A stochastic chiller optimization operation strategy based on uncertainty analysis

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Abstract. Deterministic chiller optimization control strategies, such as COP optimization strategy, are intended to save energy based on deterministic sensor measuring data and equipment characteristics. However, the sensor data and the equipment characteristics are typically uncertain due to poor calibration of sensors, poor maintenance of chillers, etc., which could harm the energy-saving performance of deterministic chiller optimization operation strategies. In order to tackle this problem, a stochastic chiller optimization operation strategy based on uncertainty analysis is proposed in this paper. The strategy consists of three steps: (1) Analyze the uncertainty of the HVAC system and specify the probability distribution of each uncertain parameter. (2) Calculate the mathematical expectation value of energy consumption and return chilled water temperature in each operation plan under uncertainty. (3) Select the operation plan with the least energy consumption expectation and limited return chilled water temperature. The performance of the proposed strategy is validated on TRNSYS with measured hourly cooling load data of an office building located in Shanghai. Compared with the deterministic optimized operation strategy, the proposed stochastic strategy performs better on robustness (i.e., keeping return chilled water temperature within safe criteria) because of the consideration of measurement uncertainty. Also, compared with traditional operation strategy without optimization, the proposed strategy performs better on saving energy.

1. Introduction

30%-40% energy consumption of the HVAC system is caused by chillers. In order to reduce the energy consumption of chillers, it’s necessary to operate chillers in appropriate strategy to enhance the energy efficiency. Traditional operation strategies are designed to keep chiller working at design condition which means the set points of a chiller don’t change with the working condition of HVAC system. While, since the chiller coefficient of performance (COP) is influenced by supplied chilled water temperature ($T_{chws}$), inlet cooling water temperature ($T_{ecw}$), cooling water flowrate ($F_c$), chilled water flowrate ($F_{ch}$), and cooling load (CL), chiller COP could be enhanced by adjusting the variables above to keep chiller working on the optimal condition, which is realized by optimization approaches.

The optimization of chiller could be classified into two categories: optimal chiller sequence (OCS) and optimal chiller load (OCL). Chang proposed a novel optimization approach based on Lagrange multiplier to enhance chiller COP by optimizing chiller load [1]. Beghi proposed an approach based on
multi-phase genetic algorithm (MPGA) to optimize chiller load and chiller sequence for multi-chiller system \[2\].

Current optimization approaches are mostly based on an assumption that the real-time data measured by sensors (e.g., water temperature sensor, water flowrate sensor) is accurate with no uncertainty, while the measured data is actually uncertain and influenced by the noise caused by sensors \[3\], which means the optimal working condition offered by a deterministic optimization approach may not actually be the optimal one. In order to optimize the chiller operation, it’s necessary to combine the deterministic optimization approach with the uncertainty analysis on the data measurement. For instance, Li and Huang proposed a stochastic chiller sequencing control strategy to optimize the chiller sequence control considering the uncertainty of cooling load and chiller cooling capacity \[3\]. In order to optimize the chiller load with consideration of measured data uncertainty (e.g., the uncertainty of measured chilled water temperature, chilled water flowrate, etc.), a stochastic chiller optimization operation strategy based on uncertainty analysis is proposed in this paper.

In the proposed approach, the uncertainties of supplied chilled water temperature ($T_{chws}$), return chilled water temperature ($T_{chwr}$), inlet cooling water temperature ($T_{ecw}$), chilled water flowrate ($F_{ch}$), and cooling load (CL) are considered. The set point of supplied chilled water temperature is iterated. At the same time, the mathematical expectation of energy consumption and return chilled water temperature under this set point is calculated. After the iteration, the set point with the least energy consumption expectation value and safe return chilled water temperature value is selected as the optimal set point.

The effectiveness of the proposed strategy is validated on TRNSYS with simulated cooling load data of an office building in Shanghai. The simulation results suggest that compared with traditional chiller operation strategy, the proposed strategy is able to reduce energy consumption with limited loss of indoor comfort. Compared with deterministic optimized operation strategy, the stochastic operation strategy is more robust on satisfying the cooling load.

The methodology of the stochastic optimization operation strategy based on uncertainty analysis is demonstrated in Section 1. The case study on TRNSYS is illustrated in Section 2. And the research is concluded in Section 3.

2. Methodology

![Diagram of the stochastic optimization operation strategy based on uncertainty analysis.]

- **MP model**
  - Performance curve: Ridge regression
  - MP model: \( \text{COP} = f(T_{chws}, T_{ecw}, \text{CL}) \)

- **Uncertainty analysis**
  - \( \Delta T_{chws}, \Delta T_{chwr}, \Delta T_{ecw}, \Delta F_{ch} \)

- **Measured value**
  - \( T_{chws}, T_{chwr}, T_{ecw}, F_{ch} \)

- **Possible value**
  - \( \text{Possible working condition} \)

- **Input**
  - \( P_l, T_{chws}, T_{chwr}, T_{ecw}, F_{ch} \)

- **Calculation of mean value**
  - \( T_{chwr,set,j} = 7:0.1:10 \) (j varies from 1 to m)

- **Better COP_{mean} and limited T_{chwr,mean}?**
  - Y

- **Record this set point**

- **Iteration finished?**
  - N

- **Output**
  - Optimal set point

- **Calculation of mean value**
  - \( CL_i = C_p \times F_l \times (T_{chwr,i} - T_{chws,i}) \)
  - \( COP_{i,j} = f(T_{chwr,set,j}, T_{ecw,set}, CL_i) \)
  - \( T_{chwr,set,j} = CL_i / (C_p \times F_l + T_{chws,set,j}) \)

- **COP_{mean}**
  - \( \text{COP}_{\text{mean}} = \sum_{i=1}^{n} COP_{i,j} \times P_l \)

- **T'_{chwr,mean}**
  - \( T'_{chwr,mean} = \sum_{i=1}^{n} T'_{chwr,i,j} \times P_l \)
The process of the proposed strategy is illustrated in Figure 1. The strategy consists of three parts: uncertainty analysis, the training of MP model and main process of optimization.

### 2.1. Uncertainty analysis of cooling system measurement

In the HVAC system, the controller needs the real-time data measured by sensors to estimate the current status of appliances and user side [4]. With the information, the controller will decide how to control the appliances. While, the data measured by sensors is not always accurate or precise, which means there are noise and error in the measured data affecting the judgement of controller. Hence, uncertainty analysis is necessary in the optimized control of chillers [5]. In this research, the uncertainties of $T_{chws}$, $T_{chwr}$, $T_{ecw}$, $F_{ch}$, and CL are considered and the classical probability distributions of each variable is listed in Table 1. The histogram of water temperature noises is illustrated in Figure 2 with normal distribution fitting curve. All the mean values of distributions in Table 1 equal 0. The standard deviation of water temperature noise distribution is 0.138 $^\circ$C, the standard deviation of water flowrate noise distribution is 2.3%. The standard deviation values are within the criteria defined by Li et al. [3] $0.03^\circ$C $\leq \sigma_T \leq 0.15^\circ$C, 1% $\leq \sigma_F \leq 5\%$.

![Figure 2. Probability distribution of water temperature measurement](image)

| Probability | $T_{chws}$ noise ($^\circ$C) | $T_{chwr}$ noise ($^\circ$C) | $T_{ecw}$ noise ($^\circ$C) | $F_{ch}$ noise (%) |
|-------------|----------------------------|-----------------------------|-----------------------------|-------------------|
| 0.16        | 0                          | 0                           | 0                           | 0                 |
| 0.15        | 0.06                       | 0.06                        | 0.06                        | 1                 |
| 0.15        | -0.06                      | -0.06                       | -0.06                       | -1                |
| 0.12        | 0.12                       | 0.12                        | 0.12                        | 2                 |
| 0.12        | -0.12                      | -0.12                       | -0.12                       | -2                |
| 0.08        | 0.18                       | 0.18                        | 0.18                        | 3                 |
| 0.08        | -0.18                      | -0.18                       | -0.18                       | -3                |
| 0.05        | 0.24                       | 0.24                        | 0.24                        | 4                 |
| 0.05        | -0.24                      | -0.24                       | -0.24                       | -4                |
| 0.02        | 0.3                        | 0.3                         | 0.3                         | 5                 |
| 0.02        | -0.3                       | -0.3                        | -0.3                        | -5                |

With the probability distributions listed above, the probabilities of each possible noise condition could be calculated according to multiplication theorem of probability. For instance, according to Table 1, the probability of $T_{chws}$ noise = 0.1$^\circ$C is 0.15, and the probability of $T_{chwr}$ noise = -0.1$^\circ$C is 0.15, the probability of $T_{ecw}$ noise = 0.1$^\circ$C is 0.15, the probability of $F_{ch}$ noise = 3$^\circ$C is 0.15. In this way, the probability that noises mentioned above happened at the same time is 0.15$^4$. Similarly, the
probabilities of total n (n = 11^4 in this research) possible noise conditions could be calculated.

Every hour the controller receives the real-time values (i.e., the measured values of T_{chws}, T_{chwr}, F_ch and T_{ecw}). With the n possible conditions summarized above, n possible true value sets are generated according to Equation (1). And the possible CL values CL_i's in each true value set could be calculated by Equation (2),

\[
\text{Possible value} = \text{Measured value} - \text{Possible noise} \tag{1}
\]

\[
CL_i = C_p \times F_i \times (T_{chwr,i} - T_{chws,i}) \tag{2}
\]

where \(C_p\) is the specified water heat capacity (kJ/(kg·K)), \(F_i\) means the \(i^{th}\) possible true value of chilled water flowrate (kg/s, \(i\) varies from 1 to \(n\)), etc.

2.2. Multiple polynomial model (MP model)

The MP model is proposed to predict the chiller COP under different working conditions. As Equation (3) shows, with values of three variables: supplied chilled water temperature (T_{chws}), inlet cooling water temperature (T_{ecw}), and cooling load (CL), chiller COP could be predicted.

\[
COP = \beta_0 + \beta_1 CL + \beta_2 T_{chws} + \beta_3 T_{ecw} + \beta_4 CL^2 + \beta_5 T_{chws}^2 + \beta_6 T_{ecw}^2 + \beta_7 CLT_{chws} + \beta_8 CLT_{ecw} + \beta_9 T_{chws} T_{ecw} \tag{3}
\]

where \(\beta\)s are undetermined coefficients which should be determined by regression with existing data of COP, CL, T_{chws}, and T_{ecw}. In this research, the MP model is trained by the data points from nominal performance curves of the chiller.

2.3. Main process of optimization strategy

As mentioned in Section 1.1, when the hourly real-time data (i.e., the measured values of T_{chws}, T_{chwr}, F_ch and T_{ecw}) are measured, n possible true value sets are listed with their probabilities calculated. Then, the set point of T_{chws} (T_{chws,set,j}) is iterated from 7°C to 10°C with a step of 0.1°C (\(j\) varies from 1 to \(m\), \(m=30\) in this research).

In each run of iteration, the current set point value is adopted by Equation (4), (5) to calculate COP values and T_{chwr} values in next time step (T_{chwr,ij}) corresponding to every possible true value set demonstrated in Section 1.1. The mean value of COP corresponding to current set point is calculated by Equation (6), similarly, the mean T_{chwr} value is calculated by Equation (7). It’s noted that the T_{chwr} values calculated by Equation (5) and (7) are the calculated values in the next time step, which are not the same as the real-time T_{chwr} values mentioned in Section 1.1.

\[
COP_{ij} = f(T_{chws,set,j}, T_{ecw,i}, CL_i) \tag{4}
\]

\[
T_{chwr,ij} = \frac{CL_i}{C_p \times F_i} + T_{chws,set,j} \tag{5}
\]

\[
COP_{mean,i} = \sum^n_{j=1} COP_{ij} \times P_i \tag{6}
\]

\[
T_{chwr,mean,i} = \sum^n_{j=1} T'_{chwr,ij} \times P_i \tag{7}
\]

After the iteration of \(m\) times, \(m\) COP mean values and \(m\) T_{chwr} mean values are acquired, corresponding to \(m\) set points, from which the optimal set point is selected. In the proposed strategy, the optimal set point must satisfy 2 requirements:

1. The corresponding T_{chwr} mean value is limited in safe criteria (less than 15°C in this research), to keep the user side cooling demand satisfied, since the supplied chilled water at high temperature could affect the heat exchange efficiency of HVAC terminals, especially when the
cooling load is high at user side.

2. The corresponding COP mean value is the max among the COP mean values of all the set points selected by the first requirement.

3. Case study

3.1. System model
The simplified cooling system model of a commercial building in Shanghai is built in TRNSYS to conduct the case study (Figure 3). Since the proposed strategy is intended to optimize single chiller, the real system (3 chillers, 3 chilled water pumps, 3 cooling water pumps, 3 cooling towers) is simplified to the system illustrated in Figure 3 (1 chiller, 1 chilled water pump, 1 cooling water pump, 1 cooling tower). And the simulated cooling load data in March is selected as input cooling load data since the cooling load of this building in transition season is less than the nominal cooling capacity of a single chiller.

![Figure 3. System model on TRNSYS](image)

| Components       | Characteristics                                           |
|------------------|-----------------------------------------------------------|
| Centrifugal chiller | Variable speed, Capacity = 3421kW, Nominal COP = 5.5      |
|                  | Chilled water temperature set point = 7~10°C              |
| Chilled water pump | Constant speed, Power = 30kW,                            |
|                  | Rated flowrate = 600000kg/hr                              |
| Cooling water pump | Constant speed, Power = 45kW,                            |
|                  | Rated flowrate = 720000kg/hr                              |
| Cooling tower    | Power = 25kW,                                            |
|                  | Rated cooling water temperature = 30.5°C/35.5°C           |

3.2. Two strategies for comparison
Traditional load control strategy and deterministic COP optimization strategy are adopted in this research as matched group to verify the effectiveness of the proposed strategy. The three strategies all
turn on the chiller when the measured cooling load is more than 5% of the chiller nominal cooling capacity. Load control strategy keeps the $T_{chws}$ set point at 7°C to strictly satisfy the cooling demand of user side. Deterministic COP optimization strategy iterates the $T_{chws}$ set point from 7°C to 10°C every hour to choose the optimal set point with the max corresponding COP value predicted by MP model, without consideration of data measurement uncertainty.

3.3. Simulation results
As demonstrated above in Section 1.2, the MP model is adopted in the proposed strategy and deterministic COP optimization strategy to optimize the $T_{chws}$ set point. The model is trained with data points on nominal performance curves of the chiller.

| Strategies                | Chilled water pump energy (kWh) | Cooling water pump energy (kWh) | Cooling tower energy (kWh) | Chiller energy (kWh) |
|---------------------------|---------------------------------|---------------------------------|----------------------------|----------------------|
| Load control strategy     | 6840                            | 17100                           | 16346                      | 59382                |
| Deterministic COP optimization | 6840                        | 17100                           | 16346                      | 55632                |
| Stochastic optimization   | 6840                            | 17100                           | 16346                      | 55918                |

As listed in Table 3, since the pumps in the case are of constant speed, and the turn-on logics of each strategy are the same, energy consumption of pumps and cooling tower doesn’t change with strategies. While the chiller energy consumption varies with the strategies, due to the $T_{chws}$ set points differs under different strategies.

![Figure 4(a). Supplied chilled water temperature under 3 strategies during the last 7 days of March (Horizontal line means the system is off)](image-url)
As is illustrated in Figure 4(a) and 4(b), the $T_{chws}$ remains low under load control strategy, the $T_{chws}$ under deterministic COP optimization strategy is similar with that under stochastic strategy. However, when the cooling load is large, the proposed stochastic strategy tends to limit the $T_{chws}$ set point to keep the heat efficiency of HVAC terminals, which is why the chiller energy consumption under the proposed stochastic strategy is slightly higher than that under deterministic optimization strategy.

4. Conclusion
A stochastic chiller optimization operation strategy is proposed in this paper, which is based on uncertainty analysis of refrigeration system. The uncertainties of supplied chilled water temperature ($T_{chws}$), return chilled water temperature ($T_{chwr}$), inlet cooling water temperature ($T_{ecw}$), chilled water flowrate ($F_{ch}$), and cooling load (CL) are considered. With the permutation and combination, possible noise conditions are listed, after which the MP model is adopted to optimize the chiller $T_{chws}$ set point according to the mean value of predicted chiller COP. Validated with the simulated cooling load of a commercial building in Shanghai, the proposed strategy could save chiller energy with limited return chilled water temperature. Because of the consideration of uncertainty, the proposed strategy performs better on robustness with uncertain system data compared to deterministic optimization strategy.

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