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Improving building energy efficiency by multiobjective neighborhood field optimization

Zhou Wu*, Xiaohua Xia, Bo Wang

Department of Electrical Electronic Computer Engineering, University of Pretoria, South Africa

A R T I C L E I N F O

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A B S T R A C T

For some existing buildings with out-of-date facilities, energy efficiency retrofit is a promising method to reduce energy consumption of buildings with small amount of investment. Among many choices of alternative efficient interventions, different strategies to select them are closely related with retrofit cost, energy saving and net present value (NPV), which are conflicted with each other. A multiobjective energy efficiency retrofit problem has been modeled to cover these essential objectives. The multiobjective neighborhood field optimization (MONFO) algorithm is utilized to solve the proposed model for finding optimal retrofit strategies. Besides retrofit strategies, maintenance strategies of repairing or replacing failed interventions are also evaluated and incorporated in the proposed model. Results in case studies indicate that MONFO is a suitable algorithm to obtain accurate and diverse Pareto optimal solutions for energy efficiency retrofit, and that optimization of maintenance strategy can improve the overall performance of project compared with empirical maintenance strategy.

1. Introduction

Due to globally increasing energy consumption, fossil fuel resources suffer from risks of over exploration and possible distinction in the near future. Meanwhile carbon and pollutant emissions caused by burning of fossil fuel have been growing over the last decade with great threat to environment. To control fossil fuel consumption and carbon emissions, it is necessary to decelerate the increasing rate of energy demand and reduce it if possible. Energy efficiency improvements of existing buildings and regulations for newly designed buildings are proposed as the most popular way to achieve reduction of energy consumption, as the building section with long life cycle contributes approximately 40% of world energy consumption [1–3]. The building section consumes energy for providing services such as space heating and cooling, water heating, and lighting. As well known, retrofitting existing buildings cost much less than newly constructing energy efficient building, so building retrofit is currently the most feasible and practical method to reduce energy demand in the building section.

As innovative technologies and energy conservation measures are nowadays widely applied in building services, energy saving is never an unreachable goal of building retrofit. Even though energy efficiency retrofit introduces additional embodied economic and environmental impacts, it is proven as a sound activity because the economic and environmental payback period could be less than 3 years [2]. During the past decades, many governments and international organizations have put significant emphasis on energy efficiency improvement for existing buildings [4]. In the United States, the federal government has given much financial support in building retrofit. In Australia, the Commercial Building Disclosure (CBD) programme has been proposed to promote energy efficiency information public for large commercial office buildings, and sufficient budget has been invested to retrofit government buildings. In Italy, energy consumption of public buildings and utilities has been evaluated in Tuscany to find the most effective and feasible way of saving energy [5].

In building retrofit projects, the main and also difficult issue is to identify those solutions that are the most effective and reliable ones over the lifetime of buildings [6–8]. Because there are a great number of alternative measures available for retrofitting each building component or service. The strategy of selecting measures within a variety of proposed alternatives can be optimally designed to compensate environmental, financial and social factors and to achieve energy efficiency improvement while satisfying each stakeholder's requirements and other practical constraints [9]. For a building retrofit project, decision makers (DM) need design a specific retrofit strategy to decide types of employed alternative measures and the number of alternative measures in each

* Corresponding author. Tel.: +274204341; fax: +27123625000.
E-mail addresses: wuzhsky@gmail.com (Z. Wu), xxia@up.ac.za (X. Xia), wb8517@gmail.com (B. Wang).

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type before start of project. Several benefits, such as energy efficiency improvement, property value increase and other technical, environmental and social concerns, can be usually achieved in the optimal design of retrofit strategies [10–12]. Among these benefits, energy efficiency improvement is the most practical and economic one, based on which many retrofitting projects have been initiated. In practise, building retrofit for improving energy efficiency has involved several conflicting objectives that cannot be optimized simultaneously [13]. For example, energy saving and retrofit investment are contradicting as normally energy-effective measures are not cost-effective and cost-effective measures are neither energy-effective. Therefore, the so-called building energy efficiency retrofit problem s a multiobjective optimization problem with multiple conflicting objectives subject to several constraints, such as building characteristics, energy saving target and payback period. The scope of this paper is to discuss how to improve energy efficiency by building retrofit, so the building retrofit problem mentioned in the following parts is defined specifically as the energy efficiency retrofit problem.

Trade-off solutions among conflicting objectives necessarily cover all possible scenarios of building retrofit for decision makers. Methods of designing these scenarios can be categorized into two kinds, i.e., empirical methods and multi-criteria (MC) methods. For the empirical method, some representative scenarios can be developed by professional building energy experts based on their knowledge and experience [14]. Information, such as characteristics and location of building, must be considered in designing these scenarios. Using energy simulation tools (e.g., Energy Plus [15] and TRNSYS [16]), practical impacts of these scenarios are evaluated and one favorite scenario is then chosen as the building retrofit strategy. However, it is difficult for experts to find an optimal strategy by such empirical trial-and-error design. In the multi-criteria (MC) method, with respect of Pareto optimality some best trade-off scenarios can be provided to decision makers for references, which are diversely distributed in the whole feasible space. In Gero et al. [17], the MC model was used in the process of building design for exploring trade-offs between thermal performance and other criteria such as capital cost and usable space. In Kaklauskas et al. [18], a multivariate design method based on the MC analysis is developed for building retrofit to determine the significance, priorities and utility degree of alternative measures. In Juan et al. [19], multiobjective genetic algorithms are applied to decision making systems that offer optimal refurbishment actions that trade off cost and quality. Some other MC-based approaches for building retrofit projects can be found from [1,6,20–22].

In most of these MC-based approaches, the initial investment of retrofitting is often considered in the economic analysis. As an important part of life-cycle cost analysis (LCCA), the maintenance cost [8] over the whole project period has been neglected in these approaches. Their weakness is the same that the optimal solution with respect to the initial investment may be cost-ineffective over the long term, because the cheap alternative measures installed may suffer more frequent failures and bring more expensive maintenance cost. The scope of maintenance includes activities required to operate and maintain facilities and their supporting infrastructure in a satisfactory condition to meet their intended function. For example, necessary maintenance of building envelope (such as windows and walls) will require extra investment cost, but energy savings caused by insulation improvement may bring higher investment benefits even though no alternative measures is installed. In practice, due to fatigues and failures energy efficiency of alternative facilities largely deteriorates if no maintenance will be conducted. A well-scheduled maintenance plan (or called strategy) can cost-effectively guarantee sustainable performance of energy savings and monetary profits. In this paper, the LCCA is used to evaluate costs associated with the initial retrofit and the following maintenance, in which maintenance cost has been optimized to achieve great energy saving and payback in the proposed multiobjective building retrofit model.

For each type of existing facilities, several different choices of measures with the same function should be considered in the optimal retrofit strategy. If only one single type of alternative measures is chosen to retrofit existing facilities, the retrofit strategy cannot be globally optimal for large and multi-functional buildings under the LCCA [6,21,13]. Based on our previous work [22], multiple choices of alternative measures are included in the proposed multiobjective model, in which the number of alternative measures for each category is optimized in the retrofit and maintenance strategies. Furthermore, another task of this paper is to answer a common question of decision makers, say, how to generate all representative scenarios for satisfying different preferences of stakeholders. To fulfil this task, multiobjective neighborhood field optimization (MONFO) algorithm proposed in [23] has been used to find Pareto optimal solutions of the building retrofit problem. Unlike the weighted sum method [21,22] in which only one optimal solution can be found for certain predefined weights, MONFO is applied to generate a diverse set of optimal solutions trading off all objectives. According to stakeholders' preferences, decision makers can choose one optimal solution that mostly satisfies these preferences. If stakeholders change their preferences, decision makers could choose another satisfactory solution from the Pareto set obtained by MONFO.

The contributions of this paper mainly include three aspects. Firstly, maintenance plan is evaluated in the proposed multiobjective building retrofit model. Unlike [21,22] without maintenance optimization, in this paper the maintenance plan as well as the retrofit strategy has been considered as variables of optimization in the LCCA. The proposed model can generalize both situations with or without optimal maintenance, which have been studied in the simulation section. Secondly, several conflicting objectives, i.e., retrofit cost, energy saving and NPV, are considered in the multiobjective model with multiple choices of alternative interventions. Thirdly, MONFO is a promising multiobjective optimization algorithm to ensure accuracy and diversity of the obtained Pareto solutions. In one single run of MONFO, comprehensive information of all possible retrofit scenarios will be provided to decision makers.

The paper is organized as follows. The multiobjective building retrofit problems are modeled in Section 2. Section 3 describes MONFO algorithm and the procedure to solve the target problem. Some numerical simulation of a building retrofit project is performed in Section 4. The paper is concluded in the last section.

2. Multiobjective energy efficiency retrofit problems

In building energy efficiency retrofit projects, there is more than one choice of alternative intervention to replace an existing facility. Both intervention type and number of interventions in each chosen type will be determined by decision makers. These numbers are called decision variable of retrofit strategy in the building retrofit problem. Before retrofitting, auditing target buildings is required for obtaining required data of existing facilities. Assume that existing facilities can be classed into K types. For the kth type of existing facilities to be retrofitted, let $J_k (k = 1, 2, \ldots, K)$ denote the types of alternative interventions. The number of alternative interventions in each type among J_k can be denoted as a vector $\mathrm{n_k} = (n_k^1, n_k^2, \ldots, n_k^{J_k})$, in which n_k^j denotes the number of alternatives of the jth type for retrofitting the kth type of existing facilities. Then the retrofit strategy can be generalized as $\mathbf{x} = (\mathbf{n}_1, \mathbf{n}_2, \ldots, \mathbf{n}_K)$ with $\sum_{k=1}^{K} J_k$ dimensions.

The objectives of building retrofit may include to minimize retrofit cost and payback period, and to maximize energy saving and net present value (NPV). In this paper, three objectives, i.e., retrofit cost, energy saving and NPV are considered as

$$f_1(\mathbf{x}) = \sum_{k=1}^{K}\sum_{j=1}^{J_k} b_k^j n_k^j, \quad (1)$$

$$f_2(\mathbf{x}) = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{K} e_{k,i}\sum_{j=1}^{J_i} a_i^j n_k^j(t), \quad (2)$$

$$f_3(\mathbf{x}) = \sum_{t=1}^{T}\frac{B(t)-C(t)}{(1+d)^t} - \sum_{k=1}^{K}\sum_{j=1}^{J_k} b_k^j n_k^j. \quad (3)$$

The first objective Eq. (1) is retrofit cost, in which b_k^j denotes the cost per item for the alternative intervention (k, j), say, the jth type of alternative interventions for retrofitting the kth type of existing facilities. The second objective Eq. (2) is energy saving, in which a_k^j denotes the energy saving per item in the alternative intervention (k, j) and $n_k^j(t)$ denotes the number of working items of the alternative intervention (k, j) in the tth sampling period. T is the evaluation period of retrofit project. In some buildings, energy saving of each type is correlated with savings of other types. For example, energy saving of chillers will be influenced by lighting retrofit as the heat of light will influence the cooling load. The correlation coefficient $e_{k,i}$ represents that how energy saving of the ith type effects energy saving of the kth type. The correlation matrix can be expressed as

$$E = \begin{bmatrix} e_{1,1} & e_{1,2} & \cdots & e_{1,K} \\ e_{2,1} & e_{2,2} & \cdots & e_{1,K} \\ \vdots & \vdots & \ddots & \vdots \\ e_{K,1} & e_{K,2} & \cdots & e_{K,K} \end{bmatrix}, \quad (4)$$

where the diagonal elements satisfy $e_{i,i} = 1$, $i = 1, 2, \ldots, K$. If $e_{k,i} > 0$, energy saving of the kth type will increase due to retrofitting of the ith type. If $e_{k,i} < 0$, energy saving of the kth type will decrease due to retrofitting of the ith type. In many real projects, correlation is ignored for simplicity, i.e. $E = I_{K\times K}$.

The third objective Eq. (3) is NPV, which is based on the life-cycle cost analysis (LCCA) over the evaluation period. NPV is calculated as the difference between discounted net profit and retrofit cost. d is the discount rate over the sampling period. $B(t)$ is the profit caused by retrofitting over the tth sampling period. $C(t)$ is the maintenance cost of project over the tth sampling period. $B(t)$ and $C(t)$ can be formulated as

$$\begin{cases} B(t) = \sum_{k=1}^{K}\sum_{j=1}^{J_k} r_k^j n_k^j(t)(1+p)^t \\ C(t) = \sum_{k=1}^{K}\sum_{j=1}^{J_k} m_k^j u_k^j(t) \end{cases}, \quad (5)$$

where r_k^j is the monetary profit per item of the alternative intervention (k,j); m_k^j is the maintenance cost per item of the alternative intervention (k, j); $u_k^j(t)$ is the number of failed items of the alternative intervention (k, j) experiencing maintenance in the tth sampling period. The cost saving r_k^j mainly comes from the electricity bill reduction that is related with energy usage and electricity price over time. Based on the LCCA, electricity price increase has been considered in the total cost saving $B(t)$ over the evaluation period, in which p is the increase rate.

The maintenance cost m_k^j comes from repairing or replacing failed items of alternative interventions in the evaluation period. Because the installed alternative interventions suffer from decay over time, the number of failed items must grow over time if no maintenance is carried out. For non-repairable products, the failed products must be replaced in the maintenance period. For repairable products, the failed products can be repaired with small amount of cost. The maintenance plan, i.e., $u_k^j(t)$ over time, could be designed according to functions of interventions and requirements of stakeholders. For simplicity, the number of working items after maintenance can be expressed as the following dynamic equation

$$n_k^j(t+1) = \Delta(n_k^j(t)) + u_k^j(t), \quad (6)$$

where $\Delta(\cdot)$ represents the decay model of the population of items, $u_k^j(t)$ is the number of failed alternatives (k, j) experiencing maintenance at the tth sampling period, and the initial number of working items is the decision variable denoted as $n_k^j(0) = n_k^j$.

According to Carstens et al. [24], the decay model can be considered as a first-order Markov Process, which means the population size at the tth sampling instant only relates to the population size at its previous sampling instant. Two kinds of decay model have been employed in building retrofit projects to estimate the population decay as

$$\Delta_1(n_k^j(t)) = \eta_k^j\theta_k^j n_k^j(t)^2/n_k^j - \eta_k^j n_k^j(t) + n_k^j(t), \quad (7)$$

$$\Delta_2(n_k^j(t)) = n_k^j(t)\exp^{-\mu_k^j}, \quad (8)$$

where η_k^j, θ_k^j and μ_k^j are parameters estimated from experimental data of facilities. The first model Eq. (7) usually can describe the population decay of non-repairable products, such as lamps, showerheads and motion sensors. The second model Eq. (8) usually can describe the population decay of repairable products, such as air conditioners, chillers or heat pumps. Note that η_k^j and θ_k^j is determined by the mean time to failure (MTTF), and μ_k^j is determined by the mean time between failure (MTBF) [22].

For a retrofit project, the alternative interventions are usually pre-specified, and the decay model of each intervention is already known before designing retrofit and maintenance strategies. For each strategy designed, all three objective values can be calculated. In the multiobjective building retrofit problem, we consider how to design a retrofit strategy as well as a maintenance plan that can optimize these three objectives simultaneously under several practical constraints. These constraints include amount limit for each type of existing facilities, energy saving target, expected payback period and maintenance limit which can be expressed as

$$\begin{cases} \sum_{j=1}^{J_k} n_k^j \le q_k, (k = 1, 2, \ldots, K) \\ \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{i=1}^{K} e_{k,i}\sum_{j=1}^{J_i} a_i^j n_k^j(t) \ge \alpha \\ T_p \le T_0 \\ n_k^j - \Delta(n_k^j(t)) - u_k^j(t) \ge 0 \end{cases}, \quad (9)$$

where q_k is the total amount of items for the kth type of existing facilities; α is the energy saving target of project; T_0 is the expected payback period of project. T_p is the discounted payback period that is defined as the first time of zero NPV appeared. The energy saving target is usually a percentage of the energy consumption of the retrofitted building (typically 10%).

In all, the multiobjective problem can be formulated as

$$\min F(\mathbf{x}, \mathbf{u}(1), \mathbf{u}(2), \ldots, \mathbf{u}(T)) = \min(f_1, -f_2, -f_3) \quad (10)$$

where $F(\cdot) = (f_1, -f_2, -f_3)$ represents three-objective function to be minimized in the building retrofit problem, and $\mathbf{u}(t)$ represents the

Table 1
Detailed information of existing facilities and alternative interventions.

Existing facilities	q_k	Alternative intervention	b_k^j ($)	a_k^j (kWh)	r_k^j ($)	m_k^j ($)
No sensors installed	202	Motion sensor 1	196	1141	155.02	196
		Motion sensor 2	150.28	1240	168.47	150.28
50 W downlight I	537	Energy saver globe 1	16.36	208	10.65	16.36
		Energy saver globe 2	16.93	223	11.42	16.93
		Energy saver globe 3	20.19	195	9.98	20.19
		Energy saver globe 4	18.95	220	11.26	18.95
50 W downlight II	145	35 W new lamp ECG 1	14.19	102	5.2	14.19
		35 W new lamp ECG 2	15.17	116	5.91	15.17
		35 W new lamp ECG 3	14.25	107	5.45	14.25
18 W recessed fitting I	270	18 W retrofitting ECG 1	11.72	21	1.07	11.72
		18 W retrofitting ECG 2	11.11	20	1.02	11.11
		18 W retrofitting ECG 3	9.47	25	1.27	9.47
54 W recessed fitting II	1271	36 W triphosphor tubes 1	65.67	232	11.88	65.67
		36 W triphosphor tubes 2	78.09	186	9.52	78.09
		36 W triphosphor tubes 3	61.54	262	13.42	61.54
		36 W triphosphor tubes 4	60.77	260	13.31	60.77
		36 W triphosphor tubes 5	65.29	199	10.19	65.29
Old chiller	4	New chiller 1	147125	25392	13775.88	14712.5
		New chiller 2	170590.31	23539	12770.57	17059.03
Electric geyser I	9	3 kW heat pump 1	1250	10989	794.11	125
		3 kW heat pump 2	1299.22	11166	807.24	129.92
		3 kW heat pump 3	1544.88	12074	872.88	154.49
Electric geyser II	3	22 kW heat pump 1	13750	1006	1854.13	1375
		22 kW heat pump 2	13767.97	875	1612.69	1375.79
		22 kW heat pump 3	12600.01	1152	2123.22	1260.01
Electric geyser III	94	9 kW heat pump 1	1250	10989	72.74	125
		9 kW heat pump 2	1335.36	12447	82.39	135.54
		9 kW heat pump 3	954.95	9019	59.7	95.5
High-flow showerheads	360	Low-flow showerheads 1	11.25	278	18.61	11.25
		Low-flow showerheads 2	10.54	254	17	10.54
No heater wraps	107	Heater wraps 1	21	273	21	21
		Heater wraps 2	24.32	326	25.08	24.32
		Heater wraps 3	22.36	243	18.69	22.36
No thermal traps	107	Thermal traps 1	8	380	8	8
		Thermal traps 2	9.13	350	7.37	9.13

maintenance action (numbers of items) for failed alternative interventions in the tth sampling period. The decision variables include the retrofit strategy $\mathbf{x}$ and the maintenance plan ($\mathbf{u}(1)$, $\mathbf{u}(2)$, ..., $\mathbf{u}(T)$).

3. Multiobjective neighborhood field optimization

A number of real-world problems involve simultaneously optimizing several conflicting objectives, which are called multiobjective optimization problems. In such a multiobjective problem, there is no single optimal solution, but rather a set of optimal trade-off solutions. These solutions are optimal in the wider sense that no other solution is superior to them when considering all objectives. When comparing two solutions x and x' (their corresponding objective variables are denoted as z and z'), there exist three types of relation. First, x can dominate x'; second, x' can dominate x; and third, x and x' are non-dominated by each other. The dominance relation is denoted as $\prec$ as defined in Definition 1. Solutions that cannot be dominated by any other feasible solution are regard as the best solutions, i.e., so-called Pareto optimal solutions as defined in Definition 2.

Definition 1. (Dominance) For a minimization problem with M objectives, $x \prec x'$ *iff* their objective variables satisfy $z_i \le z_i'$, $i = 1, 2, \ldots, M$, with at least one index m for which the inequality is strict as $z_m < z_m'$.

Definition 2. (Pareto Optimal) A solution x^* in the search space is Pareto optimal *iff* there does not exist another point x in the search space such that $x \prec x^*$.

In Wu and Chow [23], multiobjective neighborhood field optimization algorithm (MONFO) was proposed with the large performance improvement in terms of accuracy and diversity of final solutions found. In MONFO, the search engine depends on cooperatively local search that is modeled as a potential field called neighborhood field. Neighborhood field can drive each individual in the population moving towards the superior neighbor and away from the inferior neighbor [25,26]. In this paper, MONFO is applied to solve the building retrofit problem with inequality constraints. For a D dimensional multiobjective problem with M objectives, the procedure of MONFO is given as follows.

(1) Initialization: randomize N initial individuals in the search space (N is the size of population).
(2) Contouring: In each generation, sort the the population into several fronts based on the dominance in descending order, and shuffle the within-front individuals randomly. According to the resulted rankings, divide the population into L levels evenly.
(3) Mutation: In each generation G, the ith individual is denoted as $x_{i,G}$ and its level is denoted as $l(x_{i,G})$. For each individual $x_{i,G}$, recognize the superior neighbor $xc_{i,G}$ in the $(l(x_{i,G})-1)$th level and recognize the inferior neighbor $xw_{i,G}$ in the the $(l(x_{i,G})+1)$th level as

$$\begin{cases} xc_{i,G} & = arg \min\limits_{l(x_{k,G})=l(x_{i,G})-1} \| x_{k,G} - x_{i,G} \| \\ xw_{i,G} & = arg \min\limits_{l(x_{k,G})=l(x_{i,G})+1} \| x_{k,G} - x_{i,G} \| \end{cases} . \quad (11)$$

Note that if $x_{i,G}$ is in the first level, $xc_{i,G}$ is defined as as $x_{i,G}$; if $x_{i,G}$ is in the Lth level, $xw_{i,G}$ is defined as as $x_{i,G}$. Then each individual is perturbed as

$$v_{i,G} = x_{i,G} + \alpha \cdot r_1 \cdot (xc_{i,G} - x_{i,G}) - \alpha \cdot r_2 \cdot (xw_{i,G} - x_{i,G}), \quad (12)$$

Table 2
Coefficients in decay models.

Existing facilities	Alternative intervention	η_k^j	θ_k^j	μ_k^j
No sensors installed	Motion sensor 1	1.2895	0.9502	–
	Motion sensor 2	1.2521	0.9672	–
50 W downlight I	Energy saver globe 1	1.2587	0.9643	–
	Energy saver globe 2	1.2984	0.9459	–
	Energy saver globe 3	1.2458	0.9698	–
	Energy saver globe 4	1.2587	0.9643	–
50 W downlight II	35 W new lamp ECG 1	1.2587	0.9643	–
	35 W new lamp ECG 2	1.2286	0.9765	–
	35 W new lamp ECG 3	1.2398	0.9722	–
18 W recessed fitting I	18 W retrofitting ECG 1	1.2732	0.9579	–
	18 W retrofitting ECG 2	1.3403	0.9245	–
	18 W retrofitting ECG 3	1.3179	0.9361	–
54 W recessed fitting II	36 W triphosphor tubes 1	1.2658	0.9612	–
	36 W triphosphor tubes 2	1.2811	0.9542	–
	36 W triphosphor tubes 3	1.2732	0.9542	–
	36 W triphosphor tubes 4	1.3078	0.9412	–
	36 W triphosphor tubes 5	1.2732	0.9579	–
Old chiller	New chiller 1	–	–	0.5
	New chiller 2	–	–	0.4444
Electric geyser I	3 kW heat pump 1	–	–	0.5
	3 kW heat pump 2	–	–	0.4444
	3 kW heat pump 3	–	–	0.5455
Electric geyser II	22 kW heat pump 1	–	–	0.5
	22 kW heat pump 2	–	–	0.5217
	22 kW heat pump 3	–	–	0.4444
Electric geyser III	9 kW heat pump 1	–	–	0.5
	9 kW heat pump 2	–	–	0.4615
	9 kW heat pump 3	–	–	0.4615
High-flow showerheads	Low-flow showerheads 1	1.1568	0.9956	–
	Low-flow showerheads 2	1.176	0.992	–
No heater wraps	Heater wraps 1	–	–	0.2353
	Heater wraps 2	–	–	0.25
	Heater wraps 3	–	–	0.2
No thermal traps	Thermal traps 1	–	–	0.1791
	Thermal traps 2	–	–	0.2449

where r_1 and r_2 are random vectors uniformly distributed in the scale [0,1], and α is the learning rate. $v_{i,G}$ is the so-called mutant vector.

(4) Crossover: recombine the mutant vector $v_{i,G}$ with the target vector $x_{i,G}$ as

$$u_{d,i,G} = \begin{cases} v_{d,i,G}, & \text{if } \ rand(0,1) \le CR \ \text{ or } \ d = d_r \\ x_{d,i,G}, & \text{otherwise} \end{cases}, \tag{13}$$

where $u_{i,G}$ is called the trial vector; $d = 1, 2, \ldots, D$ is the dimension index; CR is the crossover probability; $rand(0, 1)$ is a uniformly distributed random number in the scale [0, 1]; d_r is a random component to accept the new mutant vector so that the trial vector is different from the target vector.

(5) Selection: in the next generation, the ith individual will be updated as the better one between $x_{i,G}$ and $u_{i,G}$ with respect to Pareto dominance as Eq. (14). If $u_{i,G}$ can dominate $x_{i,G}$, $u_{i,G}$ will be selected in the next generation, and otherwise the target solution $x_{i,G}$ will be selected as

$$x_{i,G+1} = \begin{cases} u_{i,G}, & \text{if } \ u_{i,G} \prec x_{i,G} \\ x_{i,G}, & \text{otherwise} \end{cases}. \tag{14}$$

(6) An external archive $\mathcal{E}$ is used to store $u_{i,G}$ if it is not selected in the step (5) and it is non-dominated by the target solution $x_{i,G}$. If the archive size gets larger than N, combine $\mathcal{E}$ into the main population and empty $\mathcal{E}$. For the next generation, the combined population is then pruned into N individuals according to dominance and density [27]. $G = G + 1$ and go to step (2) until stopping criteria are satisfied.

It can be noticed that the above procedure of MONFO has some changes in steps of contouring and selection [23]. In the contouring, the individuals in the same front are shuffled randomly, which is reasonable for highly multiobjective problems. In the selection, the simple Pareto dominance relation is employed for choosing the better candidate in the next generation. In addition, the external archive is used to store the failed trail vectors that may find new boundaries of objective space. These archived solutions will be combined into the main population when its size grows to N, which

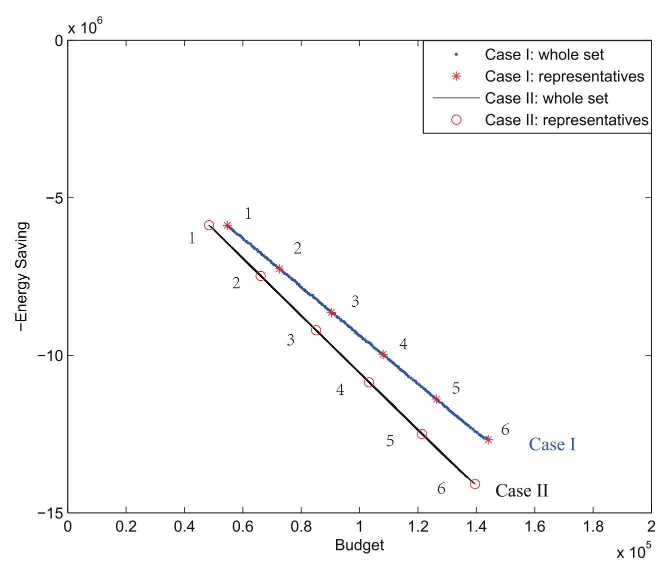

Fig. 1. Pareto front obtained by MONFO in Case I and II.

Table 3
Representative solutions in Case I: numbers of retrofitting alternatives.

Alternative intervention	1	2	3	4	5	6
Motion sensor 1	0	0	0	0	0	1
Motion sensor 2	201	201	201	202	200	201
Energy saver globe 1	188	192	189	167	190	198
Energy saver globe 2	343	316	345	350	334	327
Energy saver globe 3	1	1	1	2	3	1
Energy saver globe 4	2	14	2	12	5	2
35 W new lamp ECG 1	1	11	8	4	7	5
35 W new lamp ECG 2	14	60	5	26	2	121
35 W new lamp ECG 3	9	6	2	15	19	8
18 W retrofitting ECG 1	0	1	1	0	1	1
18 W retrofitting ECG 2	2	3	0	3	0	0
18 W retrofitting ECG 3	2	0	1	3	1	0
36 W triphosphor tubes 1	1	0	0	0	0	0
36 W triphosphor tubes 2	0	0	0	0	1	0
36 W triphosphor tubes 3	0	0	0	1	1	0
36 W triphosphor tubes 4	1	0	0	0	0	1
36 W triphosphor tubes 5	0	0	0	0	0	0
New chiller 1	0	0	0	0	0	0
New chiller 2	0	0	0	0	0	0
3 kW heat pump 1	1	1	1	1	1	1
3 kW heat pump 2	1	1	1	1	1	1
3 kW heat pump 3	1	0	0	0	0	1
22 kW heat pump 1	0	0	0	0	0	0
22 kW heat pump 2	0	0	0	0	0	0
22 kW heat pump 3	0	0	0	0	0	0
9 kW heat pump 1	1	1	1	1	1	1
9 kW heat pump 2	1	1	1	1	1	4
9 kW heat pump 3	1	20	39	58	79	89
Low-flow showerheads 1	357	357	356	356	357	356
Low-flow showerheads 2	2	3	2	3	2	2
Heater wraps 1	53	53	60	52	48	61
Heater wraps 2	37	46	45	51	45	44
Heater wraps 3	0	1	1	1	3	0
Thermal traps 1	105	105	105	105	105	104
Thermal traps 2	1	2	2	2	2	2

can enhance the diversity of population and reduce the possibility of pre-mature.

For the building retrofit problem, superiority of feasibility (SF) method mentioned in [28,29] is employed to handle constraints in this application. Equality constraints can usually be transformed into inequality forms, which is not used in this paper as the building retrofitting problem has no equality constraints. Then for each inequality constraint, the constraint violation can be obtained. For each individual x_i, all its constraint violations are normalized and summed to calculate the overall constraint violation $vc(x_i)$. In the SF method, the fitness value is expressed as

$$fitness_m(x_i) = \begin{cases} f_m(x_i) & \text{if} x_i \text{is feasible} \\ f_m^{worst} + vc(x_i) & \text{otherwise} \end{cases} \quad (15)$$

where f_m^{worst} is the maximum value of the mth objective in the found feasible solutions and $vc(x)$ is the overall constraint violation. If there is no feasible solution in the current population, f_m^{worse} is **0**. In the SF method, feasible solutions always have better fitness than infeasible ones. The infeasible solutions are expected to evolve towards the feasible region and the feasible solutions are expected to evolve towards the global Pareto front.

4. Case studies of energy efficiency retrofit

A building retrofit project mentioned in [22] is investigated in this paper. The anonymous office building was built in 1980s with several energy inefficient facilities. In the project, 12 types of existing facilities are identified for energy efficiency retrofit, including lighting facilities, chillers, geysers and other devices as shown in Table 1. Retrofitting these facilities with new efficient interventions can obtain potential improvement of energy efficiency for the target building.

For each intervention there are usually multiple alternatives with different costs and energy savings. Table 1 gives the information of each alternative intervention, including the maximum number of facilities q_k to be retrofitted, energy saving a_k^j, unit cost b_k^j, cost saving r_k^j, and maintenance cost m_k^j. For each type of facilities, the overall number of alternative items cannot exceed q_k. Unit cost refers to the cost of purchasing and installing one alternative item. Energy saving is the value of energy consumption reduced per year after using each intervention. Cost saving is the financial benefit associated with energy saving and customers' load profile pattern. Note that electricity price for the building is varying hourly and annual cost saving of each facility is audited to provide

Table 4
Performance of some representative solutions in Case I.

No.	Investment ($)	Energy saving (kWh)	NPV ($)	Payback period (Y)	Profit rate
1	5.422×10^4	5.872×10^6	3.901×10^5	1.115	7.193
2	7.159×10^4	7.212×10^6	3.726×10^5	1.502	5.204
3	8.910×10^4	8.580×10^6	3.592×10^5	1.880	4.031
4	1.079×10^5	1.002×10^7	3.475×10^5	2.247	3.222
5	1.272×10^5	1.148×10^7	3.289×10^5	2.639	2.586
6	1.443×10^5	1.279×10^7	3.318×10^5	2.864	2.300

Table 5
Representative solutions in Case II: numbers of retrofitting alternatives.

Alternative intervention	1	2	3	4	5	6
Motion sensor 1	0	0	0	0	0	0
Motion sensor 2	11	43	80	117	148	201
Energy saver globe 1	7	12	1	14	12	4
Energy saver globe 2	522	506	516	516	509	518
Energy saver globe 3	1	2	3	0	1	3
Energy saver globe 4	4	2	7	4	5	8
35 W new lamp ECG 1	2	2	2	1	0	3
35 W new lamp ECG 2	2	7	3	5	10	6
35 W new lamp ECG 3	5	4	6	4	0	6
18 W retrofitting ECG 1	1	3	1	1	4	1
18 W retrofitting ECG 2	0	0	1	0	1	0
18 W retrofitting ECG 3	0	0	0	0	0	0
36 W triphosphor tubes 1	0	0	0	0	0	0
36 W triphosphor tubes 2	0	0	0	0	0	0
36 W triphosphor tubes 3	0	0	0	0	0	0
36 W triphosphor tubes 4	1	0	0	0	0	0
36 W triphosphor tubes 5	0	0	0	0	0	0
New chiller 1	0	0	0	0	0	0
New chiller 2	0	0	0	0	0	0
3 kW heat pump 1	1	0	1	0	1	0
3 kW heat pump 2	0	0	0	0	0	1
3 kW heat pump 3	0	0	0	0	0	1
22 kW heat pump 1	0	0	0	0	0	0
22 kW heat pump 2	0	0	0	0	0	0
22 kW heat pump 3	0	0	0	0	0	0
9 kW heat pump 1	0	0	0	0	0	0
9 kW heat pump 2	1	1	0	1	1	1
9 kW heat pump 3	29	44	58	71	84	93
Low-flow showerheads 1	213	213	211	213	213	212
Low-flow showerheads 2	145	145	146	143	137	147
Heater wraps 1	7	8	5	9	5	2
Heater wraps 2	91	88	97	94	96	91
Heater wraps 3	4	4	3	3	1	2
Thermal traps 1	105	105	104	105	105	106
Thermal traps 2	1	2	3	1	1	1

enough information for the proposed model. Maintenance cost is the expense associated with repairing or replacing each failed intervention. Each intervention has its decay model, and the parameters of each decay model have been listed in Table 2.

Four cases will be studied in this section. In the first case, the first two objectives in Eq. (10), i.e., investment cost and energy saving, are considered in the building retrofit problem that has empirical maintenance plan. In the second case, the optimization of maintenance is evaluated in the two-objective building retrofit problem. In the third case, all three objectives are evaluated in the building retrofit problem with the same empirical maintenance plan. In the fourth case, the optimization of maintenance is evaluated in the three-objective building retrofit problem. In these case studies, the evaluation period is 10 years, and the sampling period is 1 year. In this project, the baseline of energy consumption is 5,870,911 kWh per year that is 58,709,110 kWh over the evaluation period. The target energy saving is 10% of the baseline of energy, i.e., 5,870,911 kWh over the evaluation period. The expected payback period is set to $T_0 = 3$ years. The correlation matrix is assumed as $E = I_{K\times K}$. Note that accurate correlation matrix can be used to guide retrofit strategy design for achieving extra energy savings. Correlation matrix can be recognized by experiments on the same kind and scale of buildings. In the post-implementation process, the actual energy savings can be measured and the correlation matrix can be learned by regression models. The obtained matrix can be used in new retrofit projects that have the same characteristics and scale. The discount rate d in NPV calculation is 9%, and the increase rate p is 7.1% in the target region. In MONFO, the population size is set to 150 for Case I and II and 300 for Case III and IV; the maximum generation is set 3000. Other parameters are the same as [23], $L = 15$, $\alpha = 1.5$ and $CR = 0.1$.

4.1. Case I: two-objective problem with empirical maintenance

In this case study, the empirical maintenance plan is defined as

$$u_k^j(t) = \begin{cases} 0, & t = 1, 3, 5\ldots \\ n_k^j - n_k^j(t), & t = 2, 4, 6\ldots \end{cases}, \tag{16}$$

which means that all failed alternative interventions are repaired or replaced in every two years. The two-objective building retrofit problem with the empirical maintenance plan can be formulated as

$$\min F_1(\mathbf{x}) = \min(f_1, -f_2), \tag{17}$$

Table 6
Performance of some representative solutions in Case II.

No.	Investment ($)	Energy saving (kWh)	NPV ($)	Payback period (Y)	Profit rate
1	4.843×10^4	5.871×10^6	1.214×10^5	2.736	2.507
2	6.608×10^4	7.485×10^6	1.472×10^5	2.984	2.228
3	8.509×10^4	9.207×10^6	1.963×10^5	2.904	2.307
4	1.032×10^5	1.086×10^7	2.295×10^5	2.973	2.223
5	1.214×10^5	1.250×10^7	2.685×10^5	2.990	2.213
6	1.396×10^5	1.409×10^7	3.387×10^5	2.778	2.427

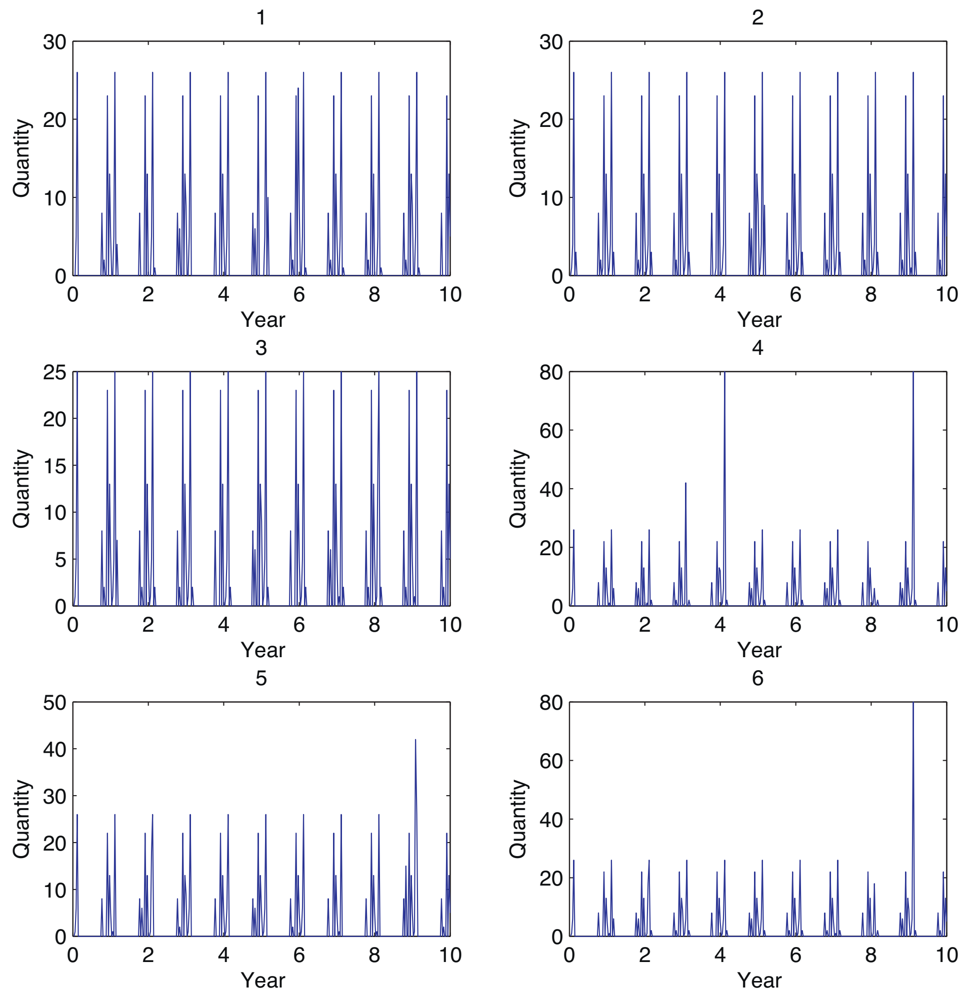

Fig. 2. Optimal maintenance plans obtained by MONFO in Case II. The horizontal axis is time, and the vertical axis is quantity of interventions experiencing maintenance.

where the decision variable is the retrofit strategy; the retrofit cost will be minimized and the energy saving will be maximized. In Case I, the optimization problem has constraints as Eq. (9). The Pareto front (image of optimal solutions in the objective space) obtained by MONFO has been given in Fig. 1. In the set of Pareto optimal solutions, investment costs are distributed in the range

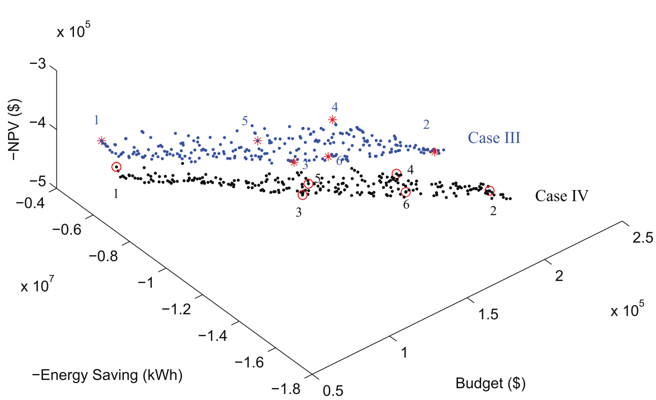

Fig. 3. Pareto front obtained by MONFO in Case III and IV.

$[5.676 \times 10^4, 1.560 \times 10^5]$ $, and energy savings are distributed in the range $[5.886 \times 10^6, 1.335 \times 10^7]$ kWh. Based on these diverse results, decision makers can choose one suitable retrofit strategy according to their different preferences.

Table 3 lists some representative solutions in the Pareto set. If the preference is the minimal initial budget, they can choose solution 1 in the table as the retrofit strategy. If the preference is the maximal energy saving, they can choose solution 6 as the retrofit strategy. If the preference is the balance between initial budget and energy saving, solution 2, 3, 4, 5 can be chosen according to specific requirements. It can be noticed from Table 3 that some interventions dominate other interventions in the same type of these retrofit solutions, such as, motion sensor 2 and 9 kW heat pumps 3. For these solutions, more motion sensor 2 is chosen than motion sensor 1 and more 9 kW heat pump 3 is chosen than other heat pumps, because they can achieve more energy saving and cost saving with less retrofit cost. Other facilities, such as energy saver globe 1 and 2, low-flow showerheads 1 and thermal traps 1, are also more preferred rather than others in the same category due to high efficiency.

To present performance of these solutions, investment cost, energy saving, NPV, payback period, and profit rate (ratio of NPV to investment cost) are evaluated and listed in Table 4. The energy savings of these solutions are larger than the energy saving target, and the payback periods are less than 3 years. The relation of NPV and energy saving is that NPV decreases when energy saving is smaller than 10^7 and increases slightly when energy saving is larger. It can

Table 7
Representative solutions in Case III: numbers of retrofitting alternatives.

Alternative intervention	1	2	3	4	5	6
Motion sensor 1	0	0	0	0	1	2
Motion sensor 2	201	202	202	199	201	200
Energy saver globe 1	210	114	82	235	195	133
Energy saver globe 2	195	217	185	191	163	200
Energy saver globe 3	24	1	1	43	1	9
Energy saver globe 4	108	200	248	48	144	187
35 W new lamp ECG 1	32	31	10	30	9	16
35 W new lamp ECG 2	36	85	84	91	27	66
35 W new lamp ECG 3	10	13	39	13	15	27
18 W retrofitting ECG 1	1	4	3	1	1	3
18 W retrofitting ECG 2	1	1	1	1	1	4
18 W retrofitting ECG 3	7	6	6	1	7	9
36 W triphosphor tubes 1	0	7	9	5	1	5
36 W triphosphor tubes 2	1	2	4	1	1	0
36 W triphosphor tubes 3	7	822	1193	6	8	927
36 W triphosphor tubes 4	13	4	6	0	19	0
36 W triphosphor tubes 5	1	6	4	3	1	1
New chiller 1	0	0	0	0	0	0
New chiller 2	0	0	0	0	0	0
3 kW heat pump 1	0	4	3	0	1	3
3 kW heat pump 2	0	0	0	0	0	1
3 kW heat pump 3	2	4	5	0	3	4
22 kW heat pump 1	1	1	1	1	1	1
22 kW heat pump 2	0	0	0	0	0	0
22 kW heat pump 3	0	0	0	0	0	0
9 kW heat pump 1	0	0	0	0	0	0
9 kW heat pump 2	1	1	0	1	0	1
9 kW heat pump 3	4	69	2	86	55	28
Low-flow showerheads 1	322	342	304	303	325	335
Low-flow showerheads 2	35	6	55	37	44	18
Heater wraps 1	24	36	14	7	20	16
Heater wraps 2	56	59	61	55	60	60
Heater wraps 3	3	11	31	44	22	14
Thermal traps 1	88	84	78	81	89	85
Thermal traps 2	17	19	11	17	15	21

also be noticed that the profit rate is largest when the investment has the smallest value in the feasible range.

4.2. Case II: two-objective problem with optimized maintenance

In this case study, the maintenance plan will be optimized together with the retrofit strategy in the two-objective model expressed as

$$\min F(\mathbf{x}, \mathbf{u}(1), \mathbf{u}(2), \ldots, \mathbf{u}(T)) = \min(f_1, -f_2) \quad (18)$$

where $\mathbf{u}(t)$ represents the numbers of failed items experiencing maintenance in the tth year; the decision variable includes the retrofit strategy and the maintenance plan for each year; the retrofit cost will be minimized and the energy saving will be maximized. Note that maintenance is conducted annually and only some of failed alternatives will be replaced or repair. The number of alternatives in maintenance is a variable determined by optimization. In Case II, the optimization problem has constraints as Eq. (9). The Pareto front obtained by MONFO has also been given in Fig. 1. In the set of Pareto optimal solutions, investment costs are distributed in the range [4.843×10^4, 1.396×10^5] \$, and energy savings are distributed in the range [5.871×10^6, 1.409×10^7] kWh. Based on these diverse results, decision makers can choose one suitable retrofit strategy according to their different preferences.

Table 5 lists some representative solutions in the Pareto set. If the preference is the minimal initial budget, they can choose solution 1 in the table as the retrofit strategy. If the preference is the maximal energy saving, they can choose solution 6 as the retrofit strategy. If the preference is the balance between initial budget and energy saving, solution 2, 3, 4, 5 can be chosen according to specific requirements. Comparing Tables 3 and 5, several observations can be found that mainly energy saver globe 2 is used instead of both globe 1 and 2, and that much less 25W ECG2 is used, and that both low-flow showerheads 1 and 2 are used instead of only using showerheads 1, and that only heater wraps 2 is used instead of using wraps 1 and 2.

For these representatives, investment cost, energy saving, NPV, payback period, and profit rate are evaluated as listed in Table 6. Like in Case I, both constraints of energy saving and payback period are satisfied. Solution 6 has achieved the largest NPV, and solution 1 has achieved the largest profit rate. All solutions in Case II have more or less the same payback period and profit rate while they have larger variations in Case I.

Table 8
Performance of some representative solutions in Case III.

No.	Investment (\$)	Energy saving (kWh)	NPV (\$)	Payback period (Y)	Profit rate
1	5.682×10^4	5.881×10^6	3.855×10^5	1.183	6.784
2	1.810×10^5	1.359×10^7	3.922×10^5	2.982	2.167
3	1.388×10^5	9.468×10^6	4.481×10^5	2.257	3.228
4	1.351×10^5	1.189×10^7	3.160×10^5	2.831	2.339
5	1.096×10^5	9.953×10^6	3.622×10^5	2.205	3.304
6	1.457×10^5	1.075×10^7	4.182×10^5	2.453	2.870

Table 9
Representative solutions in Case IV: numbers of retrofitting alternatives.

Alternative intervention	1	2	3	4	5	6
Motion sensor 1	1	0	1	0	0	1
Motion sensor 2	201	202	201	200	201	201
Energy saver globe 1	103	93	107	118	93	105
Energy saver globe 2	373	357	351	315	379	348
Energy saver globe 3	16	35	11	4	4	12
Energy saver globe 4	11	42	65	33	38	50
35 W new lamp ECG 1	5	29	5	45	28	17
35 W new lamp ECG 2	42	32	40	32	28	41
35 W new lamp ECG 3	49	74	69	38	86	35
18 W retrofitting ECG 1	1	0	2	9	1	5
18 W retrofitting ECG 2	1	6	10	2	4	1
18 W retrofitting ECG 3	19	36	5	15	19	10
36 W triphosphor tubes 1	0	1	1	3	1	1
36 W triphosphor tubes 2	1	2	4	0	1	0
36 W triphosphor tubes 3	4	597	1232	6	1015	55
36 W triphosphor tubes 4	2	2	3	0	3	2
36 W triphosphor tubes 5	0	0	2	1	2	3
New chiller 1	0	0	0	0	0	0
New chiller 2	0	0	0	0	0	0
3 kW heat pump 1	0	1	1	0	1	1
3 kW heat pump 2	7	7	7	7	7	7
3 kW heat pump 3	1	1	1	0	1	1
22 kW heat pump 1	0	0	0	0	0	0
22 kW heat pump 2	0	0	0	0	0	0
22 kW heat pump 3	0	0	0	0	0	0
9 kW heat pump 1	0	1	1	0	0	1
9 kW heat pump 2	1	1	0	1	1	1
9 kW heat pump 3	1	89	1	92	45	57
Low-flow showerheads 1	334	307	324	324	334	331
Low-flow showerheads 2	2	42	35	25	25	29
Heater wraps 1	3	3	0	1	3	1
Heater wraps 2	92	90	95	85	96	96
Heater wraps 3	5	9	5	9	7	9
Thermal traps 1	81	85	85	91	93	93
Thermal traps 2	17	8	12	10	8	14

Comparing Case I and II, it can be concluded that optimization of maintenance plan can significantly improve retrofitting performance in terms of investment cost and energy saving. As shown in Fig. 1, solutions of Case II lie in the front of solutions of Case I with respect of Pareto dominance. In other words, with the same investment cost the optimal maintenance plan can achieve more energy saving than the empirical maintenance plan; with the same energy saving the optimal maintenance plan only requires less investment cost than the empirical plan.

The maintenance plans in Case I and II are different. To visualize the optimized maintenance plan, $u(t)(t = 1, 2, \ldots, 10)$ are plotted sequentially over the evaluation period. For each year, $u(t)$ is a 35 dimensional vector that represents numbers of repaired or replaced alternatives in the maintenance plan. Fig. 2 has given optimal maintenance plans in the 6 representative solutions. For solution 1, 2 and 3, the maintenance plan of each year is almost the same as shown in the figure. For solution 4, 5 and 6, the maintenance plan of each year varies over 10 years. For example, in the solution 4 qualities of maintenance items at 4th, 5th and 10th years are larger than those at other years. It can also be noticed that the maintenance plans in these solutions are also different with each other.

4.3. *Case III: three-objective problem with empirical maintenance*

In this case study, the empirical maintenance plan is the same as Eq. (16). The three-objective problem with the empirical maintenance plan can be expressed as

$$\min F_2(\mathbf{x}) = \min(f_1, -f_2, -f_3). \tag{19}$$

where the decision variable is the retrofit strategy, the objectives are to minimize retrofit cost and to maximize energy saving and NPV. In Case III, the problem has the constraints as Eq. (9). The Pareto front obtained by MONFO is plotted in Fig. 3. The whole set of Pareto optimal solutions is approximately an plane in the 3-D objective space. Investment costs are distributed in the range $[5.682 \times 10^4, 1.890 \times 10^5]$ \$, energy savings are distributed in the range $[5.876 \times 10^6, 1.359 \times 10^7]$ kWh, and NPVs are distributed in the range $[3.160 \times 10^5, 4.481 \times 10^5]$ \$.

Table 7 lists some representative solutions in the Pareto set. According to different preferences, decisions can be made as the following examples. If the preference is the minimal budget, solution 1 can be chosen as the retrofit strategy. If the preference is the maximal energy saving, solution 2 can be chooser as the retrofit strategy. If the preference is the maximal NPV, solution 3 can be chosen as

Table 10
Performance of some representative solutions in Case IV.

No.	Investment (\$)	Energy saving (kWh)	NPV (\$)	Payback period (Y)	Profit rate
1	6.093×10^4	6.350×10^6	4.248×10^5	1.195	6.971
2	1.855×10^5	1.621×10^7	4.047×10^5	2.998	2.182
3	1.392×10^5	9.902×10^6	4.942×10^5	2.093	3.550
4	1.459×10^5	1.447×10^7	3.636×10^5	2.735	2.492
5	1.678×10^5	1.313×10^7	4.567×10^5	2.583	2.704
6	1.209×10^5	1.178×10^7	4.088×10^5	2.166	3.382

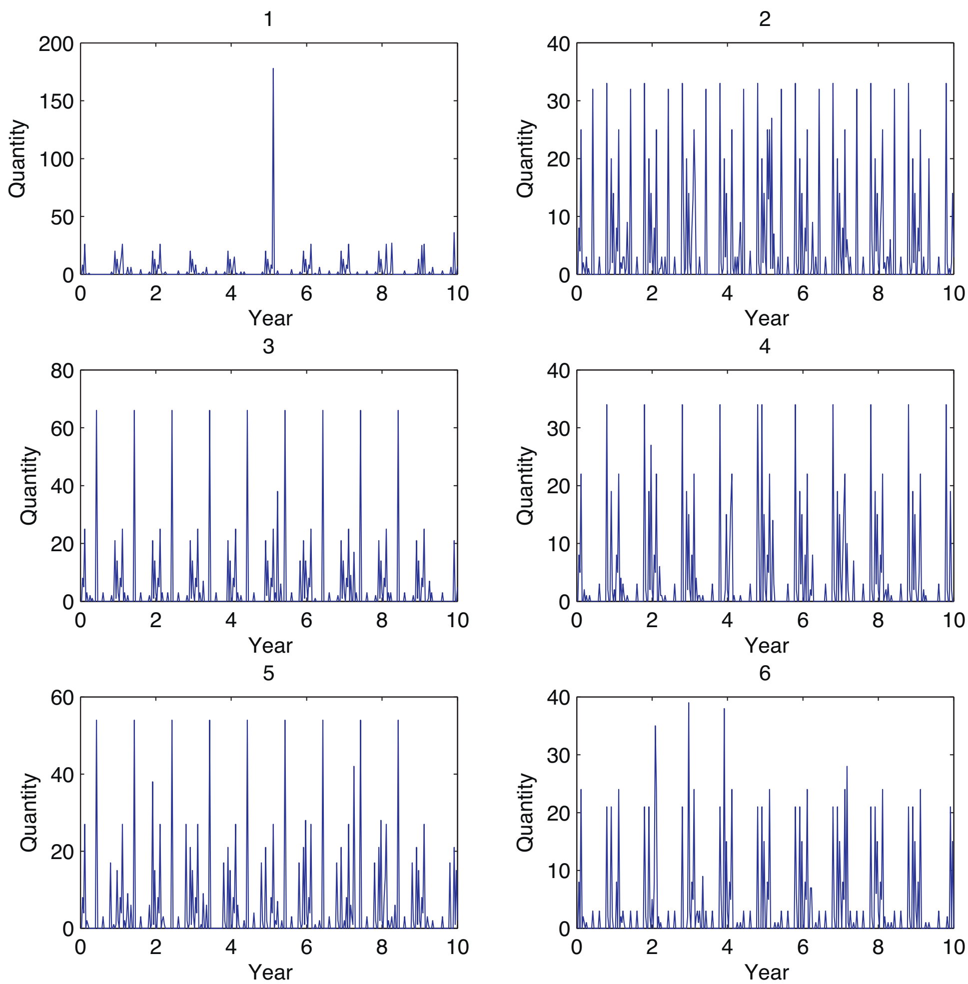

Fig. 4. Optimal maintenance plans obtained by MONFO in Case IV. The horizontal axis is time, and the vertical axis is quantity of interventions experiencing maintenance.

the retrofit strategy. If the preference is the balance among these three objectives, solution 4, 5, 6 can be chosen to satisfy specific requirements. Like Case I, similar observations can be noticed that some interventions dominate other interventions in the same type of these retrofit solutions, such as, motion sensor 2 and 9 kW heat pumps 3. For these solutions, more motion sensor 2 is chosen than motion sensor 1 and more 9 kW heat pump 3 is chosen than other heat pumps, because they can achieve more energy saving and cost saving with less retrofit cost. Other facilities, such as energy saver globe 1, 2 and 4, low-flow showerheads 1 and thermal traps 1, are also more preferred due to high efficiency.

For these representatives, investment cost, energy saving, NPV, payback period, and profit rate are evaluated as listed in Table 8. Both constraints of energy saving and payback period are satisfied. Solution 1 has achieved the smallest payback period and the largest profit rate with the least investment, which may be a good choice of limited budget. The possible reason is that the investment is only used to retrofit those facilities with most economic effects. Solution 2 has the largest payback period and the smallest profit rate with the largest energy saving, which indicates that the energy saving is a good preference for tenentes but not a good preference for owners or projectors.

4.4. Case IV: three-objective problem with optimized maintenance

In this case study, the maintenance plan will be optimized together with the retrofit strategy in the three-objective model. The three-objective problem with the optimized maintenance plan can be expressed as Eq. (10). The decision variable is the retrofit strategy and the maintenance plan. The objectives are to minimize retrofit cost and to maximize energy saving and NPV. For Case IV, the Pareto front obtained by MONFO is plotted in Fig. 3. The whole set of Pareto optimal solutions is approximately an plane in the 3-D objective space. Investment costs are distributed in the range $[6.093 \times 10^4, 2.035 \times 10^5]$ $, energy savings are distributed in the range $[6.350 \times 10^6, 1.621 \times 10^7]$ kWh, and NPVs are distributed in the range $[3.636 \times 10^5, 4.942 \times 10^5]$ $.

Table 9 lists some representative solutions in the Pareto set. According to different preferences, decisions can be made by referring these obtained solutions. If the preference is the minimal budget, solution 1 can be chosen as the retrofit strategy. If the preference is the maximal energy saving, solution 2 can be chooser as the retrofit strategy. If the preference is the maximal NPV, solution 3 can be chosen as the retrofit strategy. If the preference is the balance among these three objectives, solution 4, 5, 6 can be chosen to satisfy specific requirements. Comparing Tables 7 and 9, some differences can be found that energy saver globe 1 and 2 are mainly used; 3 kW heat pump 2 is used instead of other 3 kW heat pumps; and heat wraps 2 is mainly used instead of using heat wraps 1 and 2.

For these representatives, investment cost, energy saving, NPV, payback period, and profit rate are evaluated as listed in Table 10. Like in Case III, both constraints of energy saving and payback period are satisfied. Solution 1 has achieved the smallest payback period and the largest profit rate; solution 2 has the largest payback period and the smallest profit, but also achieves the largest energy saving. It can also be noticed that optimized maintenance plan can achieve larger energy saving 1.621×10^7\$ than empirical maintenance plan.

Like in Case II, similar observation can be obtained here that the optimization of maintenance plan can significantly improve retrofitting performance in terms of investment cost, energy saving and NPV. As shown in Fig. 3, the optimal solutions with optimized maintenance plan can dominate those solutions with empirical maintenance plan. In other words, when any two objectives are kept as constants, the remaining objective in Case IV shows better performance than that in Case III. Fig. 4 has given optimal maintenance plans for the 6 representative solutions. Due to the complexity of three-objective model, the optimal maintenance plans in Case IV are much variant compared with those in Case III. For each solution, the quantity of items in maintenance varies year by year. For solution 1, in the 5th year most maintenance will be carried out. For solution 6, more maintenance will be carried out in the 2nd, 3rd, and 4th years. For the same period,the quantities of the same item in maintenance are also different between solutions.

5. Conclusion

To improve energy efficiency of building, retrofit projects have been implemented to achieve much energy savings and less carbon and pollutant emissions. What is the best energy efficiency retrofit strategy under certain specific preferences on investment budget, energy saving and NPV? The question has been answered in the viewpoint of multiobjective optimization in this paper. The energy retrofitting retrofit problem has been modeled as a multiobjective optimization problem in terms of retrofit cost, energy saving and NPV. Both the retrofit strategy and the maintenance plan have been optimized for minimization or maximization of the considered objectives. The number of alternative interventions firstly installed and the number of repaired or replaced interventions for each year are optimized to trade off these objectives. Several Pareto optimal scenarios for retrofit and maintenance are obtained after solving the proposed model with the algorithm MONFO. The benefit of using MONFO is that the obtained scenarios are close to optimun and also diversely distributed in the whole feasible space. Referring these scenarios, decision makers can easily use such comprehensive information to select one proper scenario for implementation.

Four cases have been studied to evaluate Pareto optimal retrofit and maintenance strategies by MONFO. The first conclusion can be drawn that for either two-objective problems or three-objective problems optimal strategies with accuracy and diversity can be found by MONFO. Some representative strategies can cover possible preferences of decision makers. The second conclusion is that optimization of maintenance can improve the building retrofit performance in terms of more energy saving and NPV with less retrofit cost compared with the empirical maintenance.

The focus of this paper is to improve energy efficiency by optimally scheduling of building retrofit and maintenance. Although three objectives, i.e., retrofit cost, energy saving and NPV are considered in energy efficiency improvement, some other concerns beyond energy efficiency, such as social and environment factors, could be included in the building retrofit models as part of future work. Furthermore, maintenance can be regarded as a closed-loop control because the decay model of alternative intervention may be affected by the disturbance of failure rate. Due to the scope of this paper, the closed-loop control of maintenances is not discussed and is left as part of future work.

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