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ABSTRACT

While various models and methods have been proposed for operating and controlling building heating, ventilation and air conditioning (HVAC) systems, equipment decay (e.g., chiller tube fouling or boiler scaling), which results in lower energy efficiency and higher cost, has received limited attention. Accordingly, in this paper, we present an optimization model (mixed-integer linear programming, MILP) for predictive maintenance of HVAC systems with sufficient thermal energy storage (TES). We simultaneously consider the operation and maintenance schedule because of their close mutual interdependence. In addition, a method to accurately approximate equipment operation is provided for long-term scheduling. The proposed model offers decisions on execution of maintenance tasks based on the simultaneously optimized operation schedule (e.g., on/off status and load of equipment). Two computational experiments illustrate the applicability of the model. First, we show that the proposed model can approximate the hourly equipment operation without significant loss of accuracy. Second, we show that the model can lead to satisfactory cost saving when compared to the "fixed" schedule.

1. INTRODUCTION

1.1 Motivation

As an important end-user sector in energy systems, commercial buildings consume about 25% of the energy in the United States, and over 40% of the consumption can be attributed to HVAC systems (U.S. Energy Information Administration, 2016). However, about 15-30% of the energy is unnecessarily consumed by HVAC systems due to insufficient equipment maintenance and improper system control (Katipamula and Brambley, 2005). Apart from the increased energy consumption, poor maintenance also results in lower system reliability and safety, as well as equipment lifetime (Sullivan *et al*., 2010). Efficient maintenance scheduling can lead to energy saving, demand satisfaction, and equipment life extension.

Although hard fault (abrupt fault) detection and diagnosis have been improved over the past decades (Liang and Du, 2007; Tehrani *et al*., 2015), the research on soft fault (degradation fault) is limited. However, note that the degradation can have a significant effect on the system performance. For example, simulations show 10% reduction of the coefficient of performance (COP, defined as the ratio of heating/cooling provided to the power required) of chillers and energy efficiency of boilers due to fouling (Wang and Hong, 2013). The focus of the few publications available on HVAC maintenance is long-term planning (only provide decisions on maintenance target, e.g., specific maintenance should be provided in the following years) (Rossi and Braun, 1994; Wang *et al*., 2017). Thus, the study on the relatively shorter-term maintenance scheduling (also provides detailed maintenance execution time) considering equipment degradation remains an open question.

1.2 Predictive Maintenance

Predictive maintenance, also known as condition-based maintenance, is a modern maintenance strategy that gains popularity in recent years. Different from traditional preventive maintenance that is based on the accumulated operation time or the number of startup of equipment, predictive maintenance is decided based on the actual condition of the equipment; thus, condition monitoring is usually involved. Compared to preventive maintenance, it is estimated that predictive maintenance can lead to 8-12% cost saving (Sullivan *et al*., 2010).

Future condition prediction-based (FCPB) decision method has been developed (Ahmad and Kamaruddin, 2012) for predictive maintenance scheduling. According to this method, the future equipment condition is predicted, and maintenance is planned or scheduled once the equipment condition achieves or exceeds some predetermined failure limit. The advantage of this method is that future degradation is predicted to allow predictive maintenance schedule optimization. FCPB is further modified to provide better and more flexible maintenance schedule by considering the interdependence between operation and maintenance: equipment condition affects the utility consumption, thus complicating the operation schedule; while the operation results in further degradation, thus enforcing maintenance tasks to recover the condition. Considering this interdependence, maintenance is allowed even if equipment condition does not approach the failure limit for economic optimization.

1.3 Simultaneous Optimization of Maintenance and Operation Scheduling

To model predictive maintenance, simultaneous optimization of maintenance and operation is necessary. Although related research for HVAC systems remains an open question, approaches to this simultaneous optimization for other systems is extensive and can be divided into three categories. Approaches in the first category connect operation and maintenance only through the task-resource assignment. More specifically, the time window or frequency of maintenance is known a priori and is not affected by the equipment condition (the preventive maintenance is executed) (Dedopoulos and Shah, 1995). From the second category, the modified FCPB is utilized. For approaches in this category, equipment condition is dependent on the operation, but it does not affect the operation (e.g., operation cost, maximum load/capacity). For example, Bock *et al*. (2012) introduced the concept of "maintenance level", which will drop with the operation and be replenished by maintenance. The approaches in the third category explicitly consider closer mutual interdependence between operation and maintenance. More specifically, the effect of equipment condition to the operation is also considered. Benchmark research is as follows: Nie *et al*., (2014) developed an MILP model for semi-continuous chemical production processes, where the capacity of equipment is decreased with operation; yield decay is allowed to be dependent on the number of batches produced by the equipment for batch processes (Liu *et al*., 2014); as for the compressor network, extra electricity consumed due to degradation is proportional to operation time (Xenos *et al*., 2016). While extensive research available, its application to HVAC systems with TES is still limited.

1.4 HVAC Systems with TES

Compared to other processes, the operation of HVAC systems with TES is more complicated. Before introducing the details, we first divide the materials involved into two subsets named resources and utilities: resources (e.g., heated and chilled water) are produced and delivered to the building, while utilities (e.g., electricity and natural gas) are consumed for resource production. Hourly utility price and resource demand are usually subject to high volatility. Specifically, electricity price and resource demand are higher during the "on-peak period" (usually between noon and 6 p.m.), and lower during the "off-peak period". Apart from the charge based on the amount of electricity consumed (time-of-use charge), peak usage within a billing period is charged with a high penalty (demand charge). This peak charge can account for about 30-70% of the bills of most commercial and industrial customers (Grant *et al*., 2014). Therefore, some HVAC systems are equipped with various thermal energy storage (TES) facilities to store extra resources produced during the off-peak period, and utilized the stored resources during the on-peak period. The existence of TES also adds degrees of freedom to the optimization.

Apart from the electricity rates and the existence of TES, more challenges further complicate the optimization: (1) close interdependence between maintenance and operation; (2) approximation of long-term operation. To overcome these challenges, we develop preprocessing method and the optimization model.

1.5 Paper Outline

This paper is organized as follows. In section 2, we show the overview of the optimization approach. In section 3, the preprocessing step that provides parameters for operation approximation is introduced. In section 4, we present the

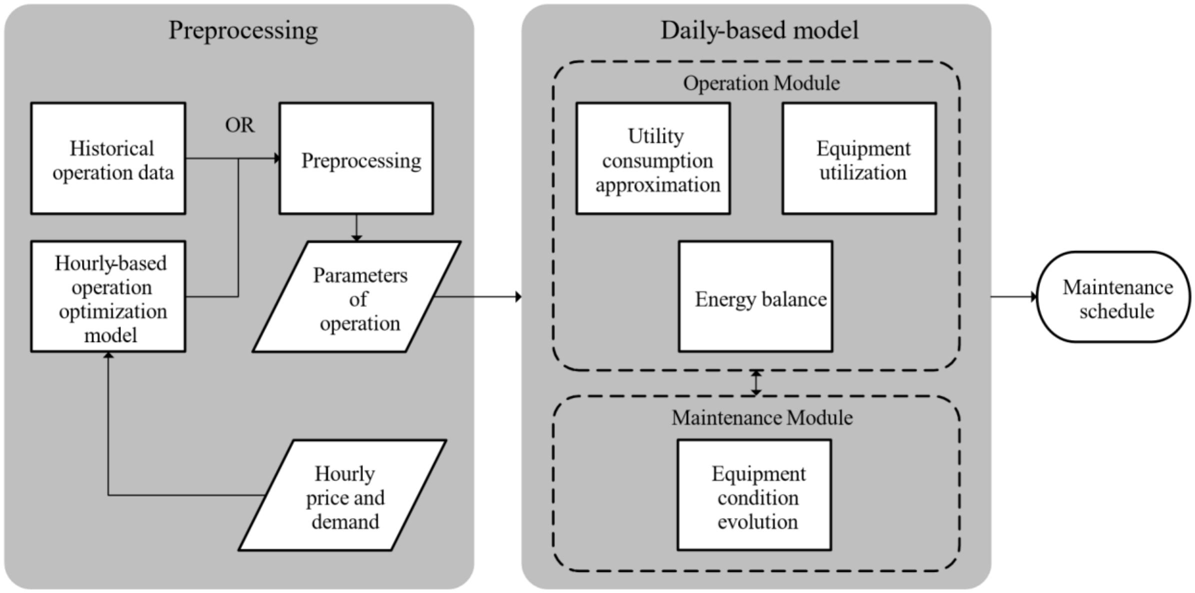


Figure 1: Schematic of the model structure

formulations of the model. Finally, in section 5, we apply the optimization approach to a central plant, and the case studies results show the accuracy of approximation and the applicability to large-scale systems.

2. APPROACH OVERVIEW

2.1 Problem Statement

The overall objective is to provide the maintenance schedule for HVAC system with sufficient TES. We are given:

(1) utility price and resource demand
(2) information on equipment condition
(3) equipment performance curves and storage capacity of TES.

We aim to solve the optimal decisions on the selection and execution time of maintenance tasks, and the operation of equipment (e.g., turn on/off, resource production, and utility consumption). For simplicity, we assume that the resource demand is known ahead of time. In addition, the ratio of utility consumption between degraded and "good-as-new" equipment is assumed to be only dependent on the equipment type and the current equipment condition. Finally, we assume that the degradation is directly related to the operation time, as well as the averaged load; however, our model can be easily modified to account for other forms of degradation. Note that the minimum unit of time in the model is the day to remain computational tractability (daily-based model), and the model only guide the maintenance while other detailed operation scheduling models should decide the actual operation. In the following discussion, we use lowercase italics for indices, uppercase bold letters for sets, uppercase italics for variables, and lowercase italic Greek letters for parameters.

The following indices, sets, and variables are used to describe the problem:

Indices/sets:

$i \in \mathbf{I}$	maintenance tasks	$\mathbf{I}_j$	tasks that can be performed in equipment j
$j \in \mathbf{J}$	equipment	$\mathbf{J}_i$	equipment that can perform maintenance task i
$k \in \mathbf{K}$	materials	$\mathbf{J}_k$	equipment that produces/consumes resource/utility k
$t \in \mathbf{T}$	time points (days)	$\mathbf{K}^+/\mathbf{K}^-$	resources/utilities
$l \in \mathbf{L}$	billing periods (months)	$\mathbf{T}_l$	days belong to billing period l

Variables

$B_{i,j,t}$	Equipment condition recovery	$P_{k,j,t}$	Utility consumption
$B^{dummy}_{i,j,t}$	Slack variable for equipment condition recovery	$P^{max}_{k,l}$	Peak usage of the utility
C^{total}	Total cost	$Q_{k,j,t}$	Resource production by equipment
$C^{tou}_{k,j,t}$	Time-of-use charge	$S_{k,t}$	Stored inventory
$D_{k,t}$	Charge/discharge of TES	$X_{i,j,t}$	Binary variable for execution of maintenance tasks
$E_{j,t}$	Relative inefficiency	$Y_{j,t}$	Binary variable for the on/off status of equipment
$H_{j,t}$	Operating hours		

2.2 Approach Structure

Figure 1 shows the structure of the proposed approach, which consists of the preprocessing and the optimization model. Since utility price and the demand is usually hourly-based, necessary preprocessing step is required to ensure the compatibility with our daily-based model. In this step, system operation pattern either from the detailed operation scheduling models or hourly historical data is processed to obtain parameters such as averaged load and COP during each billing period. For the optimization model, it can be divided into modules to model the maintenance and operation, which will be introduced in detail in the section 4.

3. PREPROCESSING

This part aims to calculate the parameters to provide utility price and demand on a daily basis, and approximate equipment operation over each billing period. For the electricity price, averaged electricity price during on-peak and off-peak period in each day are utilized; while for other utilities, we simply utilize the daily averaged price. In addition, the total daily demand of each resource is calculated. Moreover, for parameters related to operation approximation, we focus on the averaged $\frac{1}{COP}$ and load during each billing period. Although multiple challenges complicate the operation pattern of the system, according to the observed result from optimal schedule provided by operation optimization model (Risbeck et al. (2015)), we can still simplify the modeling: from figure 2, we observe that: (1) operation that consumes electricity is shifted to the off-peak period as much as possible; (2) during the off-peak period, equipment load become similar due to high demand charge. Because of these two points, we can simply approximate the operation of equipment that consumes electricity during each billing period as follows: equipment operate with the monthly-averaged load and the coresponded $\frac{1}{COP}$. Moreover, because equipment load is similar within each billing period, the degradation rate in the same billing period can be approximated as a constant. Later, we will prove that with this preprocessing method, we can approximate the system operation without significant loss of accuracy.

4. MODEL FORMULATION

Only key constraints and critical ideas of the model will be shown in this section due to limited space.

4.1 Objective Function

The objective is to minimize the total cost, which is composed of the maintenance cost and the operational cost and is calculated as:

$$C^{total} = \sum_{k\in\mathbf{K}^-}\sum_{j\in\mathbf{J}_k}\sum_{t\in\mathbf{T}} C^{tou}_{k,j,t} + \sum_{k\in\mathbf{K}^-}\sum_{l\in\mathbf{L}} \theta^{demchg}_{k,l} P^{max}_{k,l} + \sum_{i\in\mathbf{I}}\sum_{j\in\mathbf{J}_i}\sum_{t\in\mathbf{T}} \lambda_{i,j} X_{i,j,t} \quad (1)$$

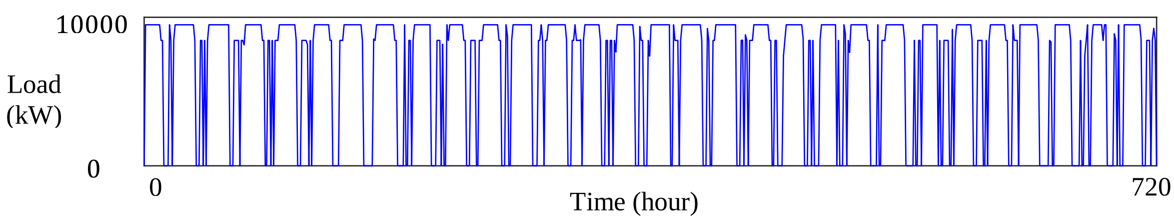


Figure 2: Optimal operation of an example chiller

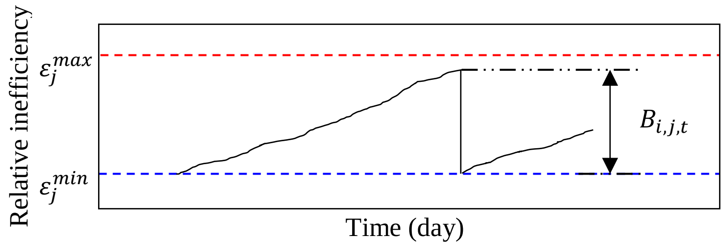


Figure 3: Schematic of equipment condition evolution

in which θ_k^{demchg} is the demand charge rate, and $\lambda_{i,j}$ is the cost of the maintenance tasks. It is clear that both time- of-use charge and demand charge are considered in the operational cost, and the maintenance cost is calculated according to the execution times of the maintenance tasks.

4.2 Equipment Condition Evolution

Equipment condition is critical to model predictive maintenance. We propose a new concept - relative inefficiency $E_{j,t}$ that denotes the degradation of any given equipment j, which is defined as follows:

$$E_{j,t} \coloneqq \frac{\text{Actual utility consumed by } j \text{ at time } t}{\text{Utility consumed by } j \text{ in "good-as-new" condition when producing the same resource}}$$

With this concept, we can conveniently model the equipment condition evolution; in addition, the utility consumed considering degradation can be calculated as the utility consumed by "good-as-new" equipment corrected by multiplying this relative inefficiency. From the definition, we know that the "good-as-new" equipment has the lowest inefficiency whose value is 1, and this value will increase with the degradation. Constraints (2)-(5) constrain the equipment condition evolution.

$$E_{j,t} = E_{j,t-1} + \alpha_{j,l} H_{j,t} - \sum_{i \in \boldsymbol{I}_j} B_{i,j,t} \;\; \forall j \in \mathbf{J}, t \in \mathbf{T}_l \tag{2}$$

$$B_{i,j,t} + B_{i,j,t}^{dummy} = E_{j,t-1} - \varepsilon_j^{min} \; \forall i \in \mathbf{I}, j \in \mathbf{J}_i, t \in \mathbf{T} \tag{3}$$

$$\beta_{i,j}^{min} X_{i,j,t} \le B_{i,j,t} \le \beta_{i,j}^{max} X_{i,j,t} \; \forall i \in \mathbf{I}, j \in \mathbf{J}_i, t \in \mathbf{T} \tag{4}$$

$$B_{i,j,t}^{dummy} \le \left(1 - X_{i,j,t}\right)\left(\varepsilon_j^{max} - \varepsilon_j^{min}\right) \;\; \forall i \in \mathbf{I}, j \in \mathbf{J}_i, t \in \mathbf{T} \tag{5}$$

Here parameter $\alpha_{j,l}$is the degradation rate during each billing period obtained in the preprocessing part; ε_j^{max}/ ε_j^{min} are the bounds of inefficiency, and $\beta_{i,j}^{min}/\beta_{i,j}^{max}$ are the bounds of recovery. Equation (2) shows that the inefficiency change is affected by the operating hours, the detailed operation status (linked by $\alpha_{j,l}$) and the recovery by maintenance task (as shown in Figure 3). Combined with the definition equation of relative inefficiency, it also reflects the assumption that utility consumption increases approximately linearly with the operation time. This formulation can also account for other forms of decay rate by revising the definition of relative inefficiency (e.g., directly related to resource production) and constraint (2). Constraints (2)-(5) ensure that equipment will recover to "good-as-new" condition after maintenance, which is realistic for a certain range of horizon length.

4.3 Energy Balance

For the energy balance, both demand balance and storage balance are considered. Here, we implement these constraints proposed by Risbeck *et al*. (2015) with minor modifications. Suppose TES exists in the system, then we have

$$S_{k,t} = D_{k,t} + \sigma_k S_{k,t-1} \; \forall k \in \mathbf{K}^+, t \in \mathbf{T} \tag{6}$$

$$\varphi_{k,t} = \sum_{j \in \mathbf{J}_k} Q_{k,j,t} - D_{k,t} \; \forall k \in \mathbf{K}^+, t \in \mathbf{T} \tag{7}$$

in which $\varphi_{k,t}$ is the demand of resource and σ_k is the fractional retention of the stored resource. Constraint (6) states that the current demand should be satisfied by resource production and discharge of storage. Constraint (7) is the storage balance, and thermal energy loss is considered by including σ_k.

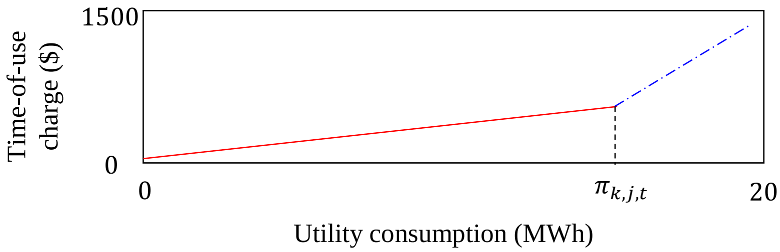


Figure 4: Piecewise linear function to approximate the time-of-use charge

4.4 Equipment utilization

From equation (7), we know that the total resource production is constrained. In addition, for multi-equipment systems, equipment utilization is of equal importance for utility consumption calculation and equipment condition evolution prediction. As shown in equation (8), resource production by each equipment is equal to the multiplication of operating hours and averaged load $\zeta_{k,j,l}$ obtained by preprocessing.

$$Q_{k,j,t} = \zeta_{k,j,l} H_{j,t} \ \forall k \in \mathbf{K}^+, j \in \mathbf{J}_k, t \in \mathbf{T}_l \tag{8}$$

Moreover, the on/off status and the execution of maintenance also affect the resource production

$$H_{j,t} \leq 24 Y_{j,t} \ \forall j \in \mathbf{J}, t \in \mathbf{T} \tag{9}$$

$$\sum_{i \in \mathbf{I}_j} \sum_{t'=t-\tau_{i,j}+1}^{t} X_{i,j,t'} + Y_{j,t} \leq 1 \forall j \in \mathbf{J}, t \in \mathbf{T} \tag{10}$$

in which $\tau_{i,j}$ is the processing time of maintenance task i in unit j. Constraint (9) states that the operating hours is nonzero only when the unit is turned on, and its value cannot exceed 24 hours. Constraint (10) forces the unit to be offline until the maintenance task finishes.

4.5 Utility Consumption

In this section, the issues from the nonlinear performance curves of equipment and the increased utility consumption due to degradation will be addressed by utilizing piecewise linear approximation. With the definition of COP, the utility consumption of "good-as-new" equipment can be calculated as

$$P_{k_1,j,t}^{new} = \left[\frac{1}{COP}\right]_{k_1,k_2,j,t}^{avg} Q_{k_2,j,t} \ \forall k_1 \in \mathbf{K}_j^-, k_2 \in \mathbf{K}_j^+, j \in (\mathbf{J}_{k_1} \cap \mathbf{J}_{k_2}), t \in \mathbf{T} \tag{11}$$

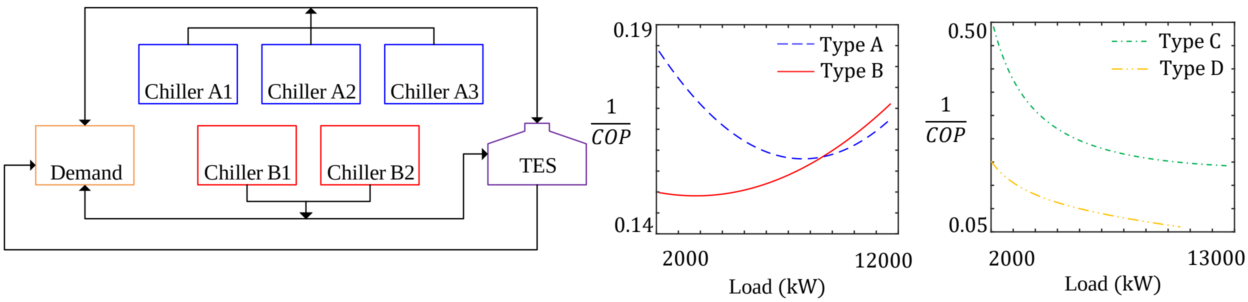
where $P_{k_1,j,t}^{new}$ is the utility consumed by "good-as-new" equipment, and $\left[\frac{1}{COP}\right]_{k_1,k_2,j,t}^{avg}$ is the averaged amount of utility k_1 consumed by unit j when producing resources k_2 at time t. For the value of $\left[\frac{1}{COP}\right]_{k_1,k_2,j,t}^{avg}$, it can be approximated as $\rho_{k_1,k_2,j,l}$, $\frac{1}{COP}$ that corresponds to the averaged cooling rate $\zeta_{k_2,j,l}$. Substituted by equation (8), utility consumed by degraded equipment is corrected as constraint (12) according to the definition of relative inefficiency.

$$P_{k_1,j,t} = \rho_{k_1,k_2,j,l} \zeta_{k_2,j,l} H_{j,t} E_{j,t} \ \forall k_1 \in \mathbf{K}_j^-, k_2 \in \mathbf{K}_j^+, j \in (\mathbf{J}_{k_1} \cap \mathbf{J}_{k_2}), t \in \mathbf{T}_l \tag{12}$$

For the bilinear term involved in constraint (12), 2-D piecewise linear approximation is utilized to maintain the model as an MILP model. By this method, feasible region of the nonlinear function is divided into several subdomains, and the value of the nonlinear function at a given point is the convex linear combination of the values at extreme points of the subdomain to which the point belongs.

4.6 Utility Cost

Both the time-of-use charge and the demand charge are considered in this model. For systems with TES, from section 3 we know that units usually operate during the on-peak period only if resources produced during the off-peak period are not sufficient to satisfy the demand. Thus, we can approximate the time-of-use charge as follows: before consuming a certain amount of electricity $\pi_{k,j,t}$, the electricity rate is the averaged off-peak price during that day; while the electricity consumption that exceeds this specific amount is charged according to the averaged on-peak price. $\pi_{k,j,t}$ is the amount of electricity consumed by equipment if it operates with the averaged load $\zeta_{k,j,l}$ from the beginning to the end of the off-peak period during day t. Accordingly, we can use a 1-D piecewise linear function to approximate the time-of-use charge (shown in Figure 4). Solid and dash-dot line segments represent the time-of-use



(a) Structure of system I (b) Performance curves of system I (c) Performance curves of system II

Figure 5: Information on systems for computational experiments

charge before and after consuming electricity $\pi_{k,j,t}$. The slope of the solid/dash-dot line segments is the averaged off-peak/on-peak electricity price, respectively. For the demand charge, it can be calculated from the maximum load and the relative inefficiency of all equipment in the system.

5. APPLICATION

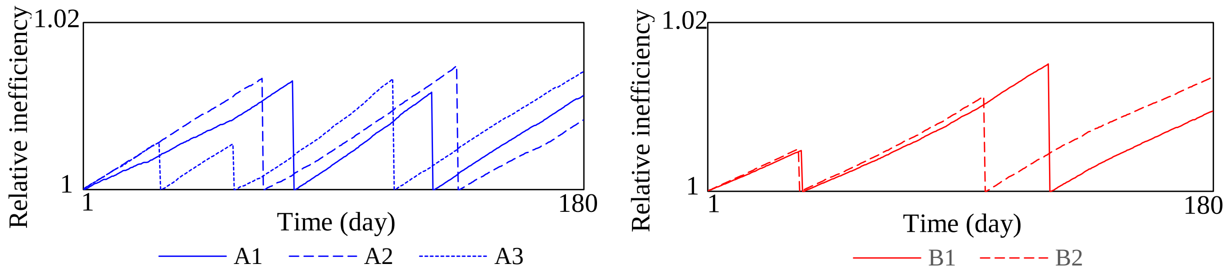
5.1 Accuracy Analysis

To test the accuracy of the operation approximation, computational experiments are performed. Note that only objective function (1), constraints (2)-(10) in the previous section are included in the MILP model, while the others are shown to illustrate the concepts. Operation scheduling of two representative systems is optimized by our daily-based model and the hourly-based operation scheduling model developed by Risbeck *et al*. (2015), respectively. Both systems are mainly composed of two types of chillers (system I: three type A chillers and two type B chillers; system II: three type C chillers and two type D chillers) and sufficiently large TES (as shown in Figure 5(a) for system I, and system II has a similar structure). Performance curves of chillers in these two systems are shown in Figure 5(b) and 5(c), respectively. The critical difference between these systems is that there is an intersection point on the performance curves of the system I; thus, these chillers will work simultaneously within a specific range of load while demand fluctuates. However, for system II, type D chiller is obviously given priority, which results in a more significant change of cooling rate of type C chillers under demand fluctuation. The horizon of this test problem is one month, and degradation is not considered here because of computation difficulty for the hourly-based model, as well as little impact from degradation over such a short horizon.

The relative error between results obtained from the daily-based model and the hourly-based model is shown in Table 1. According to the table, the relative error of systems I is lower than system II, which is expected. Also, our daily-based model tends to underestimate utility cost due to the inability to consider the hourly loss of storage and the inaccurate estimation of $\frac{1}{COP}$ (which is evident for system II). The relative error of total cost is larger than the demand charge and utility consumption due to the inaccuracy of averaged electricity price. However, it is worth noting that the estimation of total operating hours of each type of chillers does not deviate significantly. According to constraint (2), equipment degradation rate is approximately proportional to the operating hours and the related to $\alpha_{j,l}$ derived from cooling rate during that billing period. Consequently, the model can predict equipment operation and degradation without significant loss of accuracy when considering equipment degradation.

Table 1: Relative error between the daily-based model and the hourly-based model

	Operating hours (%)				Demand charge (%)	Utility consumption (%)	Total cost (%)
	Type A	Type B	Type C	Type D			
System I	-4.17	+3.96	-	-	-2.40	-3.20	-4.41
System II	-	-	-9.32	-0.28	-4.86	-6.22	-7.23



(a) Equipment condition evolution of type A chillers (b) Equipment condition evolution of type B chillers

Figure 6: Equipment condition evolution in the large-scale case study

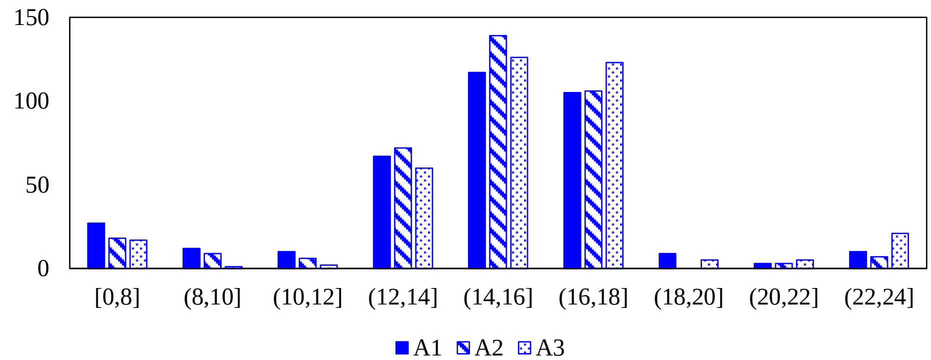


Figure 7: Distribution of operation hours of type A chillers in the large-scale case study

Table 2: Model statistics of the large-scale case study

Obj. ($)	Gap (%)	Total Var.	Discrete Var.	CPU (s)
2482283	1.24	34933	7200	3600

5.2 Large-scale Case Study

We optimize the maintenance scheduling of system I in the previous subsection over a one-year horizon in GAMS 24.8.5, and solved using CPLEX 12.7.1 running on Windows 10 with 3.2-GHz Intel Core (i5-6500) processor and 16 GB RAM. One type of maintenance task is considered, and it can be performed in all equipment. The problem is solved with optimality gap of 1.24% after 3600 seconds (model statistics are shown in table 2), and the optimized efficiency evolution is shown in Figure 6, where relative inefficiency increases roughly proportional to time. However, note that the slope of the curve also slightly changes with the fluctuation of demand (evident for the curve of chiller A1), which shows that our model can consider the effect of operation time and detailed operation status. Apart from this, the vertical drops of the curves reflect the equipment condition recovery to “good-as-new” condition after maintenance. This schedule saves about 1.12% cost compared to the no-maintenance case, and it can save 12% more cost than the heuristic fixed schedule. Note the total benefit is more than the utility cost saving when considers the equipment life extension and increased system reliability and safety.

To examine the close interaction between maintenance and operation, distribution of operation hours of type A chillers is given in figure 7. We observe that there is higher possibility that A3 operates longer that A1 and A2 during each day. Equipment condition evolution in figure 6 can explain this: A3 has the overall lower relative inefficiency because of more frequent maintenance, thus consuming less utility than A1 and A2 when producing same resources. Note that the heuristic maintenance schedule for the same type of equipment is usually similar without considering the operation, and research on operation scheduling models usually assumes no effect from equipment degradation. However, the counterintuitive result shown here reveals the importance of our research.

6. CONCLUSIONS

In this paper, we present an MILP predictive maintenance scheduling model for HVAC system with TES over a multi-months horizon. It simultaneously optimizes the maintenance and system operation with the consideration of equipment degradation, and the formulations are easy to be modified to account for different systems with various forms of degradation. To consider medium- to long- horizon, we also develop a preprocessing method to approximate system hourly operation on a daily basis. Two computational experiments prove the accuracy and the practicability of the proposed model, and in the large-scale case study, the counterintuitive schedule reveals the importance of maintenance optimization considering system degradation.

NOMENCLATURE

Sets

$i \in \mathbf{I}$	Maintenance tasks
$j \in \mathbf{J}$	Equipment
$k \in \mathbf{K}$	Materials
$t \in \mathbf{T}$	Time points (days)
$l \in \mathbf{L}$	Billing periods (months)

Variables

$B_{i,j,t}$	Equipment condition recovery
$B_{i,j,t}^{dummy}$	Slack variable for equipment condition recovery
C^{total}	Total cost
$C_{k,j,t}^{tou}$	Time-of-use charge
$D_{k,t}$	Charge/discharge
$E_{j,t}$	Relative inefficiency of equipment
$H_{j,t}$	Operating hours
$P_{k,j,t}$	Utility consumption
$P_{k,l}^{max}$	Peak usage of utility
$Q_{k,j,t}$	Resource production by equipment
$S_{k,t}$	Stored inventory
$X_{i,j,t}$	Binary variable to denote the execution of maintenance tasks
$Y_{j,t}$	Binary variable to denote the on/off status of equipment

Parameters

$\alpha_{j,l}$	Equipment degradation rate
$\beta_{i,j}^{max}/\beta_{i,j}^{min}$	Bounds of equipment condition recovery by a single maintenance task
$\varepsilon_j^{max}/\varepsilon_j^{min}$	Bounds of inefficiency allowed
$\zeta_{k,j,l}$	Averaged load
$\theta_{k,l}^{peak}$	Demand charge rate
$\pi_{k,j,t}$	Maximum utility consumption during off-peak period
$\rho_{k,k',j,t}$	Averaged $\frac{1}{\mathrm{COP}}$
$\lambda_{i,j}$	Cost of maintenance task
σ_k	Fractional retention of stored resource
$\tau_{i,j}$	Processing time of maintenance task
$\varphi_{k,t}$	Demand of resource

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