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Review article

Control problems in building energy retrofit and maintenance planning☆

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ABSTRACT

This paper presents a series of control problems in prioritizing building energy retrofit and maintenance plans through a review of recent studies. The building energy retrofits can be strategically performed on policy level, management level, system level and unit level. Based on existing research efforts, this study casts the optimal building maintenance planning problem into a general control system framework. Unlike traditional control applications, this study argues that the control system framework is also applicable to the building energy management level, which will significantly improve the sustainability of realized energy savings and cost-effectiveness of building energy retrofits. In a general control framework, a number of research problems in the control systems are formulated, namely 1) control system decay dynamics modeling; 2) control system inputs and model uncertainties; 3) control system outputs; 4) control system uncertainties and disturbances; 5) control system algorithms; and 6) grouping and modeling. The proposed control problems bring out the intrinsic relationship of reliability engineering, maintenance engineering and control engineering in the broad directions of energy efficiency and optimization. Investigations into the proposed control problems will contribute to further improvements in the building energy retrofit and maintenance plans than the currently prevailing engineering practice.

1. Introduction

Developments of building energy efficiency technologies enable various optional energy conservation measures (ECMs) to improve the building energy performance. However selection of prioritized ECMs for a building retrofit plan is very challenging due to technical barriers and financial barriers. The building energy retrofits can be strategically performed on policy, management, system and unit levels with different aspects of addressing a spectrum of financial and technical barriers. Technically, building energy retrofit is a lengthy process that includes energy audit, baseline development, retrofit planning, implementation and commission, operations and maintenance (O&M), and measurement and verification (M&V). The complexity of an effective building energy retrofit demands a non-trivial amount of information and expert knowledge about building construction, operation, and energy consumption before and after the retrofit. Financially, cost-effectiveness is usually the first concern of a building energy retrofit plan. The achievable energy and cost savings are the primary attractions to the building retrofit investors and building owners. In buildings, such energy and cost savings can be achieved from many components or subsystems. As a complex system, there are many components that pertain to power generation, building materials and envelope, electricity appliances, water consuming appliances, etc. One or several of such components can comprise a subsystem that provides additional and enhanced functionality to the building. In the building context, many such subsystems can be identified to present energy efficiency opportunities. These energy efficiency opportunities are roughly categorized into four technical functional layers, namely the power electronics layer, smart appliance layer, energy flow layer and planning layer. The power electronics layer involves energy optimization that focus on the maintaining and improving the power quality (Abo-Al-Ez, Elaiw, & Xia, 2014; Esmaeli, 2016; Liu, Zhang, Wang, & Wang, 2014; Mokgonyana, Zhang, Zhang, & Xia, 2016; Nikkhajoei & Lasseter, 2009; Sao & Lehn, 2005; Wilson, Robinett, Weaver, Byrne, & Young, 2016; Yu, Khambadkone, Wang, & Terence, 2010), which is essential to guarantee the performances of all electricity consuming components in the building. The smart appliance layer improves the building energy efficiency by bringing in energy efficiency intelligence to the appliances in addition

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to the built-in control logic (Arens, Federspiel, Wang, & Huizenga, 2005; Bijker, Xia, & Zhang, 2009; Catherine, Wheeler, Wilkinson, & de Jager, 2012; Mei, Zhu, & Xia, 2015a; 2015b; Portmess & Tower, 2015; Setlhaolo & Xia, 2015; 2016; Setlhaolo, Xia, & Zhang, 2014; Stavropoulos et al., 2015; Stavropoulos, Koutitas, Vrakas, Kontopoulos, & Vlahavas, 2016; Wang, Zhang, & Xia, 2013). The energy flow layer focuses on the energy efficiency opportunities from balancing different energy sources (Elaiw, Xia, & Shehata, 2012; 2013; Ntsaluba, Zhu, & Xia, 2016; Nwulu & Xia, 2015a; 2015b; 2015c; 2017; Sichilalu, Tazvinga, & Xia, 2016; Sichilalu & Xia, 2015a; 2015b; Tazvinga, Xia, & Zhang, 2013; Tazvinga, Zhu, & Xia, 2014; 2015; Wu, Tazvinga, & Xia, 2015a; Xia & Elaiw, 2010; Xia, Zhang, & Elaiw, 2009; 2011; Zhang & Xia, 2011; Zhu, Tazvinga, & Xia, 2015). The planning level actually contributes a series of investment decisions and budget competitions at the building energy management level to improve the overall cost effectiveness, or overcoming the financial barrier of an energy efficiency project, e.g., a retrofit project (Malatji, Zhang, & Xia, 2013; Wang, Xia, & Zhang, 2014; Wu, Wang, & Xia, 2016; Wu, Xia, & Wang, 2015b). Although huge amount of studies have been conducted at the first three layers, in particular, in the framework of a control system (Xia & Zhang, 2010; 2011; 2015; Xia, Zhang, & Cass, 2012; Xia & Zhang, 2016), there lacks a systematic method to model, evaluate and optimize the building retrofit plans at the management level. Furthermore, perceived uncertainty in realized energy savings and the risk of underachieving the projected savings prevent investors and building owners from pursuing a building retrofit. At the current stage, the building energy guideline (USDOE, 2011) indicates that the energy savings of the building energy retrofit actions are quantified by the M&V process. But the verified energy savings usually couple with uncertainties from measurement, sampling and modeling efforts during the M&V process (Carstens, Xia, Zhang, & Ye, 2013; Xia & Zhang, 2013; Ye & Xia, 2014; 2016; Ye, Xia, & Zhang, 2013; 2014).

In order to facilitate the building energy retrofit, a number of energy efficiency (EE) incentive programmes and policies have been implemented to address both the technical and financial barriers, such as clean development mechanism (CDM) (Michaelowa & Jotzo, 2005), tradable white certificate (TWC) scheme (Bertoldi & Rezessy, 2008; Mundaca, 2007), demand side management (DSM) programmes (Eskom, 2011), and performance contracting (Mozzo, 1999). Taking advantage of the EE programme incentives usually improves the building energy retrofit projects' cost-effectiveness when regulations of the EE programmes are properly followed. In general, accuracy and persistency of the achieved energy savings are the major concerns in these EE programmes' crediting period. However, the energy savings from most building retrofit projects are often not sustainable given that the retrofitted EE devices will fail over time. On identification of the device failures, some existing EE programme guidelines apply a penalty factor during the energy savings accounting process instead of requiring direct maintenance activities to correct the devices failures. For instance, the CDM guidelines (UNFCCC, 2007; 2010) apply a penalty factor, which is called lamp failure rate (LFR) to the energy savings calculation and further restrict that no project rebates will be issued to the implemented projects when 50% of the initial population is failed during the project crediting period. Under these rules, the lighting projects are only considered sustainable when the survived lighting population is equal to or greater than 50% of their initial population by proper maintenance. Some latest designed lighting project guidelines UNFCCC (2011; 2012) request to perform continuous replacements of all the failed lamps. Practically, the following barriers hold the investors and building owners back from performing such a full maintenance policy. Firstly, the full maintenance is not easily implementable due to the demand of continuously monitoring and sampling the lighting devices' working conditions. Secondly, the maintenance activities also require additional investments for the procurement and installation of the new lighting devices. The extra investments sometimes contribute to a tighter project budget.

Since neither the "no maintenance" nor the "full maintenance" policy is preferable to the investors and building owners, it is thus interesting to design an optimal maintenance plan to the whole building energy retrofit process to improve its cost-effectiveness. The optimal maintenance planning (OMP) problem can be aptly formulated under the control system framework as a control problem. The control system framework is applicable for this purpose since the population decay dynamics of the retrofitted EE devices are characterized and modeled as state space equations. The population decay dynamics are taken as the plant of the control system. In order to achieve sustainable energy savings and maximum project profits, it is recommended to optimally control/replace a number of failed EE devices during each maintenance interval. The number of failed items to be replaced is taken as the control variable of the control system. As different EE technologies have different population decay dynamics and different rebate tariffs, the control inputs can be optimally decided based on the investors and building owners' budget availability.

Formulating the OMP problem into control problems exhibits following advantages. Firstly, under the control system framework, classic control theories and methodologies can be applied to improve the designed maintenance strategy. Secondly, applying the control system approach to solve the OMP problem on the building energy management level significantly improve the sustainability of realized energy savings and cost-effectiveness of building energy retrofits when comparing to traditional control applications in the building energy retrofit areas. Thirdly, the proposed control system approach also brings out the intrinsic relationship of reliability engineering and control engineering. One major issue to design the optimal maintenance plan is to characterize the population decay and performance deterioration dynamics of the building EE devices, where some deterministic or stochastic models of energy device reliability can be found in the existing reliability engineering studies. For instance, a series of common failure distributions, reliability and hazard rate functions for EE devices with various reliability characteristics are provided by O'Connor and Kleyner (2011), according to which the population degradation of various types of retrofitted items, e.g., the non-repairable products and the repairable products, can be characterized. In addition, the new applications of maintenance activities for EE purposes by the control system approach also bring new developments in the reliability engineering field, such as investigations and model developments on the population decay or performance degradation of various EE building appliances. The relevant research progress in the reliability engineering area will facilitate the control applications in improving the building EE managements, and vice versa.

Based on existing research efforts in the literature, this study casts the optimal building maintenance planing problem into a general control system framework. From the general control formulation, a number of research problems in the control systems are systematically discovered, namely 1) control system decay dynamics modeling; 2) control system inputs and model uncertainties; 3) control system outputs; 4) control system uncertainties and disturbances; 5) control objective function formulation; 6) control system algorithms; and 7) grouping and modeling. Furthermore, a case study is given to illustrate the application of control system framework in practical OMP problems. Detailed research proposals will be given in next section.

2. Control problems in building energy retrofit and maintenance

In this section, the OMP problem is mathematically formulated under the control system framework. Thereafter, the control prob-

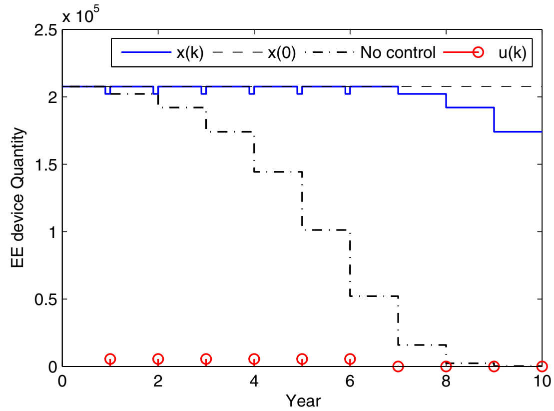

Fig. 1. Optimal maintenance strategy of a lighting retrofit project.

lems that related to the OMP problems are identified systematically, which are introduced in detail in the following subsections.

2.1. Beginning of the story

The idea to use control approach to solve the building energy retrofit and maintenance problem starts with a large-scale lighting retrofit project. To keep the story simple but interesting, only part of the whole project is introduced below. A lighting retrofit project that aims to reduce the lighting load in a fleet of commercial buildings is going to be implemented. A number of 207 693 energy efficient LEDs will be installed to replace existing inefficient halogen downlighters (HDLs). The LEDs must have very high quality with a rated life of equal to or more than 6 years. As an energy efficient project with new technologies, project developers (PDs) will receive a rebate of R[1] 0.55 per kWh savings realized from the implementation of this project. More project details from the energy audit of this project are found in Ye, Xia, Zhang, and Zhu (2015).

Scope of this project sounds easy, however PDs must comply with following general project regulation policies in order to receive their project rebates.

1. PDs will have implement the project at their own cost.
2. The crediting period of this project is 10 years during which PDs can receive their rebate on annual basis. All newly installed EE devices must be properly maintained. If more than 50% of the LEDs is malfunctioned, the rebate will be ceased.
3. The performance of the project will be reported once a year by a third-party M&V inspection company. This M&V company verifies the number of survived lamps by sampling and surveys. Once device failures are observed, PDs' are allowed to replace some (or all) of the failed EE devices at the end of each crediting year.

The first item on the programme policy makes the project a risky project since the PDs have to deposit a big amount initial investment. According to intensive project performance evaluation experience, professional M&V practitioners help the PDs design an optimal maintenance plan to replace a number of failed lamps at end of each year. The replacements keep the project rebate sustainable and ensure the savings' persistency of this project. At end of the project, PDs receive their maximum profits and the project produces its maximum energy savings. The M&V practitioner's strategy is illustrated in Fig. 1, in which the circled stems (in Red) denotes the number of replacement of failed LEDs at end of each year. The solid step lines (in Blue) represents the survived LEDs with replacements. The dash-dotted lines (in Black) show the survived LEDs would have been observed without replacements of failed ones. When looking at this figure, the PDs realize that they may only be able to claim rebates on project savings over the first 5 years due to unattended LED failures. The replacements of the failed lamps save the life of this project but necessary cost will be incurred for the rescue. To make final decisions on the project investments, the PDs asked the following immediate questions:

1. How many lamps have to be replaced? How do they cost, and when to replace?
2. If the replacements are helpful to generate more energy savings and rebates, then shall all the failed LEDs to be replaced at end of each year to produce the maximum benefits in terms of both energy savings and financial rebates?
3. If the M&V professional's maintenance plan helps with this lighting retrofit project, could more maintenance plans to be designed for other building energy retrofit projects with water heating devices, HVAC systems, plug-loads, and building envelopes?

2.2. General control system framework

Formulation of the general framework is introduced as follows. Let a large-scale building energy retrofit project to be implemented in a fleet of buildings, this project aims to replace N units of inefficient building appliances by energy efficient ones. The project is financially supported by local government through an incentive EEDSM programme, which awards an energy saving crediting period of 10 years for each implemented project. The programme regulations further request that the survived project population needs to be carefully maintained to guarantee the sustainability of the projected energy savings. Let t_0 and t_f denote the beginning and end of the project crediting period, respectively. I denoted the number of homogenous groups of the lighting population. $x_i(0)$ denotes the quantity of the initial installation of the EE devices in the ith group. Generally, the OMP problem is to find the optimal control sequences $\mathbf{u} = [u_1, u_2, \ldots, u_I]^T$ within the project crediting period. Here u_i is the control system input, which represents the number of replacements of the failed EE devices during each maintenance interval in the ith group. Then the OMP problem under the control system framework is formulated as:

$$\begin{cases} \dot{x}_i = f_i(\mathbf{x}, \mathbf{u}) + d_i, \\ y_j = h_j(\mathbf{x}) + \omega_j, \end{cases} \tag{1}$$

where $\mathbf{x}$ denotes the state variable that corresponds to the number of survival EE devices for each maintenance interval. The control system output y_j can be expressed by the sampling and measurement result of $\mathbf{x}$. $f_i(\cdot)$ denotes the function to characterize the project population decay dynamics. In addition, d_i and ω_j denote the modeling uncertainties and measurement disturbances, respectively. In the following subsections, each component in Eq. (1) will be discussed and relevant control problems will be identified for future research.

2.3. Control system decay dynamics modeling

In order to solve the OMP problem by a control system approach, the population decay dynamics model $f(\mathbf{x}, \mathbf{u})$ in Eq. (1) needs to be characterized. This links to the classic control system dynamics modeling problem, but in a new engineering field. Desired research efforts in this area can be summarized as to develop and validate a series of population decay dynamics and energy performance degradation models for various building appliances. Generally, building energy appliance are categorized into reparable and non-reparable ones. A repairable appliance can have

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multiple minor failures and be repaired before becoming salvaged. Air conditioners, heat pumps or printers are repairable appliances. A non-repairable item can only experience one catastrophic failure before the salvage. A replacement is required to remove such failure. CFLs or motion sensors are non-repairable appliances. The failure rates of the repairable and non-repairable items are usually different. The repairable and non-repairable classification is investigated at the current stage, and it is believed that there are many other available classifications in different scenarios, which remain uninvestigated. Consequently, two types of models can be developed to characterize the control system decay dynamics, namely population decay models for non-reparable failures and energy performance degradation models for reparable failures. The population decay dynamics models investigated here are merely a small part of a broad field of the reliability engineering. There are many other available models, corresponding to different categories of EE devices. It is expected that the research progress in the reliability engineering area will facilitate the advance of building energy optimization studies, and vice versa.

In our studies, we have come across non-reparable population decay models, such as the clean development mechanism (CDM) linear lamp population decay model (UNFCCC, 2010), CFL population decay model from the PELP study (Navigant, 1999), as well as reparable population decay models, such as the solar panel performance degradation model (Fan & Xia, 2015; 2017) and the exponential population decay model (Wang & Xia, 2015b), and possibly hybrid models such as the population decay models including interactive energy systems (Wang & Xia, 2015a) and a multi-stage performance degradation model (Wang, Wu, & Xia, 2017).

A linear lamp population decay model is proposed in the AMS-II.J (UNFCCC, 2010) as given in Eq. (2)

$$f(t) = \begin{cases} t \times H \times \frac{100-Y}{100 \times L}, & \text{if} \quad t \times H < L, \\ 100\%, & \text{if} \quad t \times H \geq L, \end{cases} \tag{2}$$

where $f(t)$ denotes the percentage of lamps that fails to work in the t-th year since installation, H is the annual average operating hours, L is the rated life span (in hours), and when $t \times H \geq L$, $f(t) = 100\%$, all lamps are deemed to be failed.

In Fan and Xia (2015), a function $E(t)$ is applied to characterize the solar panel linear output degradation over years, where

$$E(t) = -0.007(t-1) + 0.98. \tag{3}$$

An exponential degradation model is investigated to model the repairable failures in O'Connor and Kleyner (2011) and applied in the studies (Wang & Xia, 2014; 2015b), as shown in Eq. (4),

$$x(k) = x(0)e^{-\zeta_i k}. \tag{4}$$

The state space form of Eq. (4) is

$$x(k+1) = x(k)(1-\zeta_i), \tag{5}$$

or in continuous time,

$$\dot{x} = -\zeta_i x,$$

where θ_i denotes the Mean Time between Failures (MTBF) of the EE items, and ζ_i is calculated by:

$$\zeta_i = (\theta_i)^{-1}. \tag{6}$$

Although widely used, the models (2)–(5) are not accurate enough to characterize the lamp population decay dynamics due to unrevealed model uncertainties. For instance, the model (2) assumes a constant failure of the lighting devices, which turned out to be inaccurate from the PELP study report (Navigant, 1999). The model (3) assumes a constant performance degradation rate of the solar panels given that model does not consider the actual installation position and weather conditions of the solar panels. As commented in Carstens et al. (2013) and Carstens, Xia, and Ye (2014), the model (5) is also inappropriate to assume a constant hazard rate of the EE lighting devices.

In order to improve the model accuracy of the population decay dynamics of the EE devices, studies Carstens et al. (2013), Carstens et al. (2014) offer informative reviews on the existing lamp population decay dynamics models (Navigant, 1999), and also proposed a general form of the population decay dynamics model by recalibrating existing models established from biological population dynamics study or from reliability engineering experiments. The general form of the model is provided in Eq. (7).

$$s(t) = \frac{1}{c + ae^{bt}}, \tag{7}$$

where $s(t)$ is the percentage of survived devices at time t for a lighting project, t is counted from the implementation of a lighting retrofit project. $a = e^{-L}$ and L is the rated average life span of a certain model of the EE devices. The rated average life span is declared by the manufacturer or responsible vendor as being the expected time at which 50% of any large number of EE devices reach the end of their individual lives (UNFCCC, 2010). b is the slope of decay and c is the initial percentage lamp survival at $t = 0$. Thus, with a given L, b and c can be obtained by solving the following equations:

$$\begin{cases} s(0) = 1, \\ s(L) = 0.5. \end{cases} \tag{8}$$

The model (7) is more advantageous than the models (2)–(5) as it has a validated model uncertainty quantified by R^2=0.996. The model (7) has acceptable accuracy level to describe the population decay dynamics due to non-reparable failures. An equivalent biological population dynamic model was proposed in Carstens et al. (2014, 2013) as the following:

$$\frac{\mathrm{d}s(t)}{\mathrm{d}t} = -bs(t)(1 - cs(t)), \tag{9}$$

or in its discrete-time form,

$$s(k+1) = bc(s(k))^2 \Delta t - bs(k)\Delta t + s(k). \tag{10}$$

In practice, energy performance of some EE devices does not simply drop from a good condition to a sudden failure. Failure mechanisms of the EE devices may experience a series of performance degradation process in real cases. For instance, energy performance of EE devices may have multiple functional stages such as good status, average status, bad status, and failed status. In addition, proper maintenance actions have to ability to restore the degraded performance into a better condition if taken before the salvage. In order to characterize the performance degradation process of the EE devices, the study (Wang et al., 2017) employs a state-transition model of items from homogenous groups, as shown in Eq. (11). Eq. (11) and Fig. 2 depict a following state transition mechanism. Given a series of discrete time instants t_k, $k = 1, 2, \ldots,$ the working state of an EE device has a possibility to jump to another state over interval $[t_k, t_{k+1})$. In Fig. 2, $P_{l,\,i}(t_k)$, $i \in [1, M_l]$ denotes the probability that this item works under state i at instant t_k. $\lambda^l_{i,i-1}(t_k)$ indicates the state-transition from state i to state $i-1$ over the interval $[t_k, t_{k+1})$. The circle F denotes the malfunctioning state and $P_{l,\,F}(t_k)$ the probability of this item being malfunctioning. $\lambda^l_{i,F}(t_k)$ indicates the state-transition from state i to malfunctioning. As shown in Fig. 2, $P_{l,\,i}(t_k)$ increases due to transition $\lambda^l_{i+1,i}(t_k)$, decreases due to transition $\lambda^l_{i,i-1}(t_k)$ and transition $\lambda^l_{i,F}(t_k)$ simultaneously. $P_{l,M_l}(t_k)$ continuously decreases and $P_{l,\,F}(t_k)$ continuously increases without maintenance. An early study on the production and maintenance control for manufacturing systems (Boukas & Liu, 2001) formulates such state-transition as a partially observable Markov decision process (POMDP), with a hypothesis that the

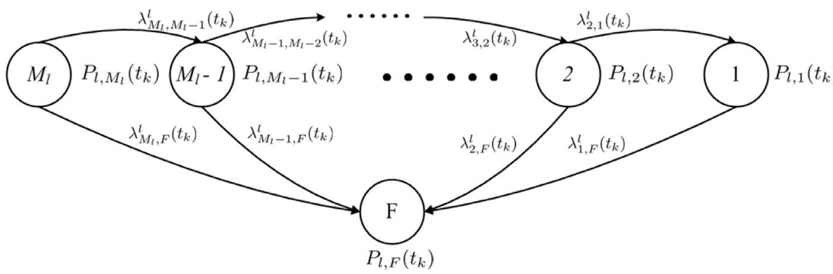

Fig. 2. The state transition of an item with M_l working states (Wang et al., 2017).

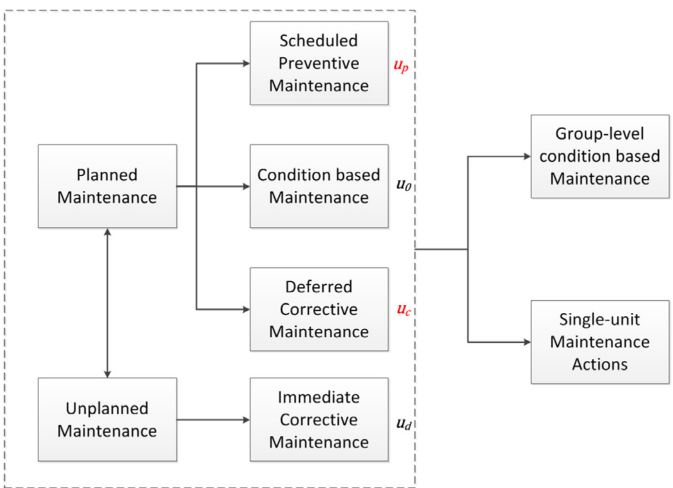

Fig. 3. Control system inputs.

transition rate to the next state depends on the current state. In Wang et al. (2017), it is assumed that for a homogeneous group l of such devices, the population dynamics of group l is commensurate with the individual item state-transition. Taking advantage of the POMDP formulation in Boukas and Liu (2001), the population changes $\triangle x_{l,\,i}(t_k)$ with $i = 1, 2, \ldots, M_l$ in group l are formulated in (11), where $f^l_{i,i-1}(\mathbf{x}_{l,i}(t_k))$ denotes the population change from subset i to subset $i-1$ that is resulted from the transition $\lambda^l_{i,i-1}(t_k)$.

$$\begin{cases} \triangle x_{l,M_l}(t_k) = -f^l_{M_l,M_l-1}(\mathbf{x}_{l,M_l}(t_k)) - f^l_{M_l,F}(\mathbf{x}_{l,M_l}(t_k)) + \sum_{i=1}^{M_l-1} u^l_i(t_k) + u^l_C(t_k), \\ \triangle x_{l,M_l-1}(t_k) = f^l_{M_l,M_l-1}(\mathbf{x}_{l,M_l}(t_k)) - f^l_{M_l-1,Ml-2}(\mathbf{x}_{l,M_l-1}(t_k)) - f^l_{M_l-1,F}(\mathbf{x}_{l,M_l-1}(t_k)) - u^l_{M_l-1}(t_k), \\ \vdots \\ \triangle x_{l,2}(t_k) = f^l_{3,2}(\mathbf{x}_{l,3}(t_k)) - f^l_{2,1}(\mathbf{x}_{l,2}(t_k)) - f^l_{2,F}(\mathbf{x}_{l,2}(t_k)) - u^l_2(t_k), \\ \triangle x_{l,1}(t_k) = f^l_{2,1}(\mathbf{x}_{l,2}(t_k)) - f^l_{1,F}(\mathbf{x}_{l,1}(t_k)) - u^l_{1,M_l}(t_k), \end{cases} \tag{11}$$

The introduced system decay dynamics models (2)–(11) are capable of characterizing the population decay or energy performance degradation dynamics for homogeneous group of EE devices, despite that there are modeling uncertainties involved in these models. In practice, interactive effects are sometimes observed across different EE device groups. For instance, existing study (Ahn, Jang, Leigh, Yoo, & Jeong, 2014) shows that heat gain from lights can significantly influence the energy consumptions of the air conditioning system. In this case, the population dynamics of the lighting group can pose significant impact on the energy performances of the air conditioners. The impact of such interaction is worthy taking into account in the control system dynamics formulation. As introduced in Wang and Xia (2015a), the population decay dynamics of interacting energy systems such as lighting and HVAC systems are formulated as

$$\begin{cases} \dot{x}_L = \hat{f}_1(x_L) + u_L, \\ \dot{x}_{AC} = \hat{f}_2(x_L, x_{AC}) + u_{AC}, \end{cases} \tag{12}$$

where x_L and x_{AC} are the state variables representing the survived lighting and HVAC systems, respectively. $\hat{f}_1(x_L)$ denotes the lamp population decay dynamics and $\hat{f}_2(x_L, x_{AC})$ denotes the HVAC system decay dynamics with the interaction of heating and cooling load from the lighting systems. An assumption is made in Eq. (12) that the HVAC systems have minimum impact to the lighting systems' life span. More details of the formulation and parameter identification in Eq. (12) can be found in Wang and Xia (2015a). Besides the lighting and HVAC system interactions, there are also other interactive effects observed to influence the reliability performance and modeling accuracy of the system decay dynamics. For instance, interactive reliability performance can be observed for a group of EE devices including both the newly retrofitted EE devices and old ones.

2.4. Control system inputs

The OMP problem is indeed an optimal control system input design problem. In the OMP scenario, the control inputs refer to the maintenance actions, which are described by the maintenance intensity and maintenance instant. The term 'maintenance intensity' describes the count of the restored items from one item group at a specific instant. Such instant is referred to as the 'maintenance instant', i.e., a time point at which the maintenance actions are scheduled to take place. The collection of maintenance instants comprise the maintenance time schedule. The maintenance intensity and time schedule are both promising optimization variables to improve the energy efficiency and cost-effectiveness of a retrofitting project.

According to the reliability engineering, there are several types of maintenances, corresponding to different purposes and strategies. At the current stage, a maintenance action classification from BSI (1984) is employed, where maintenance actions are grouped into several categories. As a fact to accommodate various EE devices' failure characteristics and mechanisms, this study proposes four types of control inputs that are commensurate with the maintenance categories, denoted as $u_p(t)$, $u_c(t)$, $u_0(t)$, and $u_d(t)$ as shown in Fig. 3 (BSI, 1984). Apparently, one may also take other classifications for the maintenance actions, which may result in more than 4 types of control inputs but also applicable for the development of an optimal maintenance plan. In addition, other possible control inputs can also be identified rather than maintenance in the building energy retrofit practice.

In Fig. 3, there are unplanned maintenance and planned maintenance. The unplanned maintenance is denoted by $u_d(t)$ that refers to the emergency maintenance action, which usually has to be carried out as an unplanned event after the failure. As a result, the maintenance time schedule are ignored for unplanned maintenance, and it might be beneficial to simply take $u_d(t)$ as input disturbances. Under the planned maintenance category, there are corrective maintenance and preventive maintenance. The planned corrective maintenance (CM) is only conducted after the occurrence of a failure, in order to restore the system into a specific working condition. The CM is denoted by $u_c(t)$. The planned CM is deferrable should the failure not affect the whole production process, i.e., the CM is carried out according to the prescribed time schedule, rather than immediately after the failure. Therefore, the planned corrective maintenance is also called deferred corrective maintenance. Unlike the CM, the preventive maintenance (PM) is carried out before the occurrence of a failure in order to reduce the probability of failure or restore the system from a degraded state to a better working condition. The PM includes both the scheduled maintenance and condition-based maintenance, which are denoted by $u_p(t)$ and $u_0(t)$, respectively. The main difference between $u_p(t)$ and $u_0(t)$ is that $u_0(t)$ must be performed at prescribed time intervals or under pre-set conditions to some fatally important systems, while the $u_p(t)$ can be deferred or scheduled. t specifies the time instant when a maintenance action takes place. Mathematically, a key problem related to the optimal control inputs for the building energy retrofit is to identify the value of $\mathbf{u}(t)$, which is a set of $\{u_p(t), u_c(t), u_0(t), u_d(t)\}$ that tells the intensity, maintenance type and schedule of the required maintenance. In fact, as $u_p(t)$ and $u_c(t)$ are subject to the prescribed maintenance plan, their intensity and schedules can be optimized simultaneously. However, $u_c(t)$ and $u_d(t)$ must be performed either at prescribed time intervals or on occurrence of emergency failures. In the literature, selected research activities to design building OMP by the control system approaches are briefly introduced below.

In studies Wang and Xia (2014; 2015b), optimized corrective maintenance activities are designed of for a broad category of failed EE devices in buildings at pre-decided maintenance time schedule. As illustrated by the case study in Wang and Xia (2015b), maintenance plays an important role to the sustainability of the EE device group population. Comparing the optimal maintenance strategy to the full maintenance strategy, the maintenance cost is reduced up to 30.7% with a loss of 1.5% of the energy savings achieved by applying the optimal maintenance.

As discussed in Section 2.3, the functional conditions of an EE device may range from a number of transition stages from perfect to failure. in Wang et al. (2017), homogeneous group population dynamics and the aggregate performance dynamics under the impacts of multi-state deteriorations and maintenances are formulated as a control system model. In this way, both the corrective maintenance and preventive maintenance are introduced into the OMP problem. Fig. 4 depicts a maintenance plan involving both maintenance actions (Wang et al., 2017). The dashed line (in Blue) indicates the CM actions and the dash-dotted lines (in Red) the PM actions. These maintenance actions are subject to pre-decided maintenance time schedule, and the optimization variables are the CM and PM intensities. In the case study from Wang et al. (2017), when comparing to the maintenance plan without preventive maintenance, the optimal maintenance strategy exhibits 5% additional energy savings and 7.5% improvements on the internal rate of return (IRR).

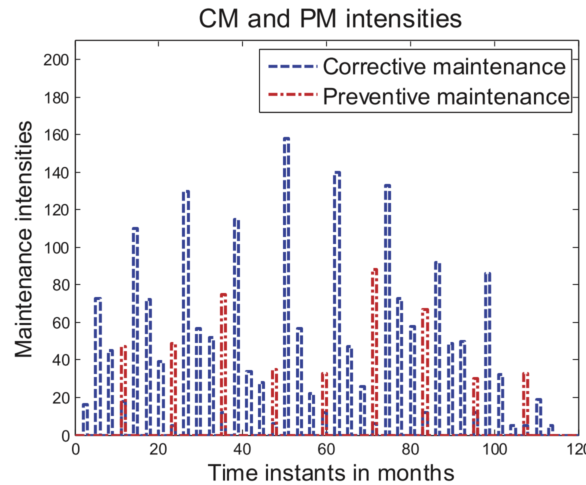

Fig. 4. Optimal maintenance intensities of PM and CM (Wang et al., 2017).

Apart from the maintenance type and intensities, the maintenance time scheduling is another major concern for an OMP problem. Based on the proposed multi-state based performance degradation models in Wang et al. (2017), a maintenance planning taking into account both the maintenance intensities and instants optimization is investigated in Wang, Wu, Zhu, and Xia (2015). Fig. 5 depicts the optimal maintenance intensities under both the scheduled and fixed maintenance intervals according to the case study in Wang et al. (2015). When comparing to the fixed maintenance schedule, the building energy retrofit project can achieve up to 21.7% additional energy savings and 5.7% of improvement on the IRR with the optimal maintenance plan if sufficient budget is provided.

To address the interactions among various building energy systems, the study (Wang & Xia, 2015a) further improves the previous developed maintenance plans. With the considerations of both the energy consumption and reliability interactions between building energy systems, the study (Wang & Xia, 2015a) finds that the optimal maintenance plan is able to provide 8.9% more energy savings and 9.6% improvements on the IRR when comparing to the maintenance activities without considering the interactive effects among building energy systems. The population decay dynamics and the maintenance intensities for the interactive lighting and HVAC systems are provided in Fig. 6.

2.5. Control system outputs

The control system outputs are related to the components y_j and $h_j(\cdot)$ in Eq. (1). For the building energy retrofits, research efforts required for the output y_j may refer to the measurement and sampling of the quantity of survived lamp population, or the M&V of the energy savings, carbon emission reductions, or cost savings of a specific building energy retrofit project. The function $h_j(\cdot)$ can be as simple as a sampling or measurement reading of the state variable $\mathbf{x}$, or a sampling approach, a set of metering instruments to observe y_j, or a performance evaluation process like M&V to determine the energy or cost savings of the building energy retrofit project. In this category, one key research problem is to identify y_j accurately with minimum measurement and sampling efforts, as accurate readings of y_j will contribute to reduce the control system disturbance of d_i and ω_j. More details are elaborated in the next subsection.

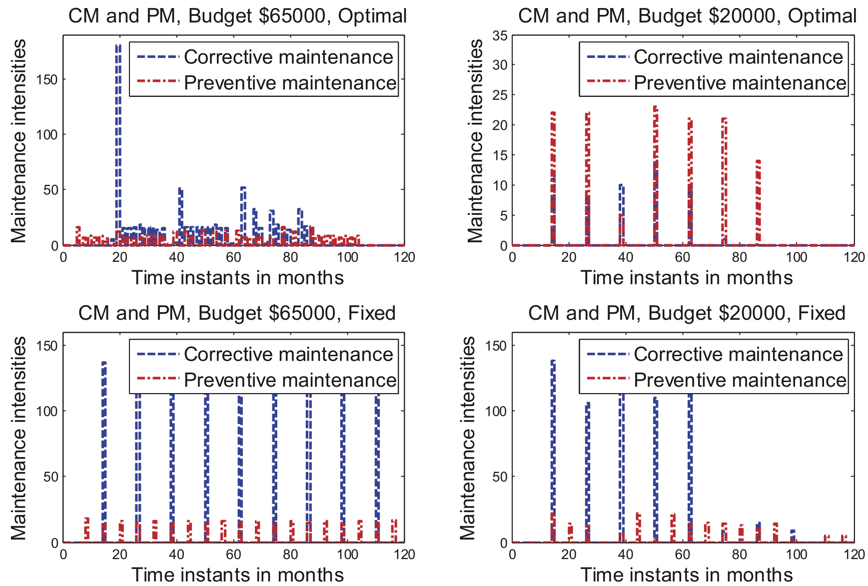

Fig. 5. Optimal maintenance intensities under scheduled and fixed maintenance intervals (Wang et al., 2015).

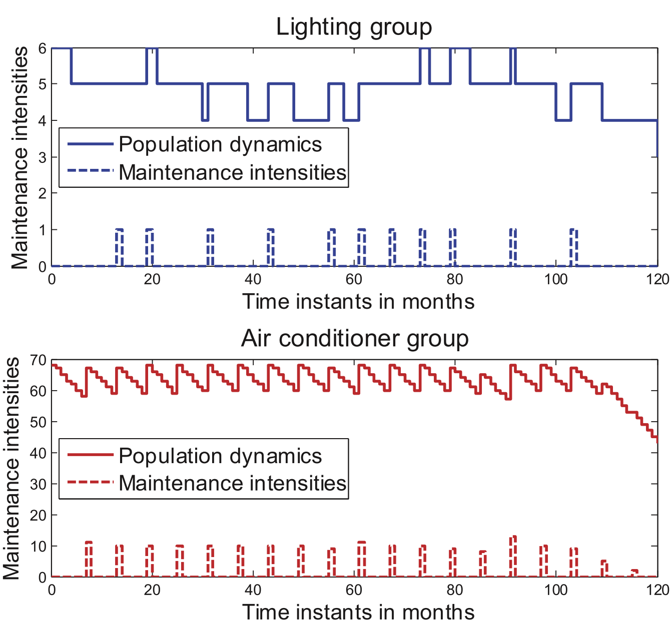

Fig. 6. Optimal maintenance intensities for interactive building energy systems (Wang & Xia, 2015a).

2.6. Control system uncertainties and disturbances

The control system uncertainties and disturbances are denoted by ω_j and d_i respectively in Eq. (1). The ASHRAE guideline (ASHRAE, 2002) introduces that quantifiable uncertainties of energy savings are categorized as modeling uncertainties, measurement uncertainties and sampling uncertainties. Such classifications are also applicable to the control systems as the modeling uncertainties delivers significant impacts to the control system performances. At the current stage, disturbances ω_j and d_i are introduced as simplified interpretations of such impact. These disturbances hereby refer to modeling mismatch of the system dynamics, which are due to the improper mathematical function form, inclusion of the irrelevant variables or exclusion of relevant variables. The measurement and sampling uncertainties are usually observed from the identification of the system outputs. The measurement uncertainties usually come from the inappropriate calibration of the measurement equipment, inexact measurement, or improper meter selection, installation or operation. The sampling uncertainties are resulted from inappropriate sampling approaches or insufficient sample sizes.

In the field of building energy retrofit, uncertainties can deliver further impacts, rather than merely to the control system performances. The relevant research activities focus on cost-effective approach to handle the three independent uncertainties that prevent M&V professionals from precisely evaluating the performances of EE device groups. Existing studies not only address the three uncertainties separately but also in combination. For instance, optimal sampling plans have been designed in Ye and Xia (2016); Ye et al. (2013; 2014) to accurately measure the daily energy consumptions of lighting systems with minimum sample sizes and cost. In Carstens and Xia (2015), the relative contribution of measurement uncertainty to combined measurement and sampling uncertainty is investigated in the context of M&V projects where the whole population is not metered. The study (Olinga, 2015) presents an M&V cost minimization model to handle M&V sampling and modelling uncertainties cost-effectively. The proposed models provide flexibility in designing optimal and easily implementable M&V plans, which either apply more accurate baseline models and fewer sample sizes or less accurate baseline models and greater sample sizes to achieve the same level of M&V accuracy. The research outcomes in the energy field can also be borrowed in the control field, for the purpose of reducing the control system disturbances and uncertainties, which further improves the accuracy and robustness of the control system.

2.7. Objective functions

In the aforementioned OMP problems, the decision maker often takes into account several contradictory considerations that leads to conflicting objectives (Evins, 2013), i.e., the OMP problems are often multi-objective optimizations. The involved objectives usually include maximizing energy savings, minimizing capital costs or maximizing financial paybacks, subject to a series of constraints, e.g., the targeted energy saving limit, budget limit, payback period limit, etc. In order to apply the control system framework in the OMP problems, a weighted sum approach is employed in the aforementioned studies to formulate the objec-

Table 1
Characteristics of retrofitted EE devices.

Retrofits	Quantities	Unit Price ($)	Unit Energy Saving (kWh)	Unit Cost Saving ($)	Preventive Cost ($)	Corrective Cost ($)
15W retrofit CFL	338	14	105.6	11.9	N/A	14
New fan coil units 3	42	380	4320	486.65	N/A	175
New fan coil units 2	0	380	3542.3	397.95	52	N/A
New fan coil units 1	0	380	2651.75	278.35	70	N/A

tive function, where the multi-objective optimization problem is translated into a minimization problem, i.e., a weighted sum of the objectives associated with a non-stationary penalty function. A general form of the objective function formulation is indicated in the following equation:

$$J = -\lambda_1 f_e(\mathbf{x}, \mathbf{u}) - \lambda_2 f_r(\mathbf{x}, \mathbf{u}) + \omega \sum_{n=1}^{k} max(0, P_n), \tag{13}$$

where λ_1 and λ_2 denote the weighting factors. $f_e(\mathbf{x}, \mathbf{u})$ denotes the energy performance indicator, e.g., the overall energy savings during the crediting period. $f_r(\mathbf{x}, \mathbf{u})$ denotes the economic performance indicator, e.g., the net present value (NPV) or internal rate of return (IRR). P_n with $n = 1, 2, \ldots, k$ denotes the penalty functions and ω is a large positive constant that emphasize the effects of the penalty functions. It a constraint is violated, $P_n > 0$. For example, assuming that the targeted energy saving limit, budget limit and payback period limit is involved in an OMP problem. P_n are accordingly defined as following:

$$P_n = \begin{cases} \alpha - ES|_{all}, & n = 1, \\ h|_{all} - \beta, & n = 2, \\ T_p - T', & n = 3 \end{cases} \tag{14}$$

where α denotes the targeted energy saving amount and $ES|_{all}$ the overall energy savings. β denotes the maintenance budget limit and $h|_{all}$ the overall maintenance costs. T_p denotes the actual payback period and T' the payback period limit. According to Eq. (14), $\sum_{n=1}^{k} max(0, P_n) > 0$ if a constraint is violated.

2.8. Control system algorithms

A great advantage to formulate the OMP problem under the control system framework is the applicability of various control system algorithms in finding the optimal controllers with tolerance of a certain level of control system uncertainties and disturbances. For instance, the results obtained by the MPC approach in Ye et al. (2015),Wang and Xia (2015b),Wang et al. (2017) exhibits better economic benefits and energy savings than those obtained by the open loop control approach in response to the added uncertainties in the control system state variables.

Due to different complexity of the control problems, other control system algorithms may also be used to solve the OMP problems. For instance, generic algorithm (GA) has been applied in Malatji et al. (2013) to identify the optimal building energy retrofit proposal, while the differential evolution (DE) approach is used in a series of articles (Wang & Xia, 2015a; Wang et al., 2014) to solve different types of OMP problems under the control system framework. In addition, neighbourhood field optimization (NFO) algorithm is adopted in Wang and Xia (2015b) to solve an multi-objective building energy retrofit and maintenance planning problem.

2.9. Grouping and modeling

Ideally, working status of each EE device over the crediting period would be continuously monitored to enable an opportunity of an immediate replacement on occurrence of a device failure. If the failure dynamics of each involved EE devcie can be monitored and observed, then a control system can be formulated based on the failure dynamics of an individual device. In this case, an N-dimensional control system can be developed that has N failure dynamics models for each device and a number of N control system inputs to record the replacement actions of the EE devices. In addition, the failure dynamics of each EE device involved in the project must also be observed to ensure the operation of the control system. The N-dimensional control system accurately reflects the device population dynamics since all the N units of the EE devices are continuously monitored. Consequently, the optimal maintenance strategy can also be designed and easily implementable to ensure sustainable project savings. However in practice, it is not feasible to continuously monitor the entire project population over 10 years, especially when the project population is large and decentralized. Worse still, the N dimension control system also brings computational burdens in finding the optimal solution.

In order to reduce the modeling cost and complexity of the unit-based control system, it is proposed develop a group-based control system. For each lighting retrofit project, it is recommended to find homogeneous lighting groups according to the devices' technical specification (i.e., model, make, rated power, life span, etc.), energy consumption patterns, and working conditions. For instance, there may be I types of EE devices involved in one building energy retrofit project, and each type of EE device exhibits the same specifications and energy usage patterns, which results in the same lamp population decay dynamics. Then the N lamps can be classified into I lighting groups, and $I \leq N$. Each of such a group consists of devices that are considered to be homogeneous ones, i.e., with the same inherent energy and reliability performances, the same operating schedules and similar operational environment.

The grouping method raises a new question that how different groupings influence the optimization results. Obviously, grouping is an inherently subjective approach. Different decision makers can have different opinions on how to implement groupings. For example, a collection of lamps can be categorized into two groups according to the geographic information or three groups according to the operating schedules. There are many possible relationships between different groupings. For two different groupings corresponding to the same collection of items, there can be overlap, containment or separation among the categorized groups. The number of groups can also be different. As a result of the common utilization of grouping methods in the aforementioned studies, a question is thereby asked: How will different groupings influence the results of the OMP problems? A preliminary theoretical analysis as to the performance robustness of the grouping method is proposed in Wang and Xia (2016). The concept 'performance robustness' is hereby introduced to facilitate the evaluation of the impacts from applying different grouping. For the OMP problems, performance robustness refers to the ability that the control system output sustains when an alternative grouping is applied. More specifically, given a set of same retrofitted items and two different groups, if the results (performances) of an arbitrary maintenance plan based on one grouping remain accessible when the other grouping is applied, the performance robustness is satisfied, and the two groupings are considered equivalent. The satisfaction

Table 2
Maintenance plan performances with optimal and full maintenance strategies.

Cases	Energy savings (kWh)	Percentage saved	IRR	Payback period (years)	NPV ($)	Maintenance cost ($)	Total investment ($)
Optimal maintenance	1395785.8	133.92%	30.95%	2.57	47724.70483	41984	70676
Full maintenance	1306983.15	125.40%	30.74%	2.58	44152.68	41959	70651

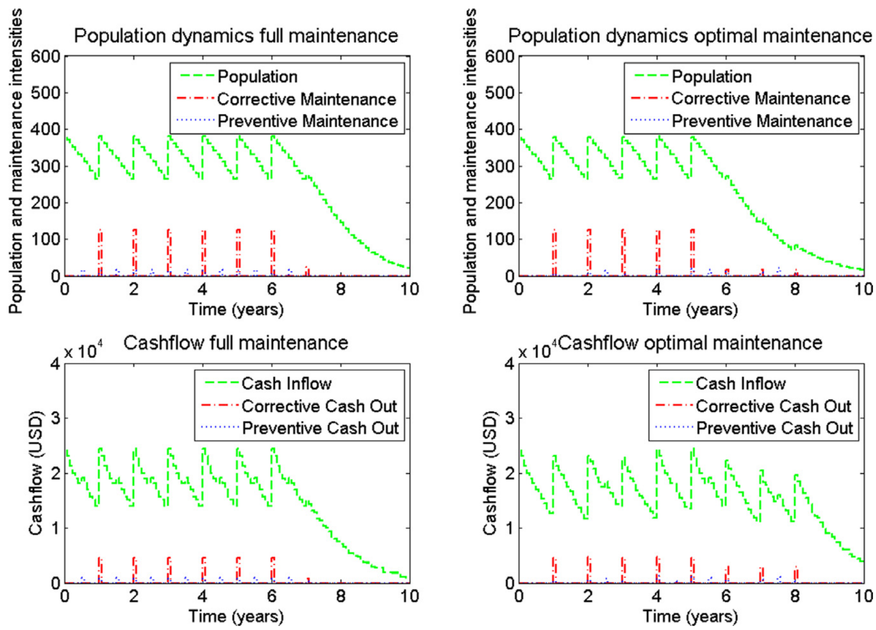

Fig. 7. The population and cash flows from the optimal maintenance and full maintenance strategies.

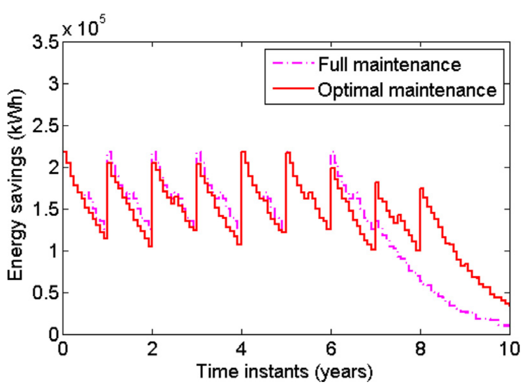

Fig. 8. The timely energy savings over the crediting period.

of the performance robustness provides the decision makers a method to evaluate alternative groupings. In Wang and Xia (2016), a mathematical description of the grouping as well as the grouping based control system formulation is proposed, and a theoretical characterization of grouping robustness is given. Taking advantage of the control system framework of the OMP problems, a distance is defined to evaluate the impacts from applying the grouping method, and a set of alternative groupings can be compared to identify the equivalence between each of them.

Moreover, there might exist an optimal I as the best grouping criterion. More research efforts are expected to find the optimal grouping criterion to minimize the modeling complexity but also ensure the accuracy of the population decay dynamics models.

3. Further discussions

Unlike most of the research articles, this paper formulates the optimal building energy retrofit and maintenance planning problems under the control system framework. Instead of giving more detailed answers to the building energy retrofit planning, this study identifies a number of control system problems that are worthy of future research and investigations. Major contribution of this study is to cast the optimal building maintenance planing problem into a general control system framework. From the general control formulation, the following major research problems in the control systems are discovered, namely

- Control system decay dynamics modeling;
- Control system inputs and model uncertainties;
- Control system outputs;
- Control system uncertainties and disturbances;
- Control system algorithm;
- Grouping and modeling.

The discovered control problems for the building energy retrofit and maintenance planning have been introduced separately in Section 2. However, intrinsic linkages are also observed among these control problems. Given a building energy retrofit project with massive EE devices involved, the grouping criteria to categorize the population into different homogeneous subgroups will influence most of the key factors in the control system formulation. For instance, the homogeneity of each subgroup does influence the system dynamics and will further affect the system state variable selection and system dynamics modeling accuracy. However, quantification of the impacts (i.e., complexity, accuracy) to the control system from different grouping criteria remains an unsolved problem. In addition, the grouping of the project population also decides the measurement and sampling plans to monitoring the projects' energy and financial performance.

3.1. A case study

A case study is given in this section to illustrate the control system framework in practical OMP problems. The case study is selected from a practical building energy retrofit project. There are two groups of retrofitted EE devices. One group consists of a set of compact fluorescent lamps (CFLs) that manifest binary working state. The CFLs are non-repairable items. The other group consists of the air conditioner fan coil units, where three working states are involved. The air conditioners are repairable items. As a result, the multi-state system model introduced in Wang et al. (2017) is employed to characterize the population decay. Due to the space limit, the detailed formulations of the population decay are excluded in this paper and can be found in Wang et al. (2017). Both the planned corrective and preventive maintenance are involved as the control inputs, where the maintenance intensities are the control variables. In this case study, maintenance instants are prescribed by fixed maintenance time schedule.

The specifications and some performance characteristics of the involved retrofitted items are illustrated in Table 1. The new fan coil unit 3, 2 and 1 denote the three working states that correspond with different savings and maintenance costs. The energy saving and cost saving are the annual average value obtained from the energy auditing. The preventive cost indicates the costs of restoring a fan coil unit from working state 2 or 1 to the best working state 3. The corrective cost indicates the costs of restoring one item from failure to normal working.

The crediting period is 10 years. An inspection is performed every month over the crediting period. From the inspection, the The targeted energy saving is 1,042,237.44 kWh. The initial cost is \$28,692. The discount rate for NPV calculation is 11% per year, and the payback period limit is 3 years. The employed budget limit in this case study is \$42,000, which is insufficient for full maintenance strategy. There are 19 preventive maintenance instants and 9 corrective maintenance instants, and the fixed preventive and corrective time schedules $Q_p = \{0.5, 1, 1.5, 2, \dots, 9.5\}$ and $Q_c = \{1, 2, 3, \dots, 9\}$. The unit of the maintenance instants is year. According to the time schedule, the maintenance instants are evenly distributed over the sustainability period. The weighted sum of two objectives: overall energy savings and IRR is employed to be the objective function. The adopted weight factors are $\lambda_1 = 0.5$ and $\lambda_2 = 0.5$, implying that the two objectives are equally considered. More detailed formulations can be found in Wang et al. (2017).

A model predictive control (MPC) controller is designed to solve the OMP problem in the case study. A DE algorithm based numerical solver is employed for the MPC controller. The solutions are illustrated in Table 2. The full maintenance strategy is the comparative baseline. In this case study, the full maintenance will restore all degraded devices to the normal working states until the all budget is consumed. The following performances are selected in Table 2: the overall energy savings during the crediting period (given in kWh), the percentage savings that indicate the ratios against the targeted energy savings, the IRR, the payback period (given in years), the NPV, the total maintenance cost and the overall investment (given in USD). According to Table 2, the optimal maintenance achieves much higher energy savings than the full maintenance strategy. The economic performances from optimal maintenance are also better. This implies that the full maintenance strategy cannot make the best use of the budget. The optimal maintenance provides further opportunities to achieve energy efficiency and cost effectiveness to decision makers. Fig. 7 depicts the population dynamics and cash flows over the crediting period from the two maintenance strategies. Fig. 8 depicts their timely energy savings. Generally, the difference between the two strategies is resulted from their maintenance actions with the air conditioners fan coil units. Due to their high savings and high maintenance costs, the optimal strategy devotes more budget to maintain the working state of the fan coil units. The optimal maintenance strategy appears to be 'smarter' to figure out more efficient options.

4. Conclusions

The ongoing and near future research in the building energy retrofit and maintenance planning by the control system approach are planned as follows: 1) to improved the modeling accuracy of the population decay and energy performance degradation dynamics of various EE devices; 2) to expand the existing population decay and/or energy performance degradation dynamics models for different types of EE devices in the same boundary whose energy usage pattern are interactive and coupling with each other, where decoupling control approaches must be used for the optimal maintenance planning; 3) to investigate the existence of an optimal grouping criterion, which results in minimal dimensions of the control system state variables and maximum control system performance; 4) to design optimal maintenance plans for building envelope retrofits; 5) to develop a software platform that designs optimal building retrofit and maintenance plans for different types of building blocks, for the purpose of maximizing energy savings and minimizing initial investment and payback periods.

References

Abo-Al-Ez, K. M., Elaiw, A., & Xia, X. (2014). A dual-loop model predictive voltage control/sliding-mode current control for voltage source inverter operation in smart microgrids. *Electric Power Components and Systems, 42*(3–4), 348–360.

Ahn, B.-L., Jang, C.-Y., Leigh, S.-B., Yoo, S., & Jeong, H. (2014). Effect of led lighting on the cooling and heating loads in office buildings. *Applied Energy, 113*, 1484–1489.

Arens, E., Federspiel, C., Wang, D., & Huizenga, C. (2005). How ambient intelligence will improve habitability and energy efficiency in buildings. In *Ambient intelligence* (pp. 63–80). Springer.

ASHRAE (2002). ASHRAE Guideline 14: Measurement of energy and demand savings. *Technical report*.

Bertoldi, P., & Rezessy, S. (2008). Tradable white certificate schemes: Fundamental concepts. *Energy Efficiency, 1*, 237–255.

Bijker, A. J., Xia, X., & Zhang, J. (2009). *Active power residential non-intrusive appliance load monitoring system*. IEEE AFRICON 2009, Nairobi, Kenya, 23–25 September.

Boukas, E., & Liu, Z. (2001). Production and maintenance control for manufacturing systems. *IEEE Transactions on Automatic Control, 46*(9), 1455–1460.

BSI (1984). Glossary of maintenance management terms in terotechnology. *Technical Report*. British Standards Institution.

Carstens, H., & Xia, X. (2015). Measurement uncertainty and risk in measurement and verification projects. *Iepec 2015*. Long Beach, California.

Carstens, H., Xia, X., & Ye, X. (2014). Improvements to longitudinal clean development mechanism sampling designs for lighting retrofit projects. *Applied Energy, 126*, 256–265.

Carstens, H., Xia, X., Zhang, J., & Ye, X. (2013). *Characterising compact fluorescent lamp population decay*. IEEE AFRICON 2013, Mauritius, 09–12 September.

Catherine, Q., Wheeler, J., Wilkinson, R., & de Jager, G. (2012). Hot water usage profiling to improve geyser efficiency. *Journal of Energy in Southern Africa, 23*(1), 39–45.

Elaiw, A., Xia, X., & Shehata, A. (2012). Application of model predictive control to optimal dynamic dispatch of generation with emission limitations. *Electric Power Systems Research, 84*(1), 31–44.

Elaiw, A., Xia, X., & Shehata, A. (2013). Hybrid de-sqp and hybrid pso-sqp methods for solving dynamic economic emission dispatch problem with valve-point effects. *Electric Power Systems Research, 103*, 192–200.

Eskom (2011). The measurement and verification guideline for demand-side management projects. *Technical report*.

Esmaeli, A. (2016). Stability analysis and control of microgrids by sliding mode control. *International Journal of Electrical Power & Energy Systems, 78*, 22–28.

Evins, R. (2013). A review of computational optimisation methods applied to sustainable building design. *Renewable and Sustainable Energy Reviews, 22*, 230–245.

Fan, Y., & Xia, X. (2015). A multi-objective optimization model for building envelope retrofit planning. *Energy Procedia, 75*, 1299–1304.

Fan, Y., & Xia, X. (2017). A multi-objective optimization model for energy-efficiency building envelope retrofitting plan with rooftop pv system installation and maintenance. *Applied Energy, 189*, 327–335.

Liu, Y., Zhang, Q., Wang, C., & Wang, N. (2014). A control strategy for microgrid inverters based on adaptive three-order sliding mode and optimized droop controls. *Electric Power Systems Research, 117*, 192–201.

Malatji, E. M., Zhang, J., & Xia, X. (2013). A multiple objective optimisation model for building energy efficiency investment decision. *Energy and Buildings, 61*, 81–87.

Mei, J., Zhu, B., & Xia, X. (2015a). *Model predictive control for optimizing indoor air temperature and humidity in a direct expansion air conditioning system*. The 27th Chinese Control and Decision Conference (CCDC 2015), Qingdao, China, 23–25 May.

Mei, J., Zhu, B., & Xia, X. (2015b). *Predictive control for thermal comfort and energy efficiency in a direct expansion air conditioning system*. 2015 Chinese Automation Congress (CAC 2015), Wuhan, China, 25–27 December.

Michaelowa, A., & Jotzo, F. (2005). Transaction costs, institutional rigidities and the size of the clean development mechanism. *Energy Policy, 33*, 511–523.

Mokgonyana, L., Zhang, J., Zhang, L., & Xia, X. (2016). Coordinated two-stage volt/var management in distribution networks. *Electric Power Systems Research, 141*, 157–164.

Mozzo, M. A. (1999). Measurement and verification of savings in performance contracting. *Energy Engineering, 96*(2), 33–45.

Mundaca, L. (2007). Transaction costs of tradable white certificate schemes: The energy efficiency commitment as case study. *Energy Policy, 35*, 4340–4354.

Navigant (1999). Evaluation of the IFC/GEF Poland efficient lighting project CFL subsidy program. *Final report, Edition 2*. Philadephia: Navigant Consulting, PA, USA.

Nikkhajoei, H., & Lasseter, R. H. (2009). Distributed generation interface to the certs microgrid. *IEEE Transactions on Power Delivery, 24*(3), 1598–1608.

Ntsaluba, S., Zhu, B., & Xia, X. (2016). Optimal flow control of a forced circulation solar water heating system with energy storage units and connecting pipes. *Renewable Energy, 89*, 108–124.

Nwulu, N. I., & Xia, X. (2015a). A combined dynamic economic emission dispatch and time of use demand response mathematical modelling framework. *Journal of Renewable and Sustainable Energy, 7*(4), 043134.

Nwulu, N. I., & Xia, X. (2015b). Implementing a model predictive control strategy on the dynamic economic emission dispatch problem with game theory based demand response programs. *Energy, 91*, 404–419.

Nwulu, N. I., & Xia, X. (2015c). Multi-objective dynamic economic emission dispatch of electric power generation integrated with game theory based demand response programs. *Energy Conversion and Management, 89*, 963–974.

Nwulu, N. I., & Xia, X. (2017). Optimal dispatch for a microgrid incorporating renewables and demand response. *Renewable Energy, 101*, 16–28.

O'Connor, P., & Kleyner, A. (2011). *Practical reliability engineering*. Wiley.

Olinga, Z. (2015). A cost-effective approach to handle measurement and verification sampling and modelling uncertainties. *MEng Thesis, University of Pretoria, South Africa*.

Portmess, L., & Tower, S. (2015). Data barns, ambient intelligence and cloud computing: the tacit epistemology and linguistic representation of big data. *Ethics and Information Technology, 17*(1), 1–9.

Sao, C. K., & Lehn, P. W. (2005). Autonomous load sharing of voltage source converters. *IEEE Transactions on Power Delivery, 20*(2), 1009–1016.

Setlhaolo, D., & Xia, X. (2015). Optimal scheduling of household appliances with a battery storage system and coordination. *Energy and Buildings, 94*, 61–70.

Setlhaolo, D., & Xia, X. (2016). Combined residential demand side management strategies with coordination and economic analysis. *International Journal of Electrical Power & Energy Systems, 79*, 150–160.

Setlhaolo, D., Xia, X., & Zhang, J. (2014). Optimal scheduling of household appliances for demand response. *Electric Power Systems Research, 116*, 24–28.

Sichilalu, S., Tazvinga, H., & Xia, X. (2016). Optimal control of a fuel cell/wind/pv/grid hybrid system with thermal heat pump load. *Solar Energy, 135*, 59–69.

Sichilalu, S. M., & Xia, X. (2015a). Optimal energy control of grid tied pv–diesel—battery hybrid system powering heat pump water heater. *Solar Energy, 115*, 243–254.

Sichilalu, S. M., & Xia, X. (2015b). Optimal power dispatch of a grid tied-battery-photovoltaic system supplying heat pump water heaters. *Energy Conversion and Management, 102*, 81–91.

Stavropoulos, T. G., Kontopoulos, E., Bassiliades, N., Argyriou, J., Bikakis, A., Vrakas, D., & Vlahavas, I. (2015). Rule-based approaches for energy savings in an ambient intelligence environment. *Pervasive and Mobile Computing, 19*, 1–23.

Stavropoulos, T. G., Koutitas, G., Vrakas, D., Kontopoulos, E., & Vlahavas, I. (2016). A smart university platform for building energy monitoring and savings. *Journal of Ambient Intelligence and Smart Environments, 8*(3), 301–323.

Tazvinga, H., Xia, X., & Zhang, J. (2013). Minimum cost solution of photovoltaic–diesel–battery hybrid power systems for remote consumers. *Solar Energy, 96*, 292–299.

Tazvinga, H., Zhu, B., & Xia, X. (2014). Energy dispatch strategy for a photovoltaic–wind–diesel–battery hybrid power system. *Solar Energy, 108*, 412–420.

Tazvinga, H., Zhu, B., & Xia, X. (2015). Optimal power flow management for distributed energy resources with batteries. *Energy Conversion and Management, 102*, 104–110.

UNFCCC (2007). Approved baseline and monitoring methodology AM0046, distribution of efficient light bulbs to household. *Version 02, Technical Report*.

UNFCCC (2010). Approved small scale methodology AMS II.J, demand-side activities for efficient lighting technologies. *Version 04, Technical Report*.

UNFCCC (2011). Approved small scale methodology AMS II.L, demand-side activities for efficient outdoor and street lighting technologies. *Version 01, Technical Report*.

UNFCCC (2012). Approved small scale methodology AMS II.N, demand-side energy efficiency activities for installation of energy efficient lighting and/or controls in buildings. *Version 01.0, Technical Report*.

USDOE (2011). Advanced energy retrofit guides: Office buildings. *Technical Report*. Pacific Northwest National Laboratory and PEC with U.S. Department of Energy.

Wang, B., Wu, Z., & Xia, X. (2017). A multi-state based control system approach towards the optimal maintenance for building energy efficiency retrofits. *IEEE Transactions on Control System Technology, 25*(1), 374–381.

Wang, B., Wu, Z., Zhu, B., & Xia, X. (2015). *Optimal control of maintenance instants and intensities in building energy efficiency retrofitting project*. The 54th IEEE Conference on Decision and Control (CDC 2015), Osaka, Japan, 15–18 December.

Wang, B., & Xia, X. (2014). *A control system approach to corrective maintenance planning of building retrofitted facilities*. The 19th World Congress of the International Federation of Automatic Control (IFAC 2014), Cape Town, South Africa, 24–29 August.

Wang, B., & Xia, X. (2015a). *Maintenance plan optimization in building retrofitting with interacting energy efficiency effects*. 2015 Chinese Automation Congress (CAC 2015), Wuhan, China, 25–27 December.

Wang, B., & Xia, X. (2015b). Optimal maintenance planning for building energy efficiency retrofitting from optimization and control system perspectives. *Energy and Buildings, 96*, 299–308.

Wang, B., & Xia, X. (2016). *A preliminary study on the robustness of grouping based maintenance plan optimization in building retrofitting*. 2016 International Conference on Applied Energy (ICAE 2016), Beijing, China, 08–11 October.

Wang, B., Xia, X., & Zhang, J. (2014). A multi-objective optimization model for the life-cycle cost analysis and retrofitting planning of buildings. *Energy and Buildings, 77*, 227–235.

Wang, N., Zhang, J., & Xia, X. (2013). Energy consumption of air conditioners at different temperature set points. *Energy and Buildings, 65*, 412–418.

Wilson, D. G., Robinett, R. D., Weaver, W. W., Byrne, R. H., & Young, J. (2016). Nonlinear power flow control design of high penetration renewable sources for ac inverter based microgrids. In *2016 international symposium on power electronics, electrical drives, automation and motion (speedam)* (pp. 701–708). IEEE.

Wu, Z., Tazvinga, H., & Xia, X. (2015a). Demand side management of photovoltaic–battery hybrid system. *Applied Energy, 148*, 294–304.

Wu, Z., Wang, B., & Xia, X. (2016). Large-scale building energy efficiency retrofit: concept, model and control. *Energy, 109*, 456–465.

Wu, Z., Xia, X., & Wang, B. (2015b). Improving building energy efficiency by multiobjective neighborhood field optimization. *Energy and Buildings, 87*, 45–56.

Xia, X., & Elaiw, A. (2010). Optimal dynamic economic dispatch of generation: A review. *Electric Power Systems Research, 80*(8), 975–986.

Xia, X., & Zhang, J. (2010). Energy efficiency and control systems–from a POET perspective. *1st IFAC conference on Control Methodologies and Technology for Energy Efficiency, IFAC Proceedings Volumes, 43*(1), 255–260.

Xia, X., & Zhang, J. (2011). Modeling and control of heavy-haul trains [applications of control]. *IEEE Control Systems, 31*(4), 18–31.

Xia, X., & Zhang, J. (2013). Mathematical description for the measurement and verification of energy efficiency improvement. *Applied Energy, 111*, 247–256.

Xia, X., & Zhang, J. (2015). Operation efficiency optimisation modelling and application of model predictive control. *IEEE/CAA Journal of Automatica Sinica, 2*(2), 166–172.

Xia, X., Zhang, J., & Cass, W. (2012). Energy management of commercial buildings-a case study from a POET perspective of energy efficiency. *Journal of Energy in Southern Africa, 23*(1), 23–31.

Xia, X., Zhang, J., & Elaiw, A. (2009). *A model predictive control approach to dynamic economic dispatch problem* (pp. 1–7). PowerTech, 2009 IEEE, Bucharest, Romania, 28 June - 2 July.

Xia, X., Zhang, J., & Elaiw, A. (2011). An application of model predictive control to the dynamic economic dispatch of power generation. *Control Engineering Practice, 19*(6), 638–648.

Xia, X., & Zhang, L. (2016). Industrial energy systems in view of energy efficiency and operation control. *Annual Reviews in Control, 42*, 299–308.

Ye, X., & Xia, X. (2014). Optimal sampling and maintenance plans for the lighting retrofit projects towards sustainable energy savings. *Energy Procedia, 61*, 648–651.

Ye, X., & Xia, X. (2016). Optimal metering plan for measurement and verification on a lighting case study. *Energy, 95*, 580–592.

Ye, X., Xia, X., & Zhang, J. (2013). Optimal sampling plan for clean development mechanism energy efficiency lighting projects. *Applied Energy, 112*, 1006–1015.

Ye, X., Xia, X., & Zhang, J. (2014). Optimal sampling plan for clean development mechanism lighting projects with lamp population decay. *Applied Energy, 136*, 1184–1192.

Ye, X., Xia, X., Zhang, L., & Zhu, B. (2015). Optimal maintenance planning for sustainable energy efficiency lighting retrofit projects by a control system approach. *Control Engineering Practice, 37*, 1–10.

Yu, X., Khambadkone, A. M., Wang, H., & Terence, S. T. S. (2010). Control of parallel–connected power converters for low-voltage microgrid - part i: A hybrid control architecture. *IEEE Transactions on Power Electronics, 25*(12), 2962–2970.

Zhang, J., & Xia, X. (2011). A model predictive control approach to the periodic implementation of the solutions of the optimal dynamic resource allocation problem. *Automatica, 47*(2), 358–362.

Zhu, B., Tazvinga, H., & Xia, X. (2015). Switched model predictive control for energy dispatching of a photovoltaic-diesel-battery hybrid power system. *IEEE Transactions on Control Systems Technology, 23*(3), 1229–1236.