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Optimal maintenance planning for building energy efficiency retrofitting from optimization and control system perspectives

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ABSTRACT

This paper discusses the maintenance plan optimization problem for the energy efficiency purpose in the building energy efficiency retrofitting context. A subproblem namely the Building Retrofitted Facilities Corrective Maintenance Planning (BRFCMP) problem is proposed, where the corrective maintenance for malfunctioning retrofitted items are involved. The aggregate performances of the homogeneous retrofitted item groups, instead of the individual item performances, are the main consideration of the optimization issue. An aggregate population level optimization model is proposed to address the BRFCMP problem. When further taking into account the uncertainties, the optimization problem is cast into an optimal control problem to reduce the consequent adverse impact, given the dynamic nature of the aggregate performances of the item groups during operation. Both the optimization and control system approaches are applied to solve the BRFCMP problem without or considering uncertainties. An actual building retrofitting project is used as the case study to investigate the important role of maintenance to the building energy efficiency. The effectiveness of the proposed approaches is verified by simulation results.

1. Introduction

Building energy efficiency is one of the most popular research areas today. One major topic in this area is the energy efficiency retrofitting in existing buildings. The focuses of energy efficiency retrofitting research at the current stage are the implementation of energy conservation technologies [1–6] and the optimization of retrofitting plans [7–12]. However, only a few studies have been conducted on the maintenance part of an energy efficiency project [13–15]. The asset maintenance for reliability purpose is a widely studied topic in the reliability engineering area, whereas the maintenance for energy efficiency purpose lacks exploration.

For a building energy efficiency retrofitting project, maintenance is required for the sustainability of the energy performances. In practice, the performances of the energy efficiency retrofits can deteriorate subject to usage and failures of the retrofitted items [16]. According to the measurement and verification (M&V) principles [17,18], the energy efficiency of a retrofitting project can be evaluated by its aggregate energy saving. The energy saving cannot be directly measured, since they represent the absence of energy use. Instead, savings are determined by comparing measured use before and after implementation of a project, making appropriate adjustments for changes in conditions. Taking advantage of the corresponding energy audit results, the retrofitting plan can be optimized to maximize the aggregate energy saving of the project, subject to a series of constraints. However, most existing studies ignore the possible dynamics of the retrofits' energy performances during operation. From the energy efficiency point of view, a malfunctioning retrofitted item contributes less or even zero energy saving. Wang et al. [11] takes into account such impact when optimizing the long-term energy saving of a retrofitting project. From the management perspective, the increase of malfunctioning items, i.e., the decrease of the population of available items, implies the inconsistency of the aggregate energy performances of the project. Given the absence of the maintenance actions, such energy efficiency deterioration cannot be reversed, resulting in the inefficiency of the retrofitting project and even worse, the violation of the energy performance contract. In conclusion, it is necessary to take into account maintenance in building energy efficiency retrofitting projects.

The scope of maintenance actions includes the activities required to operate and maintain the facilities and their supporting infrastructures in a condition to be used to meet their intended function over the operating period. [1] In the reliability engineering

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[1] Comprehensive Facility Operation & Maintenance Manual, 2013, http://www.wbdg.org/om/om_manual.php.

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area, maintenance and replacement problems of deteriorating systems have been studied for many years [19]. Maintenance actions are generally classified into two categories: corrective maintenance (CM) and preventive maintenance (PM). CM involves the repairs and replacements against failures and PM refers to all actions performed in an attempt to retain an item in a specified condition, according to MIL-STD-721C.[2] In reliability engineering area, CM actions occur when the need arises, while PM actions are introduced when the system is still functioning, with the goal to restore the system to a specified better condition through systematic detection, correction of slight flaws, inspection, and other activities that will prolong system life [20]. The scheduling of PM actions is important to improve the system reliability and reduce the system downtime. However, from the viewpoint of an energy retrofitting project, the energy impacts of malfunctioning items are significant. Furthermore, in many existing office buildings, school buildings and residential buildings, PM actions are not implemented. Therefore, CM actions that reduce the population of malfunctioning items during operation are the focus of the energy efficiency related maintenance planning.

From the perspective of building energy efficiency, the implementation of CM and PM actions adjusts the aggregate population and condition of the available items to preserve the energy performances of the retrofitting project. Moreover, the operation of the retrofits can influence the fatigue and energy performance of an item over the long term, and consequently the available item population dynamics and aggregate energy performances. Given a retrofitting project, both the maintenance plan and the operating schedules of the retrofitted items can be optimized to support the sustainability of the building energy efficiency. However, a retrofitting plan is usually optimized based on the performance characteristics that are estimated over a long time period, e.g., 10 years, the population of the retrofitted item group manifests a dynamic change in 1 or 2 years due to the maintenance actions, and the operation usually concerns issues of short intervals such as days or hours. In addition, budget limits are introduced in many practical cases, which also restrict the implementation of the maintenance actions. Therefore, building energy efficiency retrofitting optimization problems with multiple time scales and substantial magnitude could become complex if the maintenance and operation of the retrofitted facilities are taken into account, due to the complexity and interplay of the retrofitting planning, maintenance and operation.

The main purpose of this paper is to propose a method to incorporate the maintenance planning optimization into the building energy efficiency retrofitting project. At the current stage, a subproblem of the maintenance planning optimization problem that is adopted from [13], namely the Building Retrofitted Facilities Corrective Maintenance Planning (BRFCMP), is investigated for this purpose. The retrofitted facilities refer to the totality of the retrofitted items involved in the retrofitting project. The BRFCMP problem considers only the planning of CM actions that restore the malfunctioning items from failures and breakdowns to normal working conditions. For simplicity, it is assumed that the BRFCMP issue addressed here is planning the repair and replacements of the malfunctioning items according to predefined maintenance time schedule. The optimization of maintenance periodicity is therefore excluded at the current stage. The maintenance actions are planned at the aggregate population level, rather than at the level of individual items. In the BRFCMP problem, items of the homogeneous classes corresponding to different retrofits are aggregated to obtain the managed retrofitted item groups. A hypothesis is made to obtain the classification of homogeneous retrofitted items. There are three kinds of related characteristics: the inherent energy and reliability performance, the operational environment of the items and the corresponding operating schedules. For example, a group of retrofitted items are considered as one class when they are the same model from the same producer, and they all work in a cool and dry climate, with similar workloads. Items from the same homogeneous class are assumed to manifest same energy and financial performances. The robustness of this hypothesis in practice yet remains an open problem that requires further exploration. Besides the usual CM and PM, emergency maintenance, such as restoring lost electrical power, can be taken into account in some projects. Given the emergency maintenance not an option that can be planned, the equipment concerning emergency maintenance are not included in any of the homogeneous classes. The energy and financial performances of these classes are thus the main concerns of the discussed maintenance planning.

Based on the homogeneous item groups classification, an aggregated population level optimization model for the BRFCMP problem is proposed when uncertainties are not taken into account. Given the BRFCMP a problem succeeding the retrofitting planning optimization that is often multi-objective [21], two objectives are introduced: maximizing the long-term aggregate energy saving and maximizing the economy of the project over a finite period of time. The objective functions are formulated according to a series of performance measures, and a weighted sum method is employed as the solution to the multi-objective optimization problem, as the weighted sum method provides a basic and easy-to-use approach that gives an acceptable approximation of one's preference function when the preference information is not too complex [22]. One of the key issues of applying maintenance planning optimization method is the characterization of the population deterioration of the homogeneous item groups, where the building energy optimization brings in the reliability engineering studies, where deterministic or stochastic models of facilities reliability can be found. A series of common failure distributions, reliability and hazard rate functions for facilities with various reliability characteristics is provided by O'Connor and Kleyner [23], according to which the population degradation of various types of retrofitted items, e.g., the nonrepairable products and the repairable products, can be characterized. It is expected that the research progress in the reliability engineering area will facilitate the advance of building energy optimization studies, and vice versa. The characterization of item group population degradations can also be found in some existing studies in the clean development mechanism (CDM) environment, which consider the population degradation either by a simplified linear assumption [24] or an experimental data fitting [25]. The optimization model formulation is the first part of the main work in this paper.

Another issue of the BRFCMP problem is the adverse impact of the uncertainties during operation. In practice, the measurements of the retrofitted building, namely the retrofitted plant, are usually done by the sampling and estimation methods. As a result, sampling errors can be introduced into the optimization model. The accuracy of the population degradation models is also limited. Furthermore, the influence of human behaviors, environmental factors and the stochastic reliability performances of the products are involved in practical cases, which all result in performance uncertainties. The existing optimization models lack the ability to address the problem of the uncertainties. Given the dynamic nature of the aggregate performances of the retrofitted plant, the control system approach, which is an almost unexplored perspective to solve the building energy efficiency retrofitting optimization problems with uncertainties, can be brought in. Several studies have been conducted to attempt to employ the control system approaches to solve the maintenance optimization problem for reliability purposes

[2] Military Standard: Definitions of Terms for Reliability and Maintainability, 1981, http://www.everyspec.com/MIL-STD/MIL-STD-0700-0799/MIL-STD-721C_1040/.

[26–28], whereas most of which focused on single-unit or two-component machines. The main concern of these existing studies is the control of single machine or unit. Recently, Ye and Xia [15] investigates employing the control system approach to the optimal maintenance plan for energy efficiency lighting projects. This research focuses on the replacements of the malfunctioning lamps, where the population deterioration of the lamp groups, rather than the performances of individual lamps, are taken as the plant of the control system. Wang and Xia [13] also employ the control system perspective to investigate the maintenance plan optimization in a building retrofitting context. Similarly, for the BRFCMP problem, the totality of the retrofitted item groups are taken to be our control plant, where the population of available items from each homogeneous item group as the state variables of the system. The corrective maintenance actions, i.e., the respective numbers of maintained items from the homogeneous item groups, are taken as the control inputs. The measured output of the system can be the aggregate energy savings, capital investment or other performance measures in different cases. Accordingly, the population deterioration can represents the internal dynamics of the state variables. The aforementioned uncertainty factors can be described as disturbances on the state variables or measured output. For simplicity, two further assumptions are made, namely: the disturbances of the system are generally considered as a random noise on state variables; the sampling errors are simplified as a random noise on the measured output. In this way, the BRFCMP optimization problem considering uncertainties is cast into an optimal control problem, where the optimization objectives are transformed into the control objectives. A model predictive control (MPC) based approach is employed to solve the BRFCMP optimal control problem. The MPC approach finds the optimal control inputs by predicting the future based on the present state of the system, and is inherently robust against disturbances. It has become one of the most widely used control algorithms to solve many industrial control problems in the fields of engineering, food processing, automotive applications, and aerospace applications [29], demand-side management [30] and dispatch of power generation [31]. The control system approach is the second part of our main work. As a case study, a practical building retrofitting project is used to test and verify the feasibility of the presented optimization and control approaches.

The remainder of the paper consists of five sections. Section 2 gives the formulation of the multi-objective BRFCMP optimization problem. Section 3 introduces the weighted sum method as a solution to the BRFCMP problem. Section 4 introduces the control system approach to the BRFCMP optimal control problem when considering uncertainties, and the MPC approach as a solution. Section 5 provides the details of the case study and the simulation results and analysis. Section 6 draws conclusion and discusses future research.

2. Multi-objective BRFCMP problem

2.1. Variables definitions

Assumed there are I groups of homogeneous retrofitted items involved in a building energy efficiency retrofitting project. Let $t_k = kS$, $k = 0, 1, 2, \ldots, T$ denote the sampling instants over the a finite decision horizon $[0, TS)$, namely the sustainability period, where S indicates the sampling interval. The population of the item group i at time t_k is represented by $x_i(t_k)$, and accordingly the system state can be described:

$$\mathbf{x}(t_k) = (x_1(t_k), x_2(t_k), \ldots, x_I(t_k))^T. \tag{1}$$

$\mathbf{x}(t_0) = \mathbf{x}_0$ indicates the initial state of the retrofits that is decided by the retrofitting plan. In practice, $x_i(t_k)$ with $k > 0$ are obtained by the inspection at t_k. For the energy conservatism, $x_i(t_k)$ is considered the state over interval $[t_{k-1}, t_k)$. The maintenance action for item group i is decided based on the inspection result $x_i(t_k)$ and implemented over interval $[t_k, t_{k+1})$. Let $u_i(t_k)$ denote the maintenance action applied to item group i over interval $[t_k, t_{k+1})$. The aggregate population level maintenance plan at t_k can be represented by:

$$\mathbf{u}(t_k) = (u_1(t_k), u_2(t_k), \ldots, u_I(t_k))^T. \tag{2}$$

For the convenience of further derivation, $\mathbf{x}$ and $\mathbf{u}$ are employed to represent the system states and maintenance actions over the sustainability period, where $\mathbf{u}$ are the decision variables in the BRFCMP problem. The system state at the next sampling instant can thus be estimated:

$$x_i(t_{k+1}) = D_i(x_i(t_k)) + u_i(t_k). \tag{3}$$

where $D_i(\cdot)$ denotes the population degradation of the item group i over $[t_k, t_{k+1})$. Given $D_i(\cdot)$ with $i = 1, 2, \ldots, I$ known a priori and taking advantage of Eq. (3), it is possible to find a series of maintenance actions, i.e., the optimal maintenance plan, that maximizes the selected performance measures. In our model, two types of performance measures, the energy performance indicator and the economy performance indicator are selected. The formulations are given in the next section.

2.2. Performance measures formulation

The performance measures are computed by estimating the system states over the sustainability period. The energy performance indicator in this model is the long-term energy saving i.e., the aggregate energy saving over the sustainability period. The economy performance indicator is the internal rate of return (IRR). To obtain the two performance measures, a series of performance characteristics of the involved retrofitted items are defined and utilized. Given the energy saving of the retrofitted item a performance characteristics known a priori, let $\mathbf{a}(t_k)$ denote the saving amount over interval,

$$\mathbf{a}(t_k) = (a_1(t_k), a_2(t_k), \ldots, a_I(t_k))^T, \tag{4}$$

where $a_i(t_k)$ denotes the energy saving that an item from item group i contributes over $[t_{k-1}, t_k)$. Similarly, the cost savings can be represented,

$$\mathbf{b}(t_k) = (b_1(t_k), b_2(t_k), \ldots, b_I(t_k))^T, \tag{5}$$

and the maintenance costs per item at instant t_k are given:

$$\mathbf{c}(t_k) = (c_1(t_k), c_2(t_k), \ldots, c_I(t_k))^T. \tag{6}$$

Taking advantage of these characteristics, the aggregate long-term energy saving can be obtained:

$$\mathrm{ES}|_{\mathrm{all}} = \sum_{k=1}^{T} \mathrm{ES}(\mathbf{x}(t_k), t_k) = \sum_{k=1}^{T}\sum_{i=1}^{I} a_i(t_k) x_i(t_k), \tag{7}$$

and the aggregate cost saving:

$$\mathrm{CS}|_{\mathrm{all}} = \sum_{k=1}^{T} B(\mathbf{x}(t_k), t_k) = \sum_{k=1}^{T}\sum_{i=1}^{I} b_i(t_k) x_i(t_k), \tag{8}$$

where $B(\mathbf{x}(t_k), t_k)$ denotes the aggregate cost saving over interval $[t_{k-1}, t_k)$. The cost saving in our model is considered the main income of the retrofitting project, thereby $B(\mathbf{x}(t_k), t_k)$ also represents the cash inflow over $[t_{k-1}, t_k)$, from the economy point of view.

The cash outflow is the expenditure of the maintenance actions given as following,

$$h|_{\text{all}} = h_0 + \sum_{k=1}^{T} h(\mathbf{u}(t_k), t_k) = h_0 + \sum_{k=1}^{T}\sum_{i=1}^{I} c_i(t_k)u_i(t_{k-1}), \tag{9}$$

where h_0 denotes the initial investment for the implementation of the retrofitting plan and $h(\mathbf{u}(t_k), t_k)$ the cash outflow over $[t_{k-1}, t_k)$. Taking advantage of the time-dependent cash inflow and outflow, the IRR can be obtained. The calculation of IRR is related to the net present value (NPV) which is computed as following,

$$\text{NPV} = \sum_{k=1}^{T} \frac{B(\mathbf{x}(t_k), t_k) - h(\mathbf{u}(t_k), t_k)}{(1+d)^{n-1}} - h_0, \tag{10}$$

where d is the selected discount rate. $n = 1, 2, \ldots$ represents that the sampling instant t_k lies within the nth year after the implementation of the retrofitting project. IRR, denoted by $d_R|_T$, refers to the discount rate that makes the NPV over $[0, TS)$ equal to 0. A larger IRR implies the better economy of a project.

As mentioned in the previous section, the nature of the BRFCMP problem is a multi-objective optimization problem. Taking advantage of the aforementioned performance measures, two objective functions are formulated:

$$\begin{cases} f_e(\mathbf{x}, \mathbf{u}) = \dfrac{\text{ES}|_{\text{all}}}{\alpha}, \\ f_r(\mathbf{x}, \mathbf{u}) = \text{IRR}, \end{cases} \tag{11}$$

where $\mathbf{x}$ and $\mathbf{u}$ are noted to emphasize the dynamic nature of the aggregated performances. α denotes the targeted energy saving amount that is contracted before the retrofitting. A series of constraints are involved in the BRFCMP problem, including the energy performance agreement, the maintenance budget limit, the payback period limit, and the pre-decided maintenance time schedule. The constraints are represented by the following equation,

$$\begin{cases} x_i(t_{k+1}) = D_i(x_i(t_k)) + u_i(t_k), \\ \text{ES}|_{\text{all}} \geq \alpha, \\ \displaystyle\sum_{k=1}^{T} h(t_k) \leq \beta, \\ \text{NPV}|_0^{T_p} \geq 0, \\ u_i(t_k) = 0,\ k \notin Q, \end{cases} \tag{12}$$

where β denotes the overall maintenance budget limit. $\text{NPV}|_0^{T_p}$ denotes the NPV computed over $[0, T_pS)$ where T_p represents the maximum acceptable payback period. Q represents the maintenance time schedule, where $Q = \{k_1, k_2, \ldots\}$ denotes the set of time instants over $[0, TS)$. After an arbitrary time instant from Q, the maintenance actions is planned and implemented over the following sampling interval. Accordingly, if $k \notin Q$, $u_i(t_k) = 0$. Given $f_e(\mathbf{x}, \mathbf{u})$ and $f_r(\mathbf{x}, \mathbf{u})$ as functions of $\mathbf{x}(t_k)$ the time-dependent system states that change according to the number of malfunctioning items and maintenance actions, the performance objectives are actually integrated with the loss of failures and the impact of maintenances. The loss of failures is estimated by a series of population degradation models for different item groups. The following subsection introduces formulations of such models.

2.3. Population degradation formulation

In the current BRFCMP problem, two types of population degradation models are employed to characterize the population dynamics of different item groups [13]. One corresponding to nonrepairable items such as the lighting facilities and motion sensors, and the other to repairable items such as heat pumps. Eqs. (13) and (14) describe these degradation models, respectively:

$$D_i(x_i(t_k)) = \frac{b_i c_i x_i(t_k)^2}{x_i} - b_i x_i(t_k) + x_i(t_k), \tag{13}$$

$$D_i(x_i(t_k)) = x_i(t_k) e^{-\zeta_i}, \tag{14}$$

where the coefficients b, c, ζ are estimated by the mean time to failure (MTTF) of the nonrepairable items and the mean time between failures (MTBF) of the repairable items. The population degradation model for nonrepairable products as described in Eq. (13) is taken from [25]. Let L_i denote the MTTF, i.e., the rated lifetime of the item from item group x_i. The general form of the time-domain degradation model $P_i(t) = (c_i + e^{b_i t - L_i})^{-1}$ can be found in [25], where $P_i(t)$ is the proportion of surviving items in the whole group. For this degradation model, given L_i is known, b_i and c_i can be obtained by solving out the following equations:

$$\begin{cases} P_i(0) = 1, \\ P_i(L_i) = 0.5, \end{cases} \tag{15}$$

where b_i and c_i can also be identified from the experimental data. Eq. (14) describes the degradation model for repairable products. As the rated lifetime is usually several times longer than the MTBF for such items, according to the reliability bathtub curve, the failure rate of such items is an approximately low constant before the end of the lifetime. Therefore an exponential degradation model is adopted from [23] in Eq. (14). Let θ_i denote the MTBF of the facility, ζ_i is then obtained from the following equation:

$$\zeta_i = (\theta_i)^{-1}. \tag{16}$$

Both Eqs. (13) and (14) are actually statistical models considered as first-order Markov processes in the current BRFCMP problem. Once again for simplicity of discussion, another important assumption is made: the replaced or repaired items and the malfunctioning items are from the same respective homogeneous classes, they thus share the same failure pattern. The MTTF and MTBF are known a priori according to the model. Such information can be obtained from the equipment producers or the historical performances of the items.

The population degradation models are employed as a constraint of the optimization problem. From the control system perspective, the degradation models indicate the system dynamics. Given the degradation model in Eq. (13), the involved system is a discrete non-linear system. Although the stability of such a closed-loop system is trivial as the states variables are naturally bounded, the objective functions become non-linear and non-analytic given the non-linear system dynamics, as Eq. (11) implies. Therefore, one cannot expect that the involved optimization problem is convex, and a differential evolution (DE) algorithm solution is consequently employed. The solution is introduced in the following section.

3. The weighted sum solution to the BRFCMP problem

3.1. The weighted sum of objective functions

At the current stage, a weighted sum method that has been utilized in similar studies [10,11] is employed to solve the multi-objective BRFCMP problem. Taking advantage of Eqs. (11) and (12), the multi-objective optimization problem is translated into the minimization of a utility function, which is the weighted sum of the objective functions associated with stationary penalty functions corresponding to the constraints, given by Eq. (17):

$$J = -\lambda_1 f_e(\mathbf{x}, \mathbf{u}) - \lambda_2 f_r(\mathbf{x}, \mathbf{u}) + \omega \sum_{n=1}^{3} \max(0, P_n), \tag{17}$$

where λ_1, λ_2 are positive constants, i.e., the weight factors, subject to $\lambda_1 + \lambda_2 = 1$. The weight factors imply the preference of the decision maker on different objectives. Larger weight factor implies that the corresponding objective has higher priority. ω is a large positive integer that amplifies the penalties of violating constraints. P_n are the penalty functions defined as following:

$$P_n = \begin{cases} \alpha - \mathrm{ES}|_{\mathrm{all}}, & n = 1, \\ \displaystyle\sum_{k=1}^{T} h(t_k) - \beta, & n = 2, \\ -\mathrm{NPV}|_0^{T_p}, & n = 3 \end{cases} \tag{18}$$

The BRFCMP optimization problem is actually to find a **u** to minimize the utility function in Eqs. (17) and (18). The DE algorithm is employed to solve this minimization problem over the interval [0, *TS*). The details of the DE algorithm is introduced in the following section.

3.2. A differential evolution algorithm solution

In existing studies, DE and other evolutionary algorithms are widely and successfully applied to solve the energy optimization problems. The DE algorithm is easy to implement, and it is verified to be effective for a similar optimization problem in [11]. Given the non-analytic objective function in Eq. (11), the DE algorithm is more feasible than conventional NLP algorithm. In DE algorithm, a set of candidate solutions, namely individuals, are adopted to represent the possible values of the decision variables **u**. These individuals are moved around in the search-space which is regulated by the boundary of the problem. By implementing a series of mathematical operations including *Mutation*, *Corssover* and *Selection* (see [32] for further details), a satisfactory solution can hopefully, although not guaranteed, be discovered. The pseudo-code of the employed DE algorithm is given in Algorithm 1.

In Algorithm 1, *D* denotes the dimension of the problem, *G* refers to the maximum step of iteration and *NP* represents the population size. The *CR* and *F* are the crossover probability and the learning rate respectively. $X^p_{\mathrm{best},g}$ is selected from the 10% best vectors of the current population. $X_{r1,g} - X_{r2,g}$ is a differential vector for the mutation operation, where $X_{r1,g}$, $X_{r2,g}$ are randomly selected from the current population. The mutation vector $V_{i,g}$ and the child vector $U_{i,g}$ are accordingly generated. $J(\cdot)$ denotes the utility function in Eq. (17). After *Mg* steps, the individual with smallest utility function value is the output of the DE algorithm.

Algorithm 1. Pseudocode of the DE algorithm.

Definition:
NP: the population size;
D: dimension of the problem;
X: the decision matrix with the size of $NP * D$;
F: the learning rate;
J: the function value vector with the size of $np * 1$;
Mg: the maximum number of generations for stopping criterion.

BEGIN
Set $CR = 0.5$; $F = 0.5$; $A = \emptyset$;
Create a random initial population $\{X_{i,0} | i = 1, 2, \ldots, NP\}$;
while $g = 1$ *to* Mg **do**
  while $i = 1$ *to* NP **do**
    Randomly select $X_{r1,g} \neq X_{i,g}$ from current population **P**;
    Randomly select $X_{r2,g} \neq X_{i,g}$ from current population **P**;
    Randomly select $X^p_{best,g}$ as one of the 10% best vectors from **P**;
    $V_{i,g} = X_{i,g} + F \cdot (X^p_{best,g} - X_{i,g}) + F \cdot (X_{r1,g} - X_{r2,g})$;
    Generate $j_{rand} = randint(1, D)$;
    while $j = 1$ *to* D
      if $j = j_{rand}$ or $rand(0, 1) < CR$
        $U_{j,i,g} = U_{j,i,g}$;
      else
        $U_{j,i,g} = X_{j,i,g}$;
      end if
    end while
    if $J(U_{i,g}) \leq J(X_{i,g})$
      $X_{i,g+1} = U_{i,g}$;
    else
      $X_{i,g+1} = X_{i,g}$;
    end if
  end while
end while
END

4. The control system approach to the BRFCMP problem considering uncertainties

The aforementioned optimization model excludes the uncertainties in the system, e.g., the model uncertainties and the sampling uncertainties. As a result, such uncertainties can deliver adverse impact to the maintenance plan, causing further deterioration of the performances. Therefore, we cast the BRFCMP problem into an optimal control problem, based on which the control system approach is introduced for the robustness of the performances against uncertainties. The formulation of the optimal control problem is given in the following section.

4.1. The control system framework formulation

Taking advantage of the system states and decision variable in Eqs. (1) and (2), the control system formulation that describes the system dynamics can be obtained via rewriting Eq. (3):

$$\begin{cases} \mathbf{x}(t_{k+1}) = \mathbf{D}(\mathbf{x}(t_k)) + \mathbf{u}(t_k) + \mathbf{w}(t_k), \\ \mathbf{y}(t_k) = \mathrm{ES}(\mathbf{x}(t_k), t_k) + \mathbf{d}(t_k). \end{cases} \tag{19}$$

The decision variable $\mathbf{u}(t_k)$ hereby represents the control input of the control system. The measured output $\mathbf{y}(t_k)$ is the measurement of the aggregate energy saving during the sampling period $[t_{k-1}, t_k)$. In practice, $\mathbf{y}(t_k)$ is measured according to the sampling of the item group populations at instant t_k and Eq. (7). The accuracy and confidential level of the measurement is determined by the sampling size [33]. $\mathbf{w}(t_k)$ and $\mathbf{d}(t_k)$ denote the disturbances to the system states and outputs. Such disturbances are employed to indicate the impact of the uncertainties. The objective of the BRFCMP optimal control problem is thus to find an optimal control law **u** that minimizes the performance index in Eq. (17) for the control system in Eq. (19), subject to the constraints in Eq. (12). An MPC approach is employed to solve the BRFCMP optimal control problem. The details of the MPC algorithm are given in the following section.

4.2. The MPC approach to the BRFCMP optimal control problem

In MPC approaches, an open-loop optimal control problem is repeatedly solved over a finite horizon, namely the control horizon, according to the plant performance prediction. The obtained optimal open-loop control is then used to generate the optimal control input for the problem to be solved, with which the state variables executed over the next finite horizon are estimated. As the optimal controller over the next finite horizon is actually a function of the system state from the previous control step, a closed-loop feedback is thus obtained. Given the finite decision horizon in our model, such MPC algorithm is employed: let t_m denote the current instant, consider a control horizon that covers $[t_m, TS)$, i.e., the rest of the sustainability period. A mathematical transformation of the BRFCMP optimal control problem is applied, and the open-loop optimal control problem over the control horizon $[t_m, TS)$ is accordingly defined as the following minimization problem:

$$\min J_{\prime} = -\lambda_1 f_{e^\prime}|_m(\mathbf{x},\mathbf{u}) - \lambda_2 f_{r^\prime}|_m(\mathbf{x},\mathbf{u}), \tag{20}$$

where $f_{r'}|_m(\mathbf{x}, \mathbf{u})$ indicates the discount rate that makes $\mathrm{NPV}'|_m = 0$, with

$$\begin{cases} f_{e^\prime}|_m(\mathbf{x},\mathbf{u}) = \displaystyle\sum_{k=1}^{m} \mathrm{ES}(\mathbf{x}(t_k), t_k) + \sum_{k=m+1}^{T} \mathrm{ES}(\mathbf{x}|_m(t_k), t_k), \\ \mathrm{NPV}_{\prime}|_m = \displaystyle\sum_{k=1}^{m} \frac{B(\mathbf{x}(t_k), t_k) - h(\mathbf{u}(t_k), t_k)}{(1+d)^{n-1}} \\ \qquad + \displaystyle\sum_{k=m+1}^{T} \frac{B(\mathbf{x}|_m(t_k), t_k) - h(\mathbf{u}|_m(t_k), t_k)}{(1+d)^{n-1}} - h_0, \end{cases} \tag{21}$$

subject to

$$\begin{cases} \mathbf{x}(t_{k+1}) = \mathbf{D}(\mathbf{x}(t_k)) + \mathbf{u}(t_k) + \mathbf{w}(t_k), \\ \displaystyle\sum_{k=1}^{m} \mathrm{ES}(\mathbf{x}(t_k), t_k) + \sum_{k=m+1}^{T} \mathrm{ES}(\mathbf{x}|_m(t_k), t_k) \geq \alpha, \\ \displaystyle\sum_{k=1}^{m} h(\mathbf{u}(t_k), t_k) + \sum_{k=m+1}^{T} h(\mathbf{u}|_m(t_k), t_k) \leq \beta, \\ \mathrm{NPV}|_0^{T_p} \geq 0, \\ u_i(t_k) = 0, \quad k \notin Q, \end{cases} \tag{22}$$

where $\mathbf{x}|_m(t_k)$ denotes the predictive system states and $\mathbf{u}|_m(t_k)$ the scheduled control inputs after t_m. The employed MPC approach takes the existing performances before t_m into account to estimate the long-term performances of the project, based on which the open-loop control problem over the control horizon is solved. Given the non-analytic component in Eq. (20), we continue to employ the aforementioned DE algorithm to solve the open-loop control problem.

By applying DE algorithm, a series of optimal control inputs are obtained, represented by $\mathbf{u}'|_m = \{\mathbf{u}'|_m(t_k) : k = m, m+1, \ldots, T-1\}$. Only the optimal control action over the first sampling period $[t_m, t_{m+1})$ is applied, represented by $\hat{\mathbf{u}}|_m = \{\mathbf{u}_{\prime}|_m(t_m)\} = \{\hat{\mathbf{u}}|_m(\mathbf{x}(t_m), t_m)\}$, where the last equation is to emphasize the functional dependence of the optimal control on the initial state $\mathbf{x}(t_m)$ of the MPC formulation in Eqs. (20)–(22). After $\hat{\mathbf{u}}|_m$ is applied, the predictive state $\mathbf{x}|_m(t_{m+1})$ can be obtained. Due to the influences of uncertainties that is represented by disturbance $\mathbf{w}(t_m)$, the actual state $\hat{\mathbf{x}}(t_{m+1}) = \mathbf{x}|_m(t_{m+1}) + \mathbf{w}(t_m)$. In practice, $\hat{\mathbf{x}}(t_{m+1})$ must be obtained by the inspection. $\hat{\mathbf{x}}(t_{m+1})$ then becomes the initial condition of the MPC formulation over the next control horizon $[t_{m+1}, TS)$. When $m \notin Q$, the control input $\mathbf{u}(t_m) = 0$ is implemented as a solution. These take place consecutively over the sustainability period to obtain the optimal control inputs $\hat{\mathbf{u}}$. The measured output $\mathbf{y}(t_k)$ is obtained by Eq. (19). $\mathbf{x}(t_{k+1})$ is also applied as the initial state for the open-loop optimal control problem over the next control horizon. In summary, the following MPC algorithm can be formulated:

4.3. The MPC algorithm

Initialization: Let initial state $\mathbf{x}(t_0) = \mathbf{x}_0$ and $m = 0$.

(i) Compute the open-loop optimal solution $\{\mathbf{u}'|_m(t_k)\}$ of the problem formulation (20)–(22), where $k = m, m+1, \ldots, T-1$.
(ii) The MPC controller $\hat{\mathbf{u}}|_m = \{\mathbf{u}_{\prime}|_m(t_m)\}$ is applied after the sampling instant t_m. The remains of the open loop optimal solution $\{\mathbf{u}'|_m(t_k) : k = m+1, \ldots, T-1\}$ are discarded. The predictive state $\mathbf{x}|_m(t_{m+1})$ is then obtained according to:

$$\mathbf{x}|_m(t_{m+1}) = \mathbf{D}(\mathbf{x}(t_m)) + \mathbf{u}_{\prime}|_m.$$

Given the impact of disturbance $\mathbf{w}(t_m)$, the actual state $\hat{\mathbf{x}}(t_{m+1}) = \mathbf{x}|_m(t_{m+1}) + \mathbf{w}(t_m)$.
(iii) Let $\hat{\mathbf{x}}(t_{m+1})$ be the initial state for the next predictive horizon, $m := m+1$ and go back to step (i).

According to the constraint (22), $\mathbf{u}(t_m) = 0$ when $m \notin Q$, where step (i) is skipped and $\hat{\mathbf{x}}(t_{m+1}) = \mathbf{D}(\mathbf{x}(t_m)) + \mathbf{w}(t_m)$. The above MPC algorithm will go over the sustainability period to solve out the optimal control strategy.

5. Simulation and verification

5.1. Case study

To verify the effectiveness of the proposed approaches, a small retrofitting project is introduced as our case study. The retrofitting plant is a fifteen-floor concrete office building for government affairs, erected in 1960s. A deep audit has been applied to identify the energy efficiency potentials and impacts of the retrofits. The maintenance plan optimization is applied based on the obtained retrofitting plan to further improve the energy efficiency and cost-effectiveness of the retrofitting project. The sustainability period is 10 years, which is an average value in similar projects. The baseline energy consumption in the pre-implementation year is 4,397,572 kWh, and the targeted energy saving amount that is contracted to be achieved by this retrofitting project is 15% of the 10-year baseline consumptions, i.e., 6,596,358 kWh. The investor and the stakeholders are the same party in this project, i.e., the government as the building owner. The financial benefit of the project thereby lies in the cost saving from the saved energy as well as from the investor taking into account the maintenance cost as part of the investment. Therefore, the overall investment is the summation of the initial installation cost and the maintenance cost during operation. The cost saving from the energy saving is considered the main income of the project. The calculation of NPV takes into account these two cash flows. A full maintenance strategy, i.e., all the malfunctioning items are repaired during the maintenance, is introduced as the baseline performance.

The specifications of the retrofits are illustrated in Table 1. There are 5 categories of retrofits involved, including the motion sensors, the 20 W retrofit compact fluorescent lamps (CFL), the 23 inch LCD monitors, the 3 kW heat-pumps and the 23 L microwave ovens. The retrofitted items corresponding to the same homogeneous class are from one item group. The population degradation of the item groups of motion sensors, 20 W CFL and 23 inch LCD monitors are corresponding to the population degradation model in Eq. (13), and item groups of heat-pumps and microwave ovens the degradation model in Eq. (14). Table 1 indicates different performance characteristics of the retrofits, including the prices to apply the retrofit to one item, the energy savings and cost savings per retrofitted item, and the corrective maintenance costs to replace or repair one malfunctioning item. To be noticed, the illustrated energy savings and cost savings are the annual average values. Table 1 also indicates the type of the population degradation model that corresponds to the retrofit, and the quantities of the retrofitted item involved in this energy efficiency retrofitting project, i.e., the initial state $\mathbf{x}_0$. The

Table 1
Characteristics of involved retrofits.

Pre-retrofitting	Retrofits	Type	Quantities	Unit price ($)	Unit energy saving (kWh)	Unit cost saving ($)	Corrective cost ($)
No motion sensor	Motion sensor	I	123	196	1140	121.1	196
Halogen classic 75 W	20 W retrofit CFL	I	408	14	105.6	11.9	14
Old CRT monitor	23 inch LCD monitor	I	250	150	87.8	10.8	150
Electrical geyser	3 kW heat-pumps	II	85	1250	8640	973.3	201
Inefficient oven	23 L microwave oven	II	35	88	72	8.3	45

Table 2
Parameters for the corresponding population deterioration models.

Retrofits	Type	MTTF/MTBF	b_i	c_i	ζ_i
Motion sensor	I	1.13	1.299	0.895	N/A
20 W retrofit CFL	I	1.49	1.2165	0.9494	N/A
23 inch LCD monitor	I	2.71	1.115	0.996	N/A
3 kW heat-pumps	II	2.08	N/A	N/A	0.24
23 L microwave oven	II	1.98	N/A	N/A	0.25

parameters of the corresponding population deterioration models are given in Table 2.

During the post-implementation period, an inspection will be performed at the end of every 6 months, implying that our decision horizon $k = \{0, 1, 2, \ldots, 24\}$. As above-mentioned, for the sake of the energy conservatism, the inspection result is considered to be the state of the item groups during the prior sampling period [24]. The maintenance actions are scheduled to take place at the end of each year except the last year, i.e., every two sampling periods. Therefore, $Q = \{2, 4, 6, \ldots, 22\}$. The initial investment to implement the retrofitting project is $176,650. The desired payback period is 3 years.

The maintenance planning optimization involves long-term, management level item group performances. The case study involves maintenance actions scheduling over 10-year period. It is infeasible to wait for actual operations during such a long time. We thereby examine the impact of our proposed method by software simulation based on the item group population degradation models in Eqs. (13) and (14). Our simulation involves five different cases, including the no maintenance case that reveals the adverse impact of the deterioration, the full maintenance case that is considered the baseline performance, and three optimal cases that employ different weights. The three optimal cases are: the *Optimal balance* case with $\lambda_1 = 0.5$ and $\lambda_2 = 0.5$, the *Energy prior* case with $\lambda_1 = 1.0$ and $\lambda_2 = 0$, and the *Economy prior* case with $\lambda_1 = 0$ and $\lambda_2 = 1.0$. The *Optimal balance* case shows that the two objectives are equally considered. The *Energy prior* case and *Economy prior* case actually cast the BRFCMP problem into a constrained single objective optimization problem, considering only the energy objective and the economy objective respectively. For the optimal cases, there are two different maintenance budget limits, denoted by tight and sufficient. The tight budget is $125,000 over the sustainability period and the sufficient budget $200,000. The two budget limits imply two different contexts: the tight budget is a proportion of the maintenance costs under full maintenance strategy over the sustainability period, when the sufficient budget is able to cover full maintenance costs. We introduce these two budget limits to examine the effective of our method in different contexts. Performances with different objectives under different budget limits will be given to illustrate the effectiveness of the optimal maintenance strategy and our optimization model. The disturbances are represented by a random noise in our simulation. As system output feedback is employed in the applied MPC approach, this noise is added as a total on the system states. The range of the noise is $\pm 0.1\mathbf{x}(t_k)$.

5.2. Illustrative results and analysis

The performances of the maintenance plan without considering disturbances are illustrated in Table 3. Table 3 illustrates the

Table 3
Comparison of the performances of cases without disturbances.

Cases	Budget limit ($)	Energy savings (kWh)	Percentage saved	IRR	Payback period (years)	NPV ($)	Maintenance cost ($)	Total investment ($)
No maintenance	N/A	2,065,742	4.69%	0.69%	N/A	−18,755.68	0	176,650
Full maintenance	N/A	8,830,340	20.08%	40.54%	2.71	314,556.3	179,223	355,873
Optimal balance	125,000	8,219,041	18.69%	40.56%	2.7	310,439.4	124,963	301,613
Optimal balance	200,000	8,827,172	20.07%	40.65%	2.7	315,168.6	178,233	354,883
Energy prior	125,000	8,219,041	18.69%	40.56%	2.7	310,439.4	124,963	301,613
Energy prior	200,000	8,830,340	20.08%	40.54%	2.71	314,556.3	179,223	355,873
Economy prior	125,000	8,219,041	18.69%	40.56%	2.7	310,439.4	124,963	301,613
Economy prior	200,000	8,737,285	19.87%	40.79%	2.69	318,225.4	162,328	338,978

Table 4
Comparison of the performances of cases including disturbances.

Cases ($)	Budget limit	Energy savings (kWh)	Percentage saved	IRR	Payback period (years)	NPV ($)	Maintenance cost ($)	Total investment ($)
Balance open-loop	125,000	7,685,571	17.47%	38.43%	2.65	274,193.7	125,361	302,011
Balance with feedback	125,000	7,878,323	17.92%	38.78%	2.81	287,191.1	125,179	301,829
Balance open-loop	200,000	8,051,623	18.31%	39.24%	2.64	272,539.8	180,795	357,445
Balance with feedback	200,000	8,810,725	20.04%	40.97%	2.59	307,000.8	196,249	372,899
Energy open-loop	125,000	7,167,616	16.30%	33.54%	3.16	232,309.7	125,585	176,650
Energy with feedback	125,000	7,467,160	16.98%	35.29%	3.05	254,924	124,999	301,649
Energy open-loop	200,000	7,719,358	17.55%	37.33%	2.68	249,480	180,144	356,794
Energy with feedback	200,000	8,674,394	19.72%	39.63%	2.58	293,014.1	199,996	376,646
Economy open-loop	125,000	7,063,163	16.06%	36.69%	2.77	258,692	80,259	256,909
Economy with feedback	125,000	7,512,802	17.08%	37.60%	2.81	277,871.4	94,552	271,202
Economy open-loop	200,000	7,368,024	16.75%	36.04%	2.73	233,466.1	165,144	341,794
Economy with feedback	200,000	7,640,285	17.37%	39.55%	2.71	282,598.7	112,158	288,808

following information: the aggregate energy saving (kWh) and the percentage saving in comparison with the energy baseline, the IRR, the payback period (years), the NPV ($), the maintenance cost ($) and the total investment of the project ($). First of all, the performances where no maintenances are applied, are unacceptable. The no maintenance performances are illustrated to manifest the important role of maintenance. Then the full maintenance performances are given as the baseline performances. The performances of the *Optimal balance* case, *Energy prior* case and *Economy prior* case with different budget limits are illustrated following the full maintenance performances. An interesting result can be observed from the cases with sufficient budget. In the *Energy prior* case, the solutions are same with the full maintenance solution. In the *Optimal balance* case, the IRR is slightly improved with a little lose of the energy saving. Even in the *Economy prior* case, there are no significant differences. Such performances imply that, when budget is sufficient, the full maintenance strategy is one of the best choices. However, in practice, the maintenance budget can often be insufficient to support full maintenance strategy. In cases with tight budget limits, maintenance plan optimization is necessary. In our case study, the obtained optimal maintenance plans in the three optimal cases with tight budget are the same one. This reveals that the two objectives employed in our optimization model are not very contradictory. The energy savings are well preserved while the maintenance costs are significantly reduced in comparison with the full maintenance case. The performances of the optimal maintenance plan with tight budget limits verify the effectiveness of our optimization method.

Table 4 illustrates the performances of the maintenance plan under the impact of uncertainties, where the *Balance open-loop*, *Energy open-loop* and *Economy open-loop* represent that, in these cases, the open-loop maintenance plans that are obtained without considering uncertainties are applied when there actually are uncertainties during operation. In contrary to the open-loop cases, *Balance with feedback*, *Energy with feedback* and *Economy with feedback* represent that the applied maintenance plan are obtained via the control system approach with state feedback. The random noises in the corresponding open-loop cases and with feedback cases are the same for a clear comparison of the performances. Generally, from Table 4, the performances in with feedback cases outperform the ones in open-loop cases, showing that the proposed control system approach is robust against uncertainties. The results can prove the effectiveness of the control approach to reduce the adverse impact of uncertainties during operation.

Figs. 1–6 illustrate the energy and economy performances of the *Balance with feedback*, *Balance with feedback* and *Economy with feedback* cases, where the performances are influenced by uncertainties. The energy savings and cash flows during each sampling interval in the three cases are illustrated. In Figs. 1–3, the thin dashed lines represent the performances in the with feedback cases. In contrary to the maintenance plan with feedback,

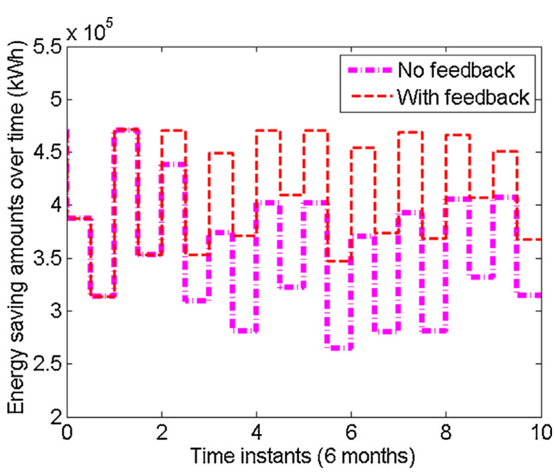

Fig. 1. Energy performances of the maintenance plans with and without feedback in *Optimal balance* case with sufficient budget.

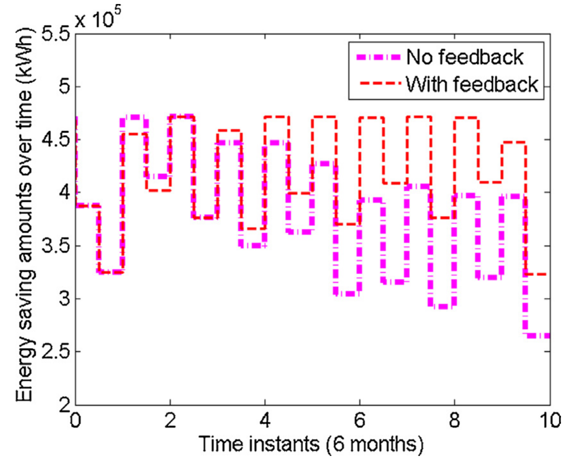

Fig. 2. Energy performances of the maintenance plans with and without feedback in *Energy prior* case with sufficient budget.

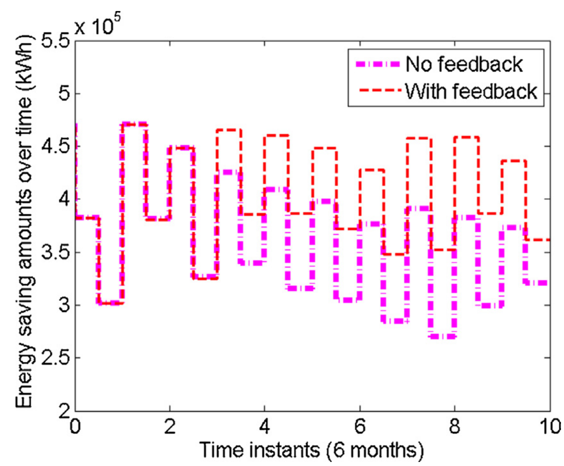

Fig. 3. Energy performances of the maintenance plans with and without feedback in *Economy prior* case with sufficient budget.

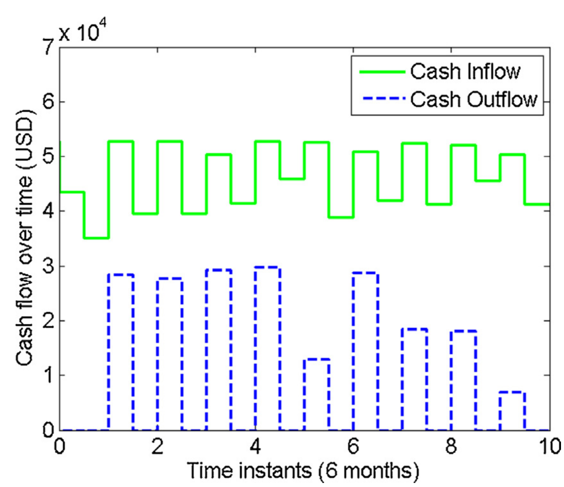

Fig. 4. Cash flows of the maintenance plans with feedback in *Optimal balance* case with sufficient budget.

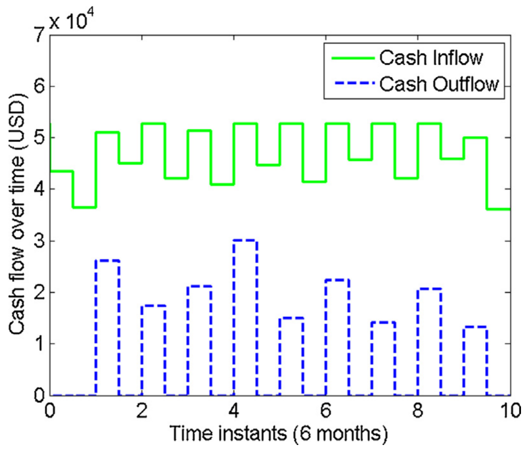

Fig. 5. Cash flows of the maintenance plans with feedback in *Energy prior* case with sufficient budget.

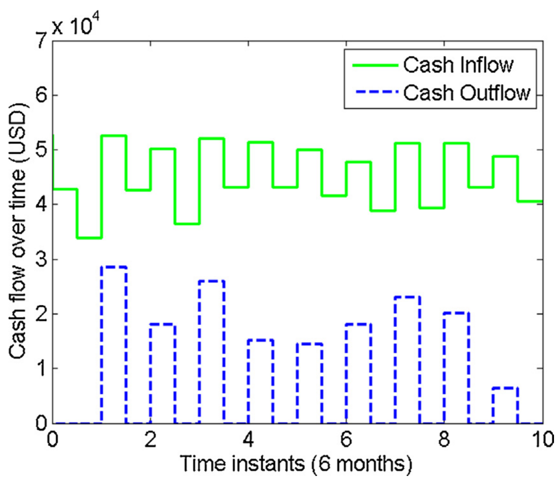

Fig. 6. Cash flows of the maintenance plans with feedback in *Economy prior* case with sufficient budget.

the thick dashdot lines represent the energy savings from the open-loop cases, showing that the open-loop maintenance plan lose more energy savings with uncertainties during operation. In Figs. 4–6, the cash flows from the with feedback cases are chosen to be illustrated. The solid lines represent the cash inflows and the dashed line the cash outflows which indicate the level of the corrective maintenance efforts during operation. Fig. 7 compares the performance measures of the following cases under the tight budget limit, i.e., $125,000: the *Optimal balance* without disturbance or with feedback control, and the *Full maintenance* strategy without disturbance or with feedback control. The *Full maintenance* strategy is applied until the entire budget is used. The performance measures are normalized for a clear demonstration. From Fig. 7, the optimized maintenance plan outperforms the full maintenance strategy with limited budget. The effectiveness of the maintenance plan optimization method is thereby illustrated.

6. Conclusion

The main work of this paper is to investigate the important role of maintenance to the building energy efficiency in the building energy efficiency retrofitting context, and the potential of improving the performances of an energy efficiency retrofitting project by the maintenance plan optimization. A subproblem namely the Building Retrofitted Facilities Corrective Maintenance Planning (BRFCMP) is adopted as our subject investigated at the current stage. An aggregate population level optimization model is proposed to address the BRFCMP problem without taking into account the uncertainties. Given the BRFCMP a problem succeeding the retrofitting planning optimization that is often multi-objective, two objective are introduced in the optimization model: maximizing the long-term aggregate energy saving over the sustainability period and maximizing the internal rate of return of the project. The objective functions are formulated according to a series of performance measures, and a weighted sum method is employed as the solution to the multi-objective optimization problem. Moreover, when taking into account the uncertainties that can deliver adverse impact to the actual performances of the project, the control system approach as an unexplored perspective is introduced, where the optimization objectives are transformed into the control objectives. A model predictive control (MPC) based approach is employed to solve the BRFCMP optimal control problem.

A practical building retrofitting project is used to test and verify the feasibility of the presented optimization and control approaches, and the simulation results reveal that, when the budget is sufficient, the full maintenance strategy that have all the malfunctioning items repaired becomes the best option. However, the

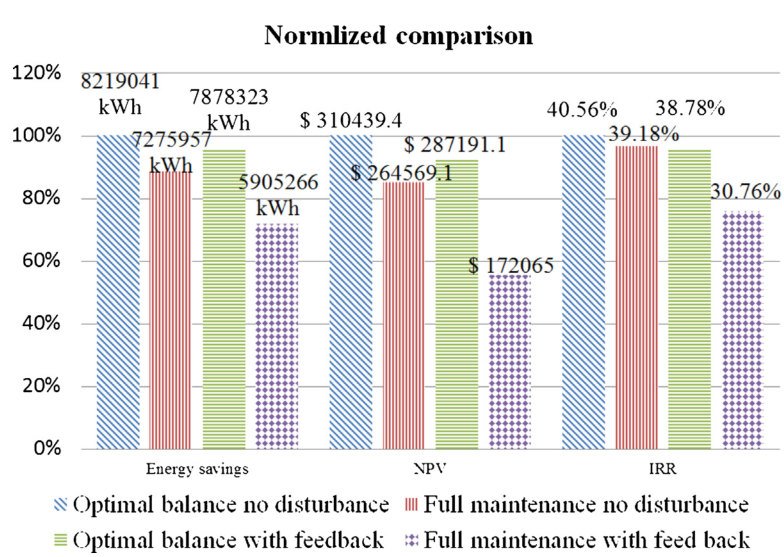

Fig. 7. Performances comparison between the *Optimal balance* and full maintenance under same budget condition.

proposed optimization method can preserve the performances while the cost is significantly reduced. Taking advantage of the proposed method, the objectives can be well achieved with tight maintenance budget limit. Furthermore, the performances of the maintenance plans with feedback outperform the open-loop strategy performances, showing robustness against uncertainties. The effectiveness of the optimization and control approaches is thus verified.

Several topics call for further studies on the investigated topic: the retrofitting planning optimization can be combined with the maintenance planning optimization; the robustness of the classification of the retrofitted facilities remains an open problem; the uncertainties factors are possible to be recognized and taken into account in the optimization; the operating schedule optimization can be introduced to further improve the building energy performance. Relaxing the assumption that maintenance actions are kept within the homogeneous class of facilities may call for new modeling and control of systems of varying dimensions.

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