Discrete model-based operation of cooling tower based on statistical analysis

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A B S T R A C T

This study is aimed to utilize the operation data to build a physical-meaningful and precise-enough model to assist the operation of a cooling tower. To do so, this work introduces a dimensionless index, which can describe the cooling capability of a cooling tower in terms of effective power utilization. In the first phase of this study, principal component analysis, one of factor analysis methods, is used to investigate effects of ambient air temperature and relative humidity on the cooling capability of a cooling tower. Based on the proposed cooling capability index, the operation data are partitioned into different groups by the fuzzy c-mean clustering algorithm. The resulted groups are distinctly categorized by the conditions of ambient air temperature and relative humidity. In the second phase of the study, data within the same mode of a set of fans are partitioned by the fuzzy c-mean clustering algorithm. The resulted groups of data are then modeled by linear regression. The acquired multiple models are highly accurate in predicting the output temperature of cooling water from the cooling tower. The acquired models assist the operator to accurately select the proper fan mode when process conditions, e.g., cooling loading, or environment conditions, e.g., ambient air temperature, change. It results in electricity saving. This study is concluded by the presentation of a discrete model-based approach to determine the fan mode. The application to a real cooling tower in an iron and steel plant is promising in saving electricity consumed by the fan set.

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1. Introduction

The conceptual design of the cooling tower can be traced back to Merkel’s work [1], which firstly developed a theory for the thermal calculation with some simplifying assumptions. Afterward, effectiveness-NTU method [2] and Poppe method [3] were proposed to improve Merkel’s approximations. Kloppers and Kröger [4] presented a comprehensive review on those works. In the last decade, based on the rapid development of software simulation, researchers studied the cooling tower design in more details [5–11], including the effect of special fill material and fill style to cool-
water, the authors presented a model-based assessment approach to investigate the on-line performance of a cooling tower [20].

Besides design and performance assessment, some researches pay attention to the issue of optimal operation for a cooling tower [21,22]. Based on the mass/energy conservation laws and mass/heat transfer equations, CFD (computational fluid dynamics) models were developed to simulate the cooling tower operation [16,23]. However, differences between the modeling world and the actual operations keep the simulation models from being utilized in the real-time operation. In general, the model based on the actual process data can reflect the actual process, but conventional linear model is not competent for the nonlinear and time-varying characteristic of a cooling tower. Artificial neural networks and bee colony algorithm were used for modeling cooling tower [24–27], but the results were beyond understanding and hardly provided any physical knowledge for reference. Recently, a linear multi-model based approach is proposed by the authors with an automatic clustering approach [28].

Although many authors have studied cooling tower operations and optimization, following two issues have not been addressed:

(i) A data driven, physically meaningful model that is clear to the operators has not been reported.

(ii) Application of a model based control to a real plant has not been addressed.

In this section, principal component analysis (PCA) and fuzzy c-mean clustering (FCM) algorithm and the clustering results are analyzed to reveal physical meaning. The partitioned groups are subsequently used to build a set of multiple linear models. A discrete model-based approach for selecting fan mode is presented and the implementation of the proposed optimal operation is demonstrated by the studied cooling tower.

The rest of the paper is organized as follows. The next section describes the studied system. In Section 3, a cooling capability index is defined and statistical analysis methods are utilized to investigate the effect of ambient air temperature and relative humidity on the cooling capability of a cooling tower. Fuzzy c-mean clustering (FCM) algorithm is used to categorize operating data into groups and the characteristics of the cooling tower are modeled by multiple model method in Section 4. The implementation of the proposed model-based operation for setting fan mode is demonstrated in Section 5. Some remarks with a summary are concluded in the last section.

### 2. System background description

A pump draws water and sends it to the top of the fill and water is evenly sprayed over the cooling tower fill, while ambient air is pulled into the tower from wall sides by fans. After absorbing heat from the hot water stream, the air stream is expelled through the top of the cooling tower. As a result of rejecting heat to the air stream, temperature of the water stream drops, and then, air temperature rises.

The studied subject is one of cooling towers in a large iron and steel plant in Taiwan. Cooling water from the studied unit provides service for tandem cold mill and continuous annealing line. The cooling tower unit has three fans. Each fan has 3 operating modes, namely, closed, low speed and high speed. The fan set usually operates in one of the following seven modes from low to high level: three closed (C3_L0_H0), two closed and one low-speed (C2_L1_H0), one closed and two low-speed (C1_L2_H0), three low-speed (C0_L3_H0), two low-speed and one high-speed (C0_L2_H1), one low-speed and two high-speed (C0_L1_H2), three high-speed (C0_L0_H3). The operation target is to not allow temperature of outlet water to exceed 33.5 °C.

The operation variables used in this cross-flow induced draft tower can be partitioned into two parts, i.e., (1) cooling water related: water mass flow rate $F_{cw}$, inlet water temperature $T_{cw,in}$ and outlet water temperature $T_{cw,out}$; (2) ambient air related: dry bulb temperature of inlet air $T_{ab,in}$, relative humidity of inlet air $RH_{air,in}$, mass flow rate of dry air $M_{air}$ and fan power of cooling tower $W_{fan}$.

### Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$T_{cw,in}$</td>
<td>inlet water temperature of cooling tower (°C)</td>
</tr>
<tr>
<td>$T_{cw,out}$</td>
<td>outlet water temperature of cooling tower (°C)</td>
</tr>
<tr>
<td>$F_{cw}$</td>
<td>water mass flow rate of cooling tower (10$^3$ kg/h)</td>
</tr>
<tr>
<td>$T_{air,in}$</td>
<td>ambient air temperature, i.e., dry-bulb temperature of inlet air to the cooling tower (°C)</td>
</tr>
<tr>
<td>$M_{air}$</td>
<td>mass flow rate of dry air (kg/h)</td>
</tr>
<tr>
<td>$RH_{air,in}$</td>
<td>relative humidity of inlet air to the cooling tower (%)</td>
</tr>
<tr>
<td>$W_{fan}$</td>
<td>cooling tower fan power (kW)</td>
</tr>
<tr>
<td>$\gamma_{ct}$</td>
<td>cooling capability index</td>
</tr>
<tr>
<td>$C_p$</td>
<td>Specific heat of water at constant pressure (kJ/(kg °C))</td>
</tr>
</tbody>
</table>

### 3. Statistical analysis of cooling capability

In this section, principal component analysis (PCA) and fuzzy c-mean clustering (FCM), are utilized to examine the effect of ambient air temperature and its relative humidity on the cooling capability of the studied cooling tower.
3.1. PCA analysis for ambient air and cooling capability

In order to precisely describe the cooling capability in terms of unit energy consumption, the following dimensionless index is defined as the ratio of rejected thermal energy from cooling water to consumed electric energy by the fan driver. The dimensionless cooling capability index is termed as $c_{ct}$ and defined as follows:

$$c_{ct} = \frac{(T_{cw,in} - T_{cw,out})F_{cw}C_p}{W_{fan}}$$  \(1\)

At the beginning of this study, correlation analysis was straightforwardly conducted on the relationship between the cooling capability index $c_{ct}$ and the plain properties of ambient air, i.e., $T_{D,air,in}$ and $RH_{air,in}$, in the cooling tower operation. It resulted in unimpressive 19.6% of $R^2$ between $c_{ct}$ and $T_{D,air,in}$, and 7.0% of $R^2$ between $c_{ct}$ and $RH_{air,in}$.

Aimed to further explore the hidden factors in the data, principal component analysis (PCA) was applied to treat the data regarding ambient air properties. Two principal components were obtained. The 1st PC scores 68% while the 2nd PC 32%. Correlation analysis was then conducted to investigate the relationship between the cooling capability index $c_{ct}$ and the two PCs. It turned out with an impressive 32.1% of $R^2$ between $c_{ct}$ and 2nd PC. Fig. 2 shows the results of PCA. It means that the 1st PC could explain 68% of variations of the data regarding $T_{D,air,in}$ and $RH_{air,in}$ while the 2nd PC accounts for the remained 32%. Table 1 summarizes correlation analysis results. The above analysis reveals that the major variation of data is along the line of from the points of high $T_{D,air,in}$ and low $RH_{air,in}$ to the points of low $T_{D,air,in}$ and high $RH_{air,in}$, but what matters on the cooling capability of a cooling tower operation is the linear combination of low $T_{D,air,in}$ and low $RH_{air,in}$, which is 2nd PC.

### Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>$R^2$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{D,air,in}$</td>
<td>19.6</td>
</tr>
<tr>
<td>$RH_{air,in}$</td>
<td>7.0</td>
</tr>
<tr>
<td>$T_{D,air,out}$</td>
<td>1.5</td>
</tr>
<tr>
<td>$\Delta T_{air}$</td>
<td>3.3</td>
</tr>
<tr>
<td>1st PC</td>
<td>6.2</td>
</tr>
<tr>
<td>2nd PC</td>
<td>32.1</td>
</tr>
</tbody>
</table>

![Fig. 1. Historical data of main operation variables at the sampling interval of 5 min.](image_url)

![Fig. 2. The first and second PC of $T_{D,air,in}$ and $RH_{air,in}$.](image_url)
3.2. FCM analysis for data of different levels of cooling capability

With the knowledge acquired in the above section, this study further investigate what the roles of ambient air temperature and relative humidity play on the cooling capability of the cooling tower by conducting Fuzzy c-mean clustering (FCM) on the operation data.

Fuzzy c-mean clustering is based on the minimization of distances between data points and the prototype of cluster centers [29]. For the purpose of minimization, the following cost function is used:

$$J_{FCM}(U, \Phi) = \sum_{k=1}^{N} \sum_{i=1}^{c} u_{ik}^c ||\Phi(k) - \nu_i||^2$$  \hspace{1cm} (2)

where $N$ is the number of all the data points, $c$ is the given cluster number, $U = \{u_{ik} \in [0,1]||\sum_{i=1}^{c} u_{ik} = 1; \sum_{k=1}^{N} u_{ik} > 0; k = 1, \ldots, c\}$ is a membership matrix, $V = \{\nu_1, \ldots, \nu_c\}$ is a cluster center set. For a given cluster number, the objective function is minimized by an alternating optimization algorithm [30].

The FCM partitioning was made based on the cooling capability level, i.e., $\gamma_{ct}$. After several trials, it was found that the partitioning of eight groups provided the best and clear results. The eight clustering central points within obtained groups of data are plotted in Fig. 3. With descending order, eight cooling capability levels are denoted as from $\gamma_{ct,1}$ to $\gamma_{ct,8}$. The value inside the parenthesis is the dimensionless cooling capability index. It is found that the cooling tower has the high cooling capability in the area with low temperature and low humidity ($T_{in,air} < 22.5^\circ C$, $RH_{in,air} < 74.5\%$) while low cooling capability groups appear in the opposite direction. With the increase of temperature and humidity, the cooling capability becomes poor. The cooling capability in the highest group, i.e., 475 is four times of that in the lowest level, 116.

The scattering plot of these eight center points has the same trend as what 2nd PC shows in Fig. 2. Both figures reflect the same phenomenon in physics. The ambient air with less saturated moisture and lower temperature a cooling tower bring in is more capable to absorb the heat from cooling water. In other words, the temperature difference between inlet cooling water and ambient air as well as the less saturation condition are the two major driving forces to effectively reject the heat from cooling water. During the real operation, operators may not timely change the fan mode responding to the weather change. Lack of physical knowledge, operators tend to be conservative in coping with the requirement of keeping outlet cooling tower temperature below the certain point demanded by the users. As a result, operators would inefficiently set all fans in high mode in the hot humid summer days while wastefully start many fans in the cold dry winter days. The local weather has distinctive characteristic in temperature difference between summer and winter, but less distinguishable in humidity conditions. The 1st PC in Fig. 2 reflects the above-mentioned characteristics. With those data, Fig. 3 shows a distorted line with both opposite ends, instead of being a straight line as shown by the 2nd PC in Fig. 2.

4. Discrete model-based operation of cooling tower

Imbedded with the knowledge revealed in the previous sections, the model-based operation of the cooling tower will be described and demonstrated in this section. Ambient air temperature and relative humidity have been proved to be correlated to the cooling capability index in the last section. Subsequently, it is reasonably supposed that the fan operating mode should be associated with the cooling capability index. After categorizing the data by the fan operating mode and calculating their average values of air temperature, relative humidity and cooling capability index, it is found that each fan operating mode had distinct averaged air temperature and cooling capability index, but indistinguishable relative humidity. By investigating the data groups partitioned by fan operating mode, the same characteristics can be found as those by FCM method. Therefore, this study decided to build the multiple models by partitioning the data based the fan operating mode. In this way, it would be easy to build the models and then implement the model-based approach in real operation.

4.1. FCM analysis

According to the previously described seven fan operating modes, denoted with corresponding fan power as $W_{fan,1}$ to $W_{fan,7}$, all the operation data are divided into seven groups and every data has five variables, namely ambient air temperature $T_{in,air}$, its relative humidity $RH_{in,air}$, inlet water temperature $T_{in,cw}$, cooling water flow rate $F_{cw}$, and fan operating mode $W_{fan}$. Within each group, fuzzy c-mean clustering (FCM) is conducted on the data with cluster number, $c$ set as 2. The data in the resulted partitioned groups in every one of seven fan operating modes are distinctly scattered in the Cartesian coordinates of ambient air temperature $T_{in,air}$ and relative humidity, $RH_{in,air}$.

Taking the examples of two fan operating modes, C3 L0 H0 and C1 L2 H0, the data with degree of membership $u_{12}$ and $u_{22}$ larger than 70% are plotted as shown in Figs. 4 and 5. It is found that the data within the same fan operating mode are divided distinctly into two groups, one with high temperature and low humidity, and the other with low temperature and high humidity. It reflects the local weather characteristics imbedded in the data.

4.2. Cooling tower modeling

From the mass and energy conservative laws, outlet temperature of cooling water $T_{out,cw}$ is known to be the function of inlet cooling water temperature $T_{in,cw}$, cooling water flow rate $F_{cw}$, ambient air temperature $T_{in,air}$, relative humidity $RH_{in,air}$, and air flow rate $M_{air}$. Because the data are partitioned by their fan operating mode, 7 in this case, the air flow rate, being the same within each group of data, is not treated as variable. Since two clusters are made by FCM in each fan operating mode, the total number of the multiple mod-
els is 14 in this case. They are constructed by the following equations.

\[
\hat{T}_{cw, out}^m(k) = \sum_{i=1}^{2} \hat{\rho}_i(\phi(k)) \cdot \hat{f}_i(X(k)) \quad (m = 1, \ldots, 7)
\]

where \( \phi(k) = [F_{cw}(k), T_{cw, in}(k), T_{out, in}^D(k), RH_{air, in}(k)] \), the cluster number \( c = 2 \), \( m \) indicates the different fan operating mode, \( k \) is the time step with interval of 5 min and

\[
\hat{\rho}_i(\phi(k)) = \frac{\exp\left(-\frac{(\phi(k) - \phi_1)^T(\phi(k) - \phi_1)}{s_1^2}\right)}{\sum_{i=1}^{2} \exp\left(-\frac{(\phi(k) - \phi_1)^T(\phi(k) - \phi_1)}{s_1^2}\right)}
\]

where \( \phi_i (i = 1, 2) \) is the cluster center, which is obtained by the minimization of the cost function shown in Eq. (2), and \( s_i \) is the width of Gaussian function. For the case of cluster number \( c = 2 \), \( s_1 = s_2 = \sqrt{(v_1 - v_2)(v_1 - v_2)^T} \). \( X(k) = [1, \phi(k)] \) and \( \hat{f}(X(k)) = X(k) \cdot \beta_i \) and \( \beta_i = [\beta_{i,0}, \beta_{i,1}, \beta_{i,2}, \beta_{i,3}, \beta_{i,4}]^T \) are coefficients of the \( i \)th local model.

Among 60,000 samples, seven batches of 500 samples randomly were taken from them for each fan operating mode. The 500 samples were partitioned into two groups by FCM method and used to build two local models in the formats of linear equations. The detailed procedures of the FCM-based multiple-model method can be referred to the authors’article [31]. The rest of the sampled data were used to test the prediction accuracy with two indexes, namely mean square error (MSE) and \( R^2 \) as shown below:

\[
MSE = \frac{1}{N} \sum_{k=1}^{N} (T_{cw, out}(k) - \hat{T}_{cw, out}(k))^2
\]

\[
R^2 = 1 - \frac{\sum_{k=1}^{N} (T_{cw, out}(k) - \hat{T}_{cw, out}(k))^2}{\sum_{k=1}^{N} (T_{cw, out}(k))^2}
\]

The prediction capability of the acquired multiple models are demonstrated in the cases of fan operating mode C3_L0_H0 and C1_L2_H0. Both of Figs. 6 and 7 show the model prediction results. Fig. 6 is for the case of fan operation mode C3_L0_H0 while Fig. 7 for C1_L2_H0. Both figures consist of a comprehensive picture showing the prediction result of the testing set of 7000 points, and a close-up picture showing that of 1000 points. They illustrate that the outlet temperatures of cooling water are well fitted by the models.

The results of prediction accuracy for all seven fan operating modes are summarized in Table 2. All of the operating modes share the similar prediction accuracy. It means that the proposed approach is stable and reliable in the whole range of the operation.
The proposed approach of partitioning the data shown above is the combination way based on knowledge and FCM. The knowledge of idea is inspired by physical sense and verified by statistical analysis.

To justify the proposed way of partitioning, the above results are compared to those by the FCM method only. Two cases of plain FCM partitioning are made, i.e., setting clustering number $c = 5$ and $C = 14$ respectively. The first number, 5, is arbitrarily chosen while 14 is the total model number of the proposed approach in this study. To make the comparison fair, both cases randomly take 3500 samples from all 60,000 data to build multiple models based on FCM clustering.

Table 3 summarizes the comparisons of both prediction indexes among three ways. Because MSE tells the absolute precision of the prediction capability, it is commonly used as an index to address the accuracy of the model for prediction. In this table, the improvement of the proposed approach is 53.4% over plain partitioning by FCM in terms of MSE (i.e., $(0.3145–0.2050)/0.2050$). If we take the square root of MSE as the index, then the improvement is 24%.

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Prediction accuracy in seven fan modes.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fan operating mode</td>
<td>Number of all data</td>
</tr>
<tr>
<td>C3_L0_H0</td>
<td>6077</td>
</tr>
<tr>
<td>C2_L1_H0</td>
<td>11401</td>
</tr>
<tr>
<td>C1_L2_H0</td>
<td>12803</td>
</tr>
<tr>
<td>C0_L3_H0</td>
<td>14049</td>
</tr>
<tr>
<td>C0_L2_H1</td>
<td>7251</td>
</tr>
<tr>
<td>C0_L1_H2</td>
<td>6922</td>
</tr>
<tr>
<td>C0_L0_H3</td>
<td>1497</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Comparison among three different partitioning ways.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prediction MSE</td>
</tr>
<tr>
<td>$c = 5$</td>
<td>0.4263</td>
</tr>
<tr>
<td>$c = 14$</td>
<td>0.3145</td>
</tr>
<tr>
<td>Combination way in this study</td>
<td>0.2050</td>
</tr>
</tbody>
</table>
The plain partitioning by FCM is no match to the proposed way, not to mention that the former way provides messy and hard-to-figure-out-meaning clustered groups.

4.3. Discrete model-based operation strategy and implementation

As the models of outlet temperature of cooling water $T_{cw, out}$ are acquired with good precision in previous section, the next task is the formulation of model-based optimal operation for the cooling tower. The objective of the optimal operation is to keep the cooling water temperature below the certain point demanded by the process end users with the minimizing the consumed electrical power. The temperature of cooling water is demanded below the level of 34 °C by the end user and the upper temperature bound is set at 33.5 °C by utility operators in this study. The control scheme is to predict the outlet temperature of cooling water based on the present conditions of operation variables. All possible modes for the next operation are reviewed based on the above model, and the optimal mode that can make the outlet temperature fall below the target with the least electricity can be acquired.

Denote the model of outlet cooling water temperature as $f_{\text{model}}(\cdot)$, with $m$ indicating the different level of the fan operating mode. The model-based approach of fan operation is formulated as follows:

$$m_{\text{optimal}}(k) = \arg \min_{m} |T_{\text{cw, out}}^m(k) - 33 \, ^\circ\mathrm{C}| \quad (m = 1, \ldots, 7)$$

subject to

$$T_{\text{cw, out}}^m(k) = \sum_{i=1}^{2} \rho_i(\phi(k)) \cdot f_i([1 \, \phi(k)])$$

$$\phi(k) = [F_{cw}(k), T_{cw,in}(k), T_{air,in}^D(k), RH_{air,in}(k)]$$

$$T_{\text{cw, out}}^m(k) < 33.5 \, ^\circ\mathrm{C}$$

The experiment was demonstrated in the period of from 8:15 to 14:50 on May 22, 2012. An off-line PC implemented with the built-in model was temporarily connected to the distributed control system. The suggested fan mode was presented based on the calculation of the model, and passed to the operator to adjust the fan mode of the cooling tower during the period of the experiment. Fig. 8 shows the historical data of inlet temperature of cooling tower $T_{cw,in}$, ambient air temperature $T_{air,in}^D$, predicted outlet temperature $\hat{T}_{cw, out}$ and measured outlet temperature $T_{cw, out}$.

Before the implementation of model-based operation, the on-duty operator set the cooling fan mode at C0_L2_H1. The move was a bit conservative and wasteful because outlet temperature was 28 °C, almost 5.5 °C below the set point of 33.5 °C. After checking the prediction accuracy, the operation was switched to the model-based control. A series of actions were taken in the 6-h experiment. The actions included the adjustment to operating mode C2_L1_H0, C3_L0_H0 and C0_L3_H0 at time 8:15, 9:20 and 11:20, respectively. The outlet temperature $T_{cw, out}$ is accurately predicted by the cluster-based models and the outlet temperature smoothly approached the set point and stayed in the proximity of 33.5 °C.

Taking the original fan mode of C0_L2_H1 mode and the associated power as the baseline, 72.36% of the electricity consumption, i.e., 608 kW h, was saved. The resulted benefit/cost ratio is significant, considering that almost no fixed cost is needed in the implementation of model-based optimal operation. In our study, we estimate that the energy saving would be up to 114 MW h/month in the summer while 16 MW h/month in the winter. It is reasonable that operators used to operate cooling fan conservatively or even wastefully in order to fulfill their duty of providing low temperature cooling water. The proposed model-based approach provides the best practical opportunity to conserve energy in the operation of a cooling tower.

5. Conclusion

This paper proposed a dimensionless cooling capability index to investigate how the operation variables affect the power efficiency of the fan operation. The analysis of PCA and FCM partitioning revealed the similar results that ambient air temperature and relative humidity played the important role. Taking the fact that the operation data within the same fan operating mode have the similar cooling capability index, the multiple models were constructed based on the combination way of partitioning data, first by the acquired knowledge and then by FCM clustering.

A discrete model-based operation was demonstrated in an experimental trial. The experiment showed the promising result...
of saving 72% of electric power. Comparing the effort taking to implement the proposed model-based operation to the effect shown in the test trial, the resulting improvement was good enough to convince the operator to shift the present practice to model-based operation. As a matter of fact, it is hard for any operator to make the optimal decision without precise knowledge on how to adjust the fan mode. The proposed approach provides the best practical opportunity in the operation of a cooling tower. Furthermore, once the operation shifts to the proposed approach, the multiple models to be further refined based on the future operation data is to be more accurate because the operation is close to optimal. The whole approach becomes a positive cycle to conserve energy in the cooling fan operation.

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