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Published in:
Energy Procedia

Published: 01/05/2017

Published version (DOI):
10.1016/j.egypro.2017.03.680

Publication details:
WANG, J., HUANG, G., & ZHOU, P. (2017). Event-driven optimal control of complex HVAC systems based on COP·mins. *Energy Procedia*, *105*, 2372-2377. https://doi.org/10.1016/j.egypro.2017.03.680

Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 105 (2017) 2372 – 2377

Energy Procedia

The 8th International Conference on Applied Energy – ICAE2016

Event-driven optimal control of complex HVAC systems based on COP·mins

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Abstract

This paper tries to answer the question: in what condition an optimization should be done? Previous methods use "time" or "PLR" to trigger the control actions. However, they are both indirect performance indicators. This paper proposes a direct performance indicator, COP·mins, based on which a COP·mins-based event-driven optimal control strategy was developed. The energy performance and computational load of different optimization strategies were compared by simulations. Result shows that the energy and computational savings of the proposed method are higher than time-driven and PLR-based event-driven methods. Meanwhile, it can enable the robustness under various load types. COP·mins is also a general parameter and is applicable in other systems where COP is the main concern. It is found that event definitions are critical in event-driven optimal control.

Peer-review under responsibility of the scientific committee of the 8th International Conference on Applied Energy.

Keywords: Event-driven optimal control; HVAC; COP·mins

1. Introduction

In complex HVAC systems, the real-time optimal control is always adopted to find the optimal control settings and operation modes to improve the operating efficiency [1, 2]. A fundamental question is: in what condition a control optimization should be done? Traditionally, the optimal control actions are driven by time in a periodic way no matter how the operational condition changes [3, 4]. However, ASHRAE handbook [1] says "Optimization of plant operation is most important when loads vary and when operation is far from design conditions for a significant period." Thus, "time" may not be a good driver for HVAC optimal control. Indeed, time-driven methods will cause unnecessary or delayed actions since the operational changes are aperiodic.

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Peer-review under responsibility of the scientific committee of the 8th International Conference on Applied Energy.
doi:10.1016/j.egypro.2017.03.680

In order to overcome these drawbacks, Wang, Huang and Sun [5] proposed an event-driven optimization method in which events are defined based on PLR. Control actions are taken only when PLR changes significantly. In this way, actions can actually adapt to the changing environment. The results show that, comparing with the time-driven optimization method, the computational load is greatly reduced together with a higher energy saving percentage. However, the PLR is not a direct performance indicator, and thus there will still be a mismatch between PLR and COP, which would lead some unfavorable control actions. As we know, the relationship between PLR and COP is nonlinear. It is possible that, when the PLR changes for a significant amount (e.g., 10%), the COP may only change a little (e.g., 1%). In such cases, the PLR-based event-driven strategy will conduct optimizations, while it is actually no need to. Moreover, the threshold value of PLR change is hard to choose since it is closely related to load profiles, which means a single threshold value will not be robust under various load conditions. Additionally, it is difficult to consider the duration of load deviation under PLR-based event-driven strategy. In fact, it should be noted that the duration of load deviation is not the real concern in HVAC optimal control. What really matters is the magnitude of COP deviation.

This paper tries to find a single parameter that can describe the condition in which a control optimization should be done. Since PLR is not a direct performance indicator, a new term, COP·mins, is proposed as a direct performance indicator for event-driven optimal control (EDOC) in HVAC systems. In order to maximize the system COP, control actions are triggered when COP deviates the maximum COP level by a certain amount (transient or accumulated). Two forms of the "COP·mins" are defined which can reflect the transient and accumulated COP deviations. To demonstrate the proposed COP·mins-based EDOC, a simulation-based method is adopted to generate the maximum COP curve under the given the load condition. Case studies are conducted to illustrate the proposed method.

2. Methodology

2.1. Optimization problem

$$Power(i) = load(i) / COP(i) \tag{1}$$

$$Energy\_Consumption = \int_j^k Power(i)dt = \int_j^k load(i) / COP(i)dt \tag{2}$$

$$\min Energy\_Consumption = \min Power(i) \tag{3}$$

$$\min Power(i) = \max COP(i) \tag{4}$$

$$\left(T^*_{cw,i}, T^*_{chw,prm,i}, T^*_{chw,\sec,i}, T^*_{sa,i}\right) = \underset{T_{cw,i}, T_{chw,prm,i}, T_{chw,\sec,i}, T_{sa,i}}{\arg\min} Power(i) = \underset{T_{cw,i}, T_{chw,prm,i}, T_{chw,\sec,i}, T_{sa,i}}{\arg\max} COP(i) \tag{5}$$

Here, the optimization problem aims to minimize the energy consumption of a typical HVAC system which contains a cooling water loop, primary and secondary chilled water loops and air distribution system. $Power(i)$ is the system total power requirement and $COP(i)$ is entire system COP. For all-electric cooling without thermal storage (which is this case), minimizing power requirement at each point in time is equivalent to minimizing energy costs (eqn. (3)) [1]. For a given load profile, since $load(i)$ is fixed, a maximal $COP(i)$ at each time point yields a minimal power requirement [6]. Therefore, the optimization problem can be represented by eqn. (4).

Four temperature set-points are treated as decision variables (eqn. (4)). Subscripts *T, cw, chw, sa, prm, sec* represent temperature, cooling water, chilled water, supply air, primary water loop and secondary water loop; superscript '*' represents the corresponding optimal values of decision variables.

2.2. COP-deviation-based event-driven optimal control strategy

While the aim of the optimal control is to maximize the operating efficiency, the COP-deviation-based EDOC strategy is formulated by the "if-then" structure as follows:

(1) If the current COP is at the maximal level (e.g., 95% of the maximal value), then no optimization is needed;

(2) If the current COP deviates the maximal COP level significantly or the accumulated COP deviation (starting from last control optimization) is significant, then an optimization will be conducted in order to bring the COP back to the maximal level.

$$e_i = \begin{cases} 0, \eta_{t_i} \le \sigma_{e_i} \\ 1, \eta_{t_i} > \sigma_{e_i} \end{cases} \tag{6}$$

Event identification strategy is shown in eqn. (6), where η is the descriptive parameter (discussed in section 2.3), e is the event, σ is the threshold value and t_i/i is time instant. "1" means event happened, while "0" means not happened. When an event is identified, a control action will be taken immediately.

2.3. Event definitions and COP·mins

The system COP value is guaranteed by the eqns. (7-1, 7-2). In other words, the allowed minimal COP is controlled by a threshold (eqn. (7-2)). Basically, events will be identified as long as the condition in eqn. (7-1) is violated. Two forms of COP deviation are defined, i.e., transient and accumulated COP deviations as shown in eqns. (8, 9).

$$COP_{\max}(i) - COP(i) \le \sigma_e \tag{7-1}$$

$$COP(i) \ge COP_{\max}(i) - \sigma_e \tag{7-2}$$

$$\Delta COP(i) = COP_{\max}(i) - COP(i) \tag{8}$$

$$\Delta COP(j-k) = \int_j^k \Delta COP(i)dt \tag{9}$$

Please note that only positive COP differences are counted and negative ones are deliberately set to zero because a performance higher than the referring maximum value is desirable. Here, a term called "COP·mins" is proposed for calculation convenience. As the name indicates, one minute is chosen to be the decision time interval, which is small enough in the HVAC real-time optimal control problems. Thus, the time period is discretized by one minute and eqns. (8, 9) can be represented as follows:

$$\text{COP} \cdot \text{mins}(i) = \Delta COP(i) = COP_{\max}(i) - COP(i) \tag{10}$$

$$\text{COP} \cdot \text{mins}(j-k) = \Delta COP(j-k) = \int_j^k \Delta COP(i)dt \approx \sum_{i=j}^k \Delta COP(i) \tag{11}$$

The “COP·mins” defined above will be used as the descriptive parameter which can formulate the EDOC strategy according to eqn. (6) when the threshold values were determined.

2.4. Finding the maximum COP by simulation(s)

To compute the COP·mins, the maximum COP curve is necessary. There are several ways, for instance, the maximum COP curve of a chiller can be obtained by manufactures’ design and part-load data or from the curve fitting of in-situ performance data [1]. Typically, the maximum COP can be formulated as a function of PLR and other necessary parameters (such as the temperature difference between the return cooling water and supply chilled water). Since the primary purpose of this paper is to illustrate the COP·mins-based EDOC method, for simplicity, a simulation-based method will be adopted to generate the maximum COP curve prior to implementations, which can be obtained by applying an extremely high optimization frequency (e.g., one optimization per 5 minutes) in the simulation for a given a load profile.

3. Case Study

Simulations were conducted to compare the PLR-based and COP·mins-based EDOC methods. 24-hour operation of the HVAC system was simulated in TRNSYS and the optimal control settings were calculated by a separate MATLAB module. Data exchange between the two software is achieved by co-simulation. Component models of cooling towers, chillers and pumps, validated in [7], were adopted. Typical spring and summer load profiles of Hong Kong were used.

3.1. Threshold value selection

Prior to implementations, an important thing is to select the threshold value for descriptive parameters defined in the events (i.e., COP·mins). The mean COP difference between the maximum COP curve the COP curve of the benchmark case was calculated. Please note that the maximum COP curves were obtained by applying a high optimization frequency (i.e., “one optimization per 5 minutes”) in the simulation. The benchmark case keeps all the settings constant, which means no optimization was conducted. The mean COP difference is 0.238 in summer case and 0.194 in spring case. Therefore, considering both cases, 0.2 is selected as the threshold for "COP·mins(i)". The threshold of "COP·mins(j-k)" was obtained by a simple calculation. Suppose the COP deviation is not significant (e.g., 0.1) at each time point and a duration of 25 minutes is considered as a significant period, the accumulated COP·mins is 2.5 which will be used as the threshold. All the values are shown in table 1.

Table 1. Threshold value selection for COP·mins

Case	Mean COP·mins (24 hours)	Threshold of "COP·mins(i)"	Threshold of "COP·mins(j-k)"
Summer	0.238	0.2	2.5
Spring	0.194		

3.2. Results

The energy and computational performance of different methods are listed in table 2. The energy saving is calculated based on the benchmark case (no optimization was conducted), while the computation saving is computed based on the time-driven case “one optimization per 15 minutes” (denoted as "15mins" in Table 2). Two event-driven strategies were tested, namely PLR-based and COP·mins-based strategies. Different threshold values (5%-10%) were tested in PLR-based strategy and 7% and 8% are selected in spring and summer cases considering both energy saving and the computational saving percentages.

Table 2. Optimization performance of different methods (Op. = Optimization; Ch. = Chiller.)

Op. methods	Energy consumption (kwh)	Energy Saving	Op. times	Op. time (s)	Computation Saving	Threshold value
			Spring case			
No Op.	**78241**	0.00%	0	0	\	
15mins	74361	4.96%	96	**69.83**	0.00%	
Ch. On/Off & PLR Change	74866	4.31%	34	30.21	56.74%	5%
	75378	3.66%	31	27.19	61.06%	6%
	74851	**4.33%**	26	23.26	**66.69%**	7%
	75411	3.62%	23	21.53	69.17%	8%
	76572	2.13%	19	16.88	75.83%	9%
	76575	2.13%	17	15.52	77.77%	10%
COP·mins	72812	**6.94%**	12	14.57	**79.14%**	0.2; 2.5
			Summer case			
No Op.	**181379**	0.00%	0	0	\	
15mins	161608	10.49%	96	**138.4**	0.00%	
Ch. On/Off & PLR Change	163257	9.99%	61	102.8	25.72%	5%
	162949	10.16%	51	84.67	38.82%	6%
	163003	10.13%	48	73.63	46.80%	7%
	162336	**10.50%**	42	72.38	**47.70%**	8%
	163868	9.65%	39	69.48	49.80%	9%
	164907	9.08%	37	59.08	57.31%	10%
COP·mins	160484	**11.52%**	16	26.27	**81.02%**	0.2; 2.5

3.3. Analysis

As shown in table 2, comparing with the time-driven method, PLR-based event-driven method can achieve a similar or better energy saving (4.33% and 10.50%) together with a considerable computational reduction (66.69% and 47.70%). This agrees well with the previous findings [5]. However, choosing the threshold is hard for optimization frequency and PLR threshold because they do not have a clear or direct relationship with COP [8]. The simple method is to conduct simulations on different threshold values, based on which a best threshold can be chose. Generally, a low load case would require a small threshold, while the high load case would need a high threshold. For instance, 7% is the best for the spring case and 8% is used for summer case (as shown in table 2). However, this method is time consuming and requires extensive simulation efforts as different load profiles may require different threshold values.

COP·mins-based EDOC method achieves 6.94% and 11.52% of energy savings and 79.14% and 81.02% of computation savings in spring and summer cases respectively, which are 2.6% and 1% higher in energy saving and 12.45% and 33.32% higher in computation saving as compared with PLR-based EDOC method. The main reason is that COP·mins is a direct performance indicator. Moreover, it has been found that a single threshold value can achieve satisfactory performance for different cases, which avoids the demanding threshold value selection. It also shows that the event definition is very important in EDOC since the performance difference between two event-driven strategies is prominent.

4. Conclusions

A COP·mins-based EDOC method has been proposed for HVAC optimal control in this paper. Previous time-driven and PLR-based EDOC methods cannot guarantee the robustness since time and PLR are indirect performance indicators, while COP·mins can directly reflect the performance. Simulation results show that the energy and computational performance of the proposed COP·mins-based EDOC method is superior to time-driven and PLR-based EDOC methods. In addition, COP·mins is able to reflect both transient and accumulated performance deviation, which enables the robustness under different load types. In terms of implementation, the threshold value selection in COP·mins-based EDOC method can be easily done and one threshold value would be satisfactory for different cases. COP·mins is also a general parameter and the proposed methodology is applicable in other industrial systems where COP is the main concern. It has been found that the event definitions are critical in EDOC since different definitions may lead to large performance deviations. Therefore, the systematic way to define events will be investigated in the future. This study limits to a simulation study and experiments will be carried out in the future.

Acknowledgements

This research was supported by a grant of Fundamental Research Project from Shen Zhen Science and Technology Innovation Committee (Project No. RIND8401) and Fundamental and Application Research Special Funding of Guang Dong Province 2015 (Project No. 2015A030313814)

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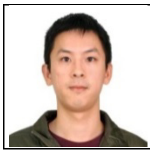

Biography

Junqi WANG is a PhD candidate in City University of Hong Kong, who focuses on the event-driven methods, event analysis and real-time optimal control in HVAC systems.