO outperforms the nine state-of-the-art MOPSOs and MOEAs in terms of epsilon, spread, and hypervolume indicator. A building cluster case is then studied to show that the AMOPSO based decision framework is able to make hourly based operation decisions which could significantly improve energy efficiency and achieve more energy cost savings for the smart buildings.

1. Introduction

In the United States, buildings use approximately 70% of the total electricity usage and emit approximately 40% of the greenhouse gases annually [1]. Today, industry is attempting to design an intelligent building termed as a "smart building" [2] which is able to meet the environmental sustainability goals, keep occupants safe and comfortable, and reduce the energy consumption and cost [2]. Although energy efficient building materials and appliances in the smart buildings are capable of energy demand reduction, it is still not sufficient to satisfy requirements of smart buildings due to ineffective operation strategies for those efficient appliances [2]. Therefore, intelligent and effective operation strategies which could achieve the greatest energy efficiency are of urgent need for smart buildings.

The initial study of building operation and control research focuses on utilizing building thermal mass to achieve cost savings. Pre-cooling a building through optimally controlling building temperature set-points can significantly reduce energy costs [3–6]. Other than using the building thermal mass, extensive research investigates utilizing thermal storage systems [7–11] and energy generation systems [12–20] to reduce energy consumption and energy costs. We want to note that the main stream of research so far has been on single building. Only recent advancements in technology enable smart buildings in the neighborhood to share energy as a local energy network [21]. To the best of our knowledge, the first attempt to make operation decisions for multiple buildings (building cluster) is a memetic algorithm (MA) based framework [22]. In the building cluster decision model, each building aims to minimize its energy cost by sharing energy with other buildings, and the MA is employed to solve a multi-objective nonlinear

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programing problem to derive Pareto operation decisions for the building cluster to manage the usage of shared energy. It is demonstrated that the building cluster is more energy efficient than a single building [22]. Due to the poor computational performance of the MA based decision framework, it is not able to study the hourly (or even less time scale) operation decision which is expected to achieve more cost savings [22].

It was demonstrated that particle swarm optimization is capable of deriving good results with low computational cost in [23]. Therefore we propose an augmented multi-objective particle swarm optimization (AMOPSO) algorithm to improve the computational performance of the decision framework. The proposed AMOPSO is augmented via the fusion of multiple search methods (e.g., sub-gradient method [24]) to improve its performance in terms of solution quality and convergence speed, and a crowding distance method is employed to maintain the non-dominated solutions found during the search process. To test the efficacy of the proposed AMOPSO, we first compare AMOPSO with several state-of-the-art multi-objective particle swarm optimization algorithms (MOPSOs) and multi-objective evolutionary algorithms (MOEAs) using the Zitzler–Deb–Thiele (ZDT) and Deb–Thiele–Laumanns–Zitzler (DTLZ) benchmark suits [25]. The AMOPSO based bi-level decentralized decision framework is then applied to a building cluster case to demonstrate its applicability to reach hourly operation decisions for a group of buildings.

This paper is organized as follows: Section 2 briefly reviews the existing research on building operation decision support; the proposed AMOPSO and its performance assessment are presented in Section 3; followed by the application of the AMOPSO for building cluster decentralized operation decision support in Section 4, and conclusions are drawn in Section 5.

2. Building operation decision support overview

Among all the consumption units, buildings are responsible for over 70% of electricity consumption with approximately half from commercial sources and the remainder from residential [26]. However, the fact is between 4 and 20% of energy used for heating, ventilating and air conditioning (HVAC), lighting and refrigeration in buildings is wasted due to problems with system operation. Thus, extensive research has been conducted to develop the operation or control strategy to improve the energy efficiency and reduce energy costs for buildings.

It is demonstrated that the building thermal mass could be efficiently used to reduce energy consumption and energy cost, therefore lots of research focuses on pre-cooling the building by developing an optimal/near-optimal operation strategy to control the set-point temperature for the HVAC system [3–6]. Pre-cooling the building could significantly reduce energy costs [3–5]. For example, the optimal strategy for building thermal mass determined by a dynamic programing and on-line simulation based technique is able to significantly reduce energy consumption and operating cost [5]. A comprehensive review on building thermal mass operation strategy research is provided in [4].

Similar to the passive thermal storage system (building thermal mass), the active thermal storage system could shift the energy demand from peak hour to off-peak hour to balance the energy demand and reduce energy costs [7–11]. Some meta-heuristic algorithms (e.g., particle swarm optimization [7]) are studied to obtain an optimal operation strategy for a thermal storage system. The rule based near-optimal control strategy for a storage system is determined from monthly simulation of a cooling system in [8]. To efficiently utilize the storage system, the model-free reinforcement learning control strategy is studied in [11] and the hybrid reinforcement learning control approach combining model-based with model-free method is presented in [9,10].

As the development of on-site generator technology advances, another mainstream for reducing energy cost is to utilize the energy generation system which could increase the buildings' resilience to power disturbances. Extensive research has been conducted to develop operation strategies to optimally utilizing a generation system [12–20]. For example, the long-term planning strategy for a single-period combined heat and power system is derived by a branch and bound algorithm in [12], and a modified dynamic programing approach is applied on a multi-period combined heat and power system planning in [13]. The short-term production plans for a hydropower system are developed using multi-stage mixed-integer linear stochastic programing in [14]. Particle swarm optimization (PSO) algorithm is also employed to study the generation system scheduling problems in [15,18]. The multi-objective optimization model is employed to study the power system scheduling in [17,20].

Based on our knowledge, most of the existing literature focuses on operation decisions for a single building, and the first attempt to make operation decisions for multiple buildings (building cluster) which could share energy locally or globally is a MA based framework [22]. A decision model based on a building cluster simulator with each building modeled by energy consumption, storage and generation sub modules is developed in [22]. Assuming each building is interested in minimizing its energy cost, a bi-level operation decision framework based on MA is proposed to study the tradeoff in energy usage among the multiple buildings [22] and is demonstrated to be more energy efficient than a single building. In this research, we focus on the operation decisions for a building cluster in a short time scale (e.g., hourly) by improving the computation performance of the decision framework with an augmented multi-objective particle swarm optimization.

3. Proposed augmented multi-objective particle swarm optimization

3.1. Multi-objective particle swarm optimization overview

Particle swarm optimization which mimics a flock of birds that communicate together as they fly was proposed in 1995 [27]. During the last two decades, PSO has attracted great attention and has been successfully applied to various industry applications [28]. In PSO with inertia weight, the velocity and position for particle p at iteration i are updated as [29],

$$\mathbf{v}_p^{i+1} = w\mathbf{v}_p^i + c_1 r_{1,p}^i \times \left(\mathbf{p}_p^i - \mathbf{x}_p^i\right) + c_2 r_{2,p}^i \times \left(\mathbf{p}_g^i - \mathbf{x}_p^i\right) \quad (1)$$

$$\mathbf{x}_p^{i+1} = \mathbf{x}_p^i + \mathbf{v}_p^{i+1} \quad (2)$$

where D-dimensional vector $\mathbf{v}_p^i$ is the velocity of the pth particle ($\mathbf{v}_p^i \in [-\mathbf{v}_{\max}, +\mathbf{v}_{\max}]$), $\mathbf{v}_{\max}$ is used to constrain the velocity for each particle and is usually set between 0.1 and 1.0 times the search range of the solution space [30]; D-dimensional vector $\mathbf{x}_p^i$ is the position of the pth particle; $\mathbf{p}_p^i$ is the best position (pBest) found so far by the pth particle; $\mathbf{p}_g^i$ is the best position (gBest) found so far by the swarm; $r_{1,p}^i$ and $r_{2,p}^i$ represent two independent random numbers uniformly distributed on [0,1]; c_1 is the cognitive learning factor which represents the attraction that a particle has toward its own success $\mathbf{p}_p^i$; c_2 is the social learning factor which represents the attraction that a particle has toward its neighbors' best position $\mathbf{p}_g^i$; w is the inertia weight.

During the last decade, extensive research has been conducted to study PSO for multi-objective optimization (MOO) problems [23] due to its simplicity of implementation and good performance. In general, the algorithms can be classified in two categories. The