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EVENT DEFINITION METHOD FOR THE EVENT-DRIVEN OPTIMAL CONTROL STRATEGY OF AIR-CONDITIONING SYSTEMS

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ABSTRACT

The event-driven optimal (EDO) control has recently been proposed for central air-conditioning (AC) systems for operation improvement. In EDO control, optimization actions are driven by pre-defined events. However, there is lack of a systematic approach to defining events in existing studies of EDO control. To address this limitation, this paper proposes a systematic method to define events for the EDO control of AC systems. Events are defined from the perspective of guaranteeing high optimization necessity. The event definition method is illustrated through a case study of an AC system.

Keywords: Air-conditioning system; Real-time optimal control; Event-driven optimal control; Event definition

1. INTRODUCTION

Real-time optimal (RTO) control is a method to minimize energy consumption or operating cost of air-conditioning (AC) systems and maintain the comfort of the indoor environment [1]. The RTO control has undergone rapid development since the 1980s [2], and a general framework has been developed [3].

For the trigger mechanism of optimization actions, almost all existing RTO controls adopt the time-driven strategy in which optimization actions are triggered at a fixed frequency. However, the time-driven optimal (TDO) control is usually hard to capture aperiodic changes in operating conditions timely [4, 5]. To overcome this drawback, the event-driven optimal (EDO) control of AC systems is proposed by Wang et al [6, 7] where the optimization is triggered with "event" rather than "time". It is the first time to apply the event-driven paradigm in the optimal control of AC systems. In Wang's study [7], the framework of the EDO control for AC systems and the application of this strategy to an AC system are presented. The application showed a batter capability of EDO control to capture dynamic changes of AC systems. However, in Wang's study events are defined using the prior knowledge-based method which is not systematic and general enough for event definition.

In this paper, an improved method to define events for the EDO control of AC systems is proposed. The event definition method is illustrated through a case study of an AC system. This paper is organized as follows. Section 2 presents the case AC system and the establishment of its simulation platform. Section 3 illustrates the event definition process for the optimal control of the AC system. To evaluate defined events, EDO control with defined events of the AC system is carried out in Section 4. The conclusion is presented in Section 5.

2. THE CASE AIR-CONDITION SYSTEM

2.1 Configuration of the air-conditioning system

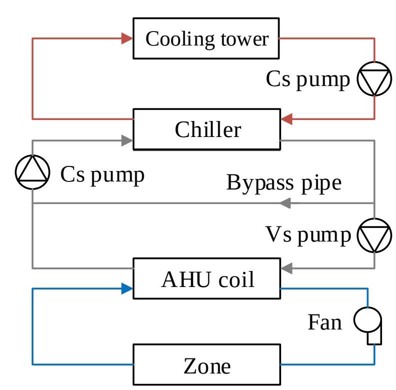

Fig 1 Configuration of the case AC system

The case AC system is shown in Fig 1. Three loops are included: the cooling water loop, the chilled water loop, and the supply air loop. Parameters of the system are presented in Table 1.

Table 1 Parameters of the system

Component	Parameter	Value
Chiller	Capacity (kW)	509
	COP	6.5
	Chilled water flow rate (kg/s)	23.6
	Cooling water flow rate (kg/s)	27.8
Cooling tower	Maximum air flow rate (m^3/s)	19.4
	Rated power (kW)	5.5
	Cooling water flow rate (kg/s)	27.8
	Cooling capacity (kW)	604
Chilled water loop cs pump	Water flowrate (kg/s)	23.6
	Head (m)	15
	Rated power (kW)	5.1
Cooling water loop cs pump	Water flowrate (kg/s)	27.8
	Head (m)	15
	Rated power (kW)	6
Chilled water loop vs pump	Water flowrate (kg/s)	23.6
	Head (m)	30
	Rated power (kW)	10.4
AHU Fan	Rated air flow rate (kg/s)	37.3
	Rated power (kW)	40

During the operation of the system, three set-point controls are involved: the supply temperature of the cooling water (T_{cw}), the supply temperature of chilled water (T_{chw}), and the supply air temperature (T_{air}).

2.2 Simulation platform of the air-conditioning system

To define events for the AC system, the simulation platform of the AC system is established, which is constructed by TRNSYS and MATLAB.

The virtual AC system is built in TRNSYS to simulate the operation. Existing models in TRNSYS are directly used to simulate components of the AC system. The performance file of Type 666 is modified according to a chiller (ReformEIRChiller Screw York YS 781kW/5.42COP/Valve) described in the software DesignBuilder.

The optimization procedure in MATLAB acts as the optimal controller to minimize the total instantaneous power of the AC system by seeking optimal settings of three decision variables (T_{cw}, T_{chw}, T_{air}). The total instantaneous power P_{tot} is calculated by Eqn. (1).

$$P_{tot} = P_{ch} + P_{ct} + P_{CHW,cs} + P_{CHW,vs} + P_{CW,cs} + P_{fan} \quad (1)$$

where P_{ch}, P_{ct}, $P_{CHW,cs}$, $P_{CHW,vs}$, $P_{CW,cs}$, and P_{fan} are the instantaneous power of the chiller, cooling tower, constant frequency pump for chilled water, variable frequency pump for chilled water, and constant frequency pump for cooling water respectively.

Models to calculate the instantaneous power of components in the MATLAB procedure is presented in Table 2.

Table 2 Components models in MATLAB procedure

Component	Model
Chiller	DOE-2 model [8]
Cooling tower	Lebrun's simplified model [9]
AHU coil	Type 508c in TRNSYS
Vs pump	Cubic Polynomial
AHU fan	Cubic Polynomial

Constraints are shown as follows. Eqn. (5) is used to limit the change of decision variables between two optimization actions into the range of 0.5℃.

$$T_{wb} + 1.5℃ \le T_{cw} \le 35℃ \quad (2)$$

$$4℃ \le T_{chw} \le 10℃ \quad (3)$$

$$12℃ \le T_{air} \le 16℃ \quad (4)$$

$$|T_{t+1} - T_t| \le 0.5℃ \quad (5)$$

where T_{wb} is the environment web-bulb temperature, and T_t is the value of the decision variable at optimization time instant t.

For the optimization technique, the exhaustive search is adopted for optimal solutions.

3. EVENT DEFINITION

The event definition includes three parts: data generation, identification of critical state transitions, and relationship determination.

3.1 Data generation

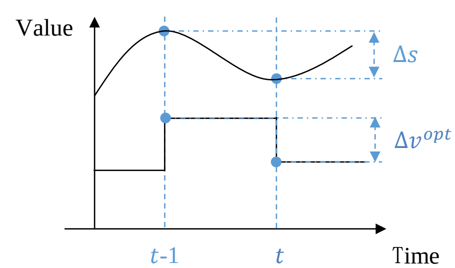

Fig 2 Variables to be researched for event definition

During the operation of the AC system with optimal control, optimal values of decision variables are affected by changes of weather and load states. Therefore, events for the optimization of decision variables derive from changes of these states. Between two optimization actions, the state transition Δs and the variation of the decision variable's optimal value Δv^{opt} are shown in Fig 2. Commonly, a large value of Δv^{opt} indicates the high necessity of optimization at time instant t. To guarantee the high optimization necessity of EDO control, events are defined by analyzing the correlation between Δs and Δv^{opt} in the generated data of TDO control.

Weather data and load profile of six summer days are collected from Hong Kong Observatory and a commercial building in Hong Kong. The TDO control of the AC system is carried out at three optimization frequencies: every 30min, 60min, and 120min. In this way, 444 sets of operating data are obtained. The correlation between the variation of three decision variables' optimal values ΔT_{cw}^{opt}, ΔT_{chw}^{opt}, ΔT_{air}^{opt}, and three state transitions ΔT_{db}, ΔT_{wb}, $\Delta \mathrm{PLR}$ is analyzed.

3.2 Identification of critical state transitions

According to the sensitive analysis methodology [10], the linear regression coefficient can be used to identify the importance of independent variables on dependent variables. The higher the coefficient, the more important. The regression coefficient matrix C in Eqn. (6) is used to identify critical state transitions for decision variables. M_s and M_v are defined as Eqn. (7) and (8), and variables in M_s and M_v are normalized by their absolute average value so that dimensions are taken away.

$$M_v = C \cdot M_s \tag{6}$$

$$M_v = [\Delta T_{cw}^{opt*}, \Delta T_{chw}^{opt\,*}, \Delta T_{chw}^{opt\,*}] \tag{7}$$

$$M_s = [\Delta T_{db}{}^*, \Delta T_{wb}{}^*, \Delta PLR^*] \tag{8}$$

The regression result of the coefficient matrix C with 444 sets of generated operation data is shown in Eqn. (9). According to Eqn. (9), critical state transitions are identified. For the variation of the cooling water supply temperature's optimal value ΔT_{cw}^{opt}, critical state transitions include the variation of ambient web-bulb temperature ΔT_{wb} and the variation of the part-load ratio ΔPLR. For the variation of the chilled water supply temperature's optimal value ΔT_{chw}^{opt} and supply air temperature's optimal value ΔT_{air}^{opt}, the critical state transition is the variation of the part-load ratio ΔPLR.

$$\begin{bmatrix} \Delta T_{cw}^{opt*} \\ \Delta T_{chw}^{opt*} \\ \Delta T_{air}^{opt*} \end{bmatrix} = \begin{bmatrix} -0.074 & \mathbf{0.943} & \mathbf{0.266} \\ 0.041 & -0.064 & \mathbf{-0.946} \\ 0.019 & -0.068 & \mathbf{-0.941} \end{bmatrix} \cdot \begin{bmatrix} \Delta T_{db}{}^* \\ \Delta T_{wb}{}^* \\ \Delta PLR^* \end{bmatrix} \tag{9}$$

3.3 Relationship between $\Delta \mathrm{s}$ *and* $\Delta \mathrm{v}^{\mathrm{opt}}$

Then, suitable mathematical functions are selected to describe the mathematical relationship between each Δv^{opt} and its critical Δss. Here, linear functions are selected. Based on generated operating data, linear models are obtained by curving fitting as Eqn. (10). The R^2 of linear models are larger than 0.9, which indicates that the variation of the three decision variables' optimal values have good linearity with their critical state transitions for this AC system.

$$\begin{cases} \Delta T_{cw}^{opt} = 0.85 \cdot \Delta T_{wb} + 1.03 \cdot \Delta PLR & (R^2 = 0.90) \\ \Delta T_{chw}^{opt} = -6.5 \cdot \Delta PLR & (R^2 = 0.94) \\ \Delta T_{air}^{opt} = -3.34 \cdot \Delta PLR & (R^2 = 0.93) \end{cases} \tag{10}$$

In previous studies of optimal control of AC systems [7, 11], set-point changes of temperatures are usually constrained within 0.4 or 0.5℃ to guarantee the system stability. Therefore, 0.5 ℃ are directly used as the threshold to define events. Considering that ΔT_{chw}^{opt} and ΔT_{air}^{opt} have the same relationship with ΔPLR, and the only difference is the coefficient of ΔPLR as shown in Eqn. (10), two events are defined in total and presented in Eqn. (11).

$$\begin{cases} e_1: |0.85 \cdot \Delta T_{wb} + 1.03 \cdot \Delta PLR| \geq 0.5 \\ e_2: |6.5 \cdot \Delta PLR| \geq 0.5 \end{cases} \tag{11}$$

4. EVALUATION

To evaluate the EDO control with defined events, the operation of the AC system is simulated for a summer day under three optimal control strategies: operation without optimal control, operation with the TDO control (frequency: every 30min, 60min, and 120min), and operation with the EDO control. In the operation without optimal control, three temperatures are fixed at specific values ($T_{cw} = 30℃, T_{chw} = 7℃, T_{air} = 15℃$). In the EDO control, when any of the two defined events occurs, three temperatures are optimized simultaneously. Weather and load conditions of the summer day is presented as Fig 3. Simulation results are shown in Table 3, where the operation without optimization is taken as the bench mark for energy-saving calculation and the TDO (30min) is the bench mark for computation-saving calculation.

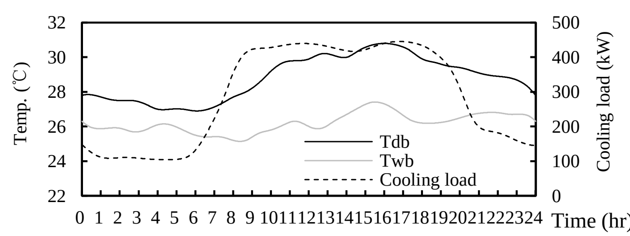

Fig 3 Profiles of operating conditions in the summer day

For the TDO control, when the optimization frequency is increased from every 120min to 30min, the energy-saving effect is enhanced from 4.7% to 7.5%, but

Table 3 Evaluation of event-driven optimization strategy

Case	Energy (kWh)	Energy saving	Optimization times	Computation time (s)	Computation saving
No opt.	1747.1	-	-	-	-
TDO (30min)	1616.1	7.5%	48	12.1	-
TDO (60min)	1633.5	6.5%	24	5.9	-
TDO (120min)	1664.4	4.7%	12	2.9	-
EDO	1616.0	7.5%	19	5.1	57.9%

the computation load is increased with it. The computation time of the TDO control is increased from 2.9s to 12.1s with the frequency from every 120min to 30min.

The EDO control with defined events achieves the energy-saving effect of 7.5%, which is the same as the TDO control with a relatively high optimization frequency of every 30min. Because optimization is triggered only when events occur, optimization times and computation time are largely reduced compared with the TDO control of the same energy-saving effect (frequency: 30min). The computation time is reduced up to 57.9%.

5. CONCLUSION

In this study, a systematic method to define events for the EDO control of AC systems is proposed. In the proposed method, events which indicated the necessity of optimization is defined by data analysis, identification of critical state transitions and relationship establishment of the variation of each decision variable' optimal value and its critical state transitions. The event definition method is illustrated through the case study of an AC system and the EDO control is carried out using defined events. Driven by defined events, the EDO control strategy for the case AC system can achieve the same energy-saving effect as the TDO control with the optimization frequency of every 30 minutes. The computation load is reduced by 57.9% compared with the TDO control (every 30 minutes). Therefore, the proposed method to define events for the EDO control of AC systems is practical for real application. It can achieve great reduction of computation load and ensuring the energy saving effect simultaneously by guaranteeing the high necessity of optimization actions.

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