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Technology Development of Energy Saving and Performance Assessment for the Cooling Tower

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This paper presents a model-based approach to assess operation performance and to optimize the operation mode of a set of fans in the cooling tower by considering the turbine-generator and cooling tower as an integrated system. The optimization was formulated in order to maximize the net power output, which is the result of subtracting the power consumption of the fans in the cooling tower from the power generated by the turbine-generator. The operation of both units were characterized by a data-driven method, a local model network, which presented a set of local models in the format of linear equations. The optimization problem was then solved by linear programming algorithm. With purely mathematical work and without any change in the existing plant, the energy saving was handily accomplished. This study reports on an energy saving of 0.5% of the power output of a TG system. With the same models, the present characteristic parameters of a cooling tower could be calculated. Comparing the design parameters, the operation effectiveness of the cooling tower could be handily calculated on line.

Keywords: Optimization, Turbine-generator, Cooling tower, Local model network, Power generation system, Operation effectiveness

1. INTRODUCTION

Over the past decades, greenhouse gas emissions and the energy crisis have gained a lot of attention, and have become urgent issues. Many initiatives have been proposed to deal with these issues. One way is to develop renewable energy resources that do not emit greenhouse gases, such as wind energy, and solar energy. Another way is to conserve energy consumption.

As a matter of fact, there is still a lot of room to conserve energy use by enhancing energy efficiency of many industrial processes. The power generation system (PGS) is the process attracting much attention, because electricity is the major energy format used in daily life and in industry. Apart from commercial power plants, cogeneration systems, which provide both of steam and electricity, are becoming popular in the community and in energy-intensive industries, such as the petrochemical, and iron and steel industries. A typical PGS comprises a boiler, turbine-generator (TG), condenser, and cooling tower (CT). In the last decades, great progress has been made to enhance the efficiency of each individual unit. Huang and Edwards(1) proposed to improve thermal efficiency of a TG system by modifying several auxiliary systems to reduce the back-pressure of the associated condenser. Chuang and Sue(2) conducted a field test on a combined cycle power plant with 457.6MW of designed power output. They concluded that decreasing 100mbar of the condenser pressure alone increased the power output by 2.5%.

Regarding the optimal operation of CT, Braun and Diderrich (3) proposed to maintain a constant approach, i.e., a constant temperature difference between the outlet cooling water temperature from CT and the inlet wet-bulb temperature of the ambient air. Besides the approach, Malcolm and James(4) studied the various fan control modes, namely, single speed, two-speed and variable-speed, under different ambient conditions. They concluded that the range of a CT, the temperature difference between the inlet and outlet of the cooling water, is a key index for conserving fan power especially in colder climates.

When coupled with the operation of the TG, the cooling water coming out of the CT condenses the exhausted steam in the vacuum condition, also known as the back pressure in the condenser, which is operated at as low a rate as possible to maximize the power output generated by the TG. On the other hand, the fans of the CT induce the ambient air to cool down the cooling water. The fans of the CT consume electrical power which is provided by the TG. Therefore, the performance of a CT is not the sole concern of this study. Without resorting to the above index concerning temperature range, this study aims to maximizing the net power generated by the TG. The net power is equal to the amount of power generated by the TG less that consumed by the fans and the cooling water pumps.

To maximize the net power generated by the TG, it is necessary to find an optimal operation, i.e., a certain resolution speed of fans and cooling water flow rate, which could result in the inlet cooling water temperature to the condenser being low enough to reduce the back pressure that maximizes the net power generated by the TG. In the plants, the optimal resolution speed of fans varies along with the changes of many factors, such as the loads of TG, and ambient air quality(5). The dynamic behaviors of the integrated operation of TG and CT embed complex nonlinear interactions(6).

To tackle the issues of optimal operation for an existing commercial plant, the best way is to identify the operation models, then solve the optimization problem mathematically. Some rigorous and empirical models for the CT and the TG have been presented in the literatures. Merkel method(7), e-NTU method(8), and Poppe method(9) are the best known methods for modeling a CT. Instead of the aforementioned theoretical approach, this work employs the data-driven modeling methods which have been gaining increasingly popularity in the industry. The accumulated historical records represent a worthy source of information, which enables engineers to build inferential models. As one of the data-driven methods, the Artificial Neural Network (ANN) has been widely used for modeling a nonlinear system. Despite the effectiveness of the ANN system, the lack of transparency keeps the resulting model from providing any physical knowledge regarding the studied system. In addition, this lack of transparency hinders the incorporation of prior knowledge about the system into the model.

Due to its transparency and ability to model a nonlinear system, the local model network (LMN) is used in this work. This technique is a typical multi-model approach used for modeling any nonlinear system, whose behavior is described as the weighted sum of a set of local linear models. The outputs of each local model are valid in a limited domain, whose boundary is determined by a clustering technique or domain knowledge. This method often gives a more manageable and transparent representation of the nonlinear system. This study applies LMN to modeling the CT and the TG with operation data. An optimal operating mode for a set of fans in the CT, which maximizes the net power output, can be obtained by solving the equation sets of acquired models with linear programming. The CTI (Cooling Tower Institute)(10) is generally regarded as a validated method to evaluate the effectiveness of a cooling tower. For each cooling tower, the manufacturer usually provides the design characteristic curve which plots the thermodynamic characteristic of the cooling tower KaV / L against the water-air mass flow rate ratio L / G . KaV / L , also known as Merkel's integral.

To calculate the present effectiveness of an existing cooling tower, test runs should be conducted under the same or similar operating conditions. The test conditions should be held within the following limits against the design conditions: (1) Circulating water flow should not vary by more than 5%; (2) Heat load should not vary by more than 5%; (3) Range should not vary by more than 5%; and (4) Instantaneous readings of wet bulb temperature may fluctuate, but the rate of change in the average wet bulb temperature should not exceed 2^{o}F per hour.

After the test characteristic curve is plotted, the effectiveness of the cooling tower is obtained by comparing the design curve and test curve. In reality, the test conditions are considered too rigid to be applicable to an existing cooling tower, whose operation conditions are very likely outside the test conditions after a long service time. With the acquired models proposed in this study, the characteristic parameters are predicted within the test conditions specified in the CTI method. Comparing with the design parameters, the effectiveness is handily evaluated on-line.

The framework proposed in this work can be handily applied to any commercial power plant. The case study on one of power generation units at China Steel (CSC) demonstrates that the proposed approach can significantly increase power output by simply conducting a mathematical computation and subsequently adjusting the revolution speed of a set of fans in the CT.

For the sake of clarity, we have taken a real power generation plant as an example to illustrate the formation of the objective function and the way of problem-solving. The studied case is just as any other typical PGS.

As shown in Fig.1, the process flow consists of two boilers, two turbine-generators (TG6 and TG7), two condensers, and a cooling tower (CT4) with six fans. High pressure steam, generated in a boiler, is introduced into a turbine which in turn drives a power generator to produce electric power. A condenser in a

PGS is usually operated under vacuum conditions. As a rule of thumb, the lower the back pressure achieved in a condenser; the more electric power is produced in a TG system. Cooling water, the most popular but not the only medium, is used in this study to condense any exhausted steam in the condenser. The cooling water circulates as the water becomes warm when absorbing heat in a condenser; then the water becomes cold when releasing its heat in a CT. When the colder cooling water enters in the condenser, a higher degree of vacuum is achieved.

Considering only the TG system depicted by the dashed line shown in Fig.1, the thermal efficiency of the TG unit can be denoted as:

$$\eta = \frac{aW_{TG}}{m_m H_m - m_1 H_1 - m_f H_{LP2,f}} \quad \text{......................} \quad (1)$$

where, $a = 3{,}600\ kJ/kW \cdot hr$ is a unit conversion constant.

Making an energy balance equation around the condenser and rearranging the equation, the enthalpy of feed water ($m_f H_{LP2,f}$) can be obtained as:

$$\begin{aligned} m_f H_{LP2,f} &= m_2 H_2 + m_3 H_3 + m_{last} H_{last} \\ &\quad - m_{CD} C_{p,w} (T_{CD,out} - T_{CD,in}) \end{aligned} \quad \text{........} \quad (2)$$

Substituting Eq.2 into Eq.1, the efficiency can be rewritten as:

$$\begin{aligned} \eta = aW_{TG} / \big(& m_m H_m - m_1 H_1 - m_2 H_2 - m_3 H_3 \\ & - m_{last} H_{last} + m_{CD} C_{p,w} (T_{CD,out} - T_{CD,in}) \big) \end{aligned}$$

$$\text{.....................................} \quad (3)$$

Because enthalpy is a function of pressure and temperature, the efficiency can be simplified as:

$$\begin{aligned} \eta = f\big(& W_{TG}, m_m, P_m, T_m, m_1, P_1, T_1, m_2, P_2, T_2, m_3, P_3, T_3, \\ & m_{last}, P_{last}, T_{last}, m_{CD}, P_{LP2,f}, T_{LP2,f}, C_{p,w}, T_{CD,out}, T_{CD,in} \big) \end{aligned}$$

$$\text{....................................} \quad (4)$$

where, $f(\cdot)$ is an unknown nonlinear function.

Considering that the evaporation rate of cooling water in comparison to the cooling water flow rate is very small and can be ignored, an energy balance around the CT can be denoted as:

$$\begin{aligned} & m_{air}^D \left(C_s (T_{air,in}^D - T_{air,out}^D) + \lambda_0 (\mathscr{H}_{in} - \mathscr{H}_{out}) \right) \\ & \quad = m_{CW} C_{p,w} (T_{CW,in} - T_{CW,out}) \end{aligned} \quad \text{......} \quad (5)$$

where, λ_0 is latent heat, C_s is humid heat. Rearranging Eq. 5 yields:

$$T_{CW,out} = T_{CW,in} - \frac{m_{air}^D \left(C_s (T_{air,in}^D - T_{air,out}^D) + \lambda_0 (\mathscr{H}_{in} - \mathscr{H}_{out}) \right)}{m_{CW} C_{p,w}}$$

$$\text{......................................} \quad (6)$$

The thermal efficiency of a TG system, as shown in Eq.4, is affected by many operation variables, including $T_{CD,in}$, which is denoted as $T_{CW,out}$ in the CT side. Most of them are related to the operation of the boiler which is not in the scope of this study. But $T_{CD,in}$ is the one which can be manipulated by the operation of the CT. As shown in Eq.6, $T_{CW,out}$ is determined by the quality and quantity of cooling water and ambient air.

In formulating the objective function of this optimization problem, power production of W_{TG6} and W_{TG7} and power consumption of W_F are mainly concerned. The former terms exist in Eq.4. And the latter

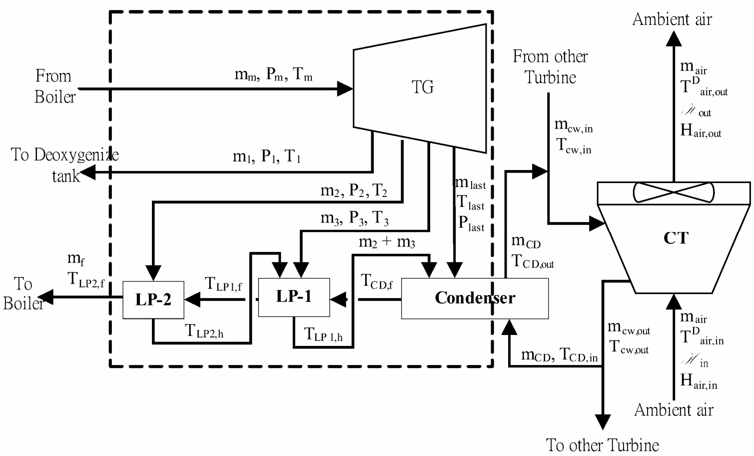

Fig.1. Process flow diagram of a typical PGS.

term, W_F determines the revolution number of fans, which in turn decides the air flow rate into the cooling water. In other words, the power consumption of the fans (W_F) can substitute the wet air flow-rates. Then, the statistical model of outlet temperature of cooling water out of CT ($T_{CW,out}$) can be rebuilt by the following function:

$$T_{CW,out} = f(T_{CW,in}, T^D_{air,in}, \mathscr{H}_{R,in}, W_F) \quad \text{.................... (7)}$$

where, $f(\cdot)$ is an unknown nonlinear function. Summarily, given Eq.4 and Eq.7, the following optimal objective function can be solved.

$$\begin{aligned}
&\max J = \max\{W_{TG6} + W_{TG7} - W_F\} \\
&s.t.\ \eta_{TG6} = f\big(W_{TG6}, m_{m,TG6}, P_{m,TG6}, T_{m,TG6}, m_{1,TG6}, P_{1,TG6}, T_{1,TG6}, \\
&\qquad m_{2,TG6}, P_{2,TG6}, T_{2,TG6}, m_{3,TG6}, P_{3,TG6}, T_{3,TG6}, m_{last,TG6}, P_{last,TG6}, \\
&\qquad T_{last,TG6}, m_{f,TG6}, T_{LP2,f,TG6}, m_{CD,TG6}, C_{p,w}, T_{CD,out}, T_{CD,in}\big) \\
&\quad \eta_{TG7} = f\big(W_{TG7}, m_{m,TG7}, P_{m,TG7}, T_{m,TG7}, m_{1,TG7}, P_{1,TG7}, T_{1,TG7}, \\
&\qquad m_{2,TG7}, P_{2,TG7}, T_{2,TG7}, m_{3,TG7}, P_{3,TG7}, T_{3,TG7}, m_{last,TG7}, P_{last,TG7}, \\
&\qquad T_{last,TG7}, m_{f,TG7}, T_{LP2,f,TG7}, m_{CD,TG7}, C_{p,w}, T_{CD,out}, T_{CD,in}\big) \\
&T_{CW,out} = f(T_{CW,in}, T^D_{air,in}, \mathscr{H}_{R,in}, W_F) \\
&T_{CD,in} = T_{CW,out} \\
&W_{F,\min} \le W_F \le W_{F,\max} \quad \text{.. (8)}
\end{aligned}$$

2. MATERIALS AND METHODS

The thermal efficiency model of a TG system in the studied plant shown in Eq.4 has 22 variables. Redundant information and collinearity are embedded among those variables. It is necessary to reduce the number of dimensions before modeling. This section begins with data pretreatment, including key variable selection, data smoothing, normal distribution examination; the section is then followed by the work of LMN.

Based on divide-and-conquer strategy, the LMN approach develops several local linear models corresponding to different operating regimes. The global output is obtained by summing local ones whose linear model are transparent and physically meaningful. The complete model output is denoted as:

$$\hat{y}(k) = \sum_{i=1}^{n} \rho_i\left(\phi(k)\right) \hat{f}_i\left(X(k)\right) \quad \text{....................... (9)}$$

where, n is number of local models, $\hat{y}(k)$ is model output at time k^{th}.$\rho_i(.)$ is a basis function which depends on the scheduling vector $\phi(k) \in \Re^{n_\phi} \cdot \hat{f}_i(\cdot)$ is a local linear model which is a function of the input vector $X(k) \in \Re^{p+1}$, as described below:

$$\hat{f}_i\left(X(k)\right) = \beta_{i,0} + \beta_{i,1}x_1(k) + \cdots + \beta_{i,p}x_p(k) = X(k)\boldsymbol{\beta}_i \quad \text{......... (10)}$$

where, $X(k) = \left[1, x_1(k), \cdots, x_p(k)\right]$ is the input vector, $\boldsymbol{\beta}_i = [\beta_{i,0}, \beta_{i,1}, \cdots, \beta_{i,p}]^T$ is coefficients of the i local model. The basis function $\rho_i(\cdot)$ is a normalized Gaussian function:

$$\rho_i(\phi(k)) = \frac{\exp\left[-\dfrac{(\phi(k)-v_i)^T(\phi(k)-v_i)}{s_i^2}\right]}{\sum_{i=1}^{n}\exp\left[-\dfrac{(\phi(k)-v_i)^T(\phi(k)-v_i)}{s_i^2}\right]} \quad \text{.... (11)}$$

where, $v_i \in \Re^{n_\phi}$ and s_i are the centers and the width of Gaussian functions.

The core task of LMN modeling is to decompose the data space into zones where linear models are adequate approximations of dynamic behaviors within the regime. Most clustering algorithms are suited for this task, such as Fuzzy c-Means (FCM), and G-K fuzzy cluster. In this study, FCM is used to divide the measured data. The division is based on the minimization of distances between two data points and the prototype of cluster centers. For the purpose of minimization, the following cost function is used:

$$J_{FCM}(U, V; \boldsymbol{\Phi}) = \sum_{k=1}^{N}\sum_{i=1}^{c} u_{ik}^{w} \left\|\boldsymbol{\phi}(k) - v_i\right\|^2 \quad \text{........ (12)}$$

where, $U \in \left\{u_{ik} \in [0,1] \middle| \sum_{i=1}^{c} u_{ik} = 1, k = 1, \cdots, N, \sum_{k=1}^{N} u_{ik} > 0, i = 1, \cdots, c\right\}$ is a membership matrix, $V = \{v_1, \cdots, v_c\}$ is a cluster center set. $w \in [1, \infty]$ is a weighting exponent which determines the degree of fuzziness of the resulting clusters (in this paper $w = 2$ has been considered). $\boldsymbol{\Phi} = \{\boldsymbol{\phi}(k)\}_{k=1}^{N}$ is scheduling vector. However, for a given cluster number, c, the objective function cannot be directly minimized with respect to its nonlinear characteristics. To obtain a feasible solution, FCM can be optimized by an Alternating Optimization (AO) algorithm.

However, users have to select the cluster number c only by their experience, and the AO algorithm is always restarted with randomly initialized cluster centers when the cluster number is changed. These changes always lead to a repetitive trial of different numbers of clusters for a satisfying result, which is responsible for the poor computation efficiency. To avoid the above problem, a SFCM algorithm is applied in this paper. The SFCM algorithm integrates FCM into LMN identification, is brief described hereafter. It begins with $c = 2$. According to the most updated results of clustering, local models are identified by Least Square Algorithm (LSA) in each cluster. The final step of LMN is to sum up all local models to obtain an estimated value. The prior set criteria of performance index, e.g., Mean Square Error (MSE) as shown in Eq.13, which is checked to determine whether a new cluster center should be added or not.

$$MSE = \frac{1}{N}\sum_{k=1}^{N}\left(y(k) - \hat{y}(k)\right)^2 \quad \text{..........................} \quad (13)$$

where $y(k)$, $\hat{y}(k)$ is real value and estimated value respectively, N is the number of measured samples.

If the LMN model is not satisfied yet, we consider that the division is not proper. Then a sample is found from the given data set, that is the most different from the existing cluster centers $v_1 \sim v_c$ as a new center v_{c+1} . With v_{c+1} as the new cluster center, the algorithm computes a new NOT-random initial partition matrix U_0 . This process is then repeated until the FCM algorithm divides the data set into optimal $c+1$ parts.

Simply speaking, this study aims to determine what the operation mode of the fans in a CT should be to balance the power output of the TG and the power consumption of the CT. In the studied plant, the CT unit (CT4) has 6 fans. Each fan has 3 operating options, namely, closed, low speed and high speed. Due to the restrictions of the turn-down ratio, the fan set usually operates in one of seven modes. So, the power consumption of the seven modes is denoted as $\{W_{F,i}\}_{i=1}^{7}$. The objective function of the optimization problem can be simplified as:

$$\begin{aligned}
&\max J = \max\left\{W_{TG6} + W_{TG7} - W_F\right\} \\
&s.t. \quad \eta_{TG6} = f\left(W_{TG6}, P_{m,TG6}, T_{LP1,f,TG6}, m_{1,TG6}, T_{CD,in}\right) \\
&\qquad\ \ \eta_{TG7} = f\left(W_{TG7}, P_{m,TG7}, m_{1,TG7}, T_{CD,in}\right) \\
&\qquad\ \ T_{CW,out} = f(T_{CW,in}, T^{D}_{air,in}, \mathscr{H}_{R,in}, W_F) \\
&\qquad\ \ T_{CD,in} = T_{CW,out} \\
&\qquad\ \ W_{F,1} \le W_F \le W_{F,7} \quad \text{..} \quad (14)
\end{aligned}$$

This is a typical linear programming problem with constraints, and can be easily solved by a linear programming algorithm. In summary, the proposed optimal algorithm is described in Fig.2.

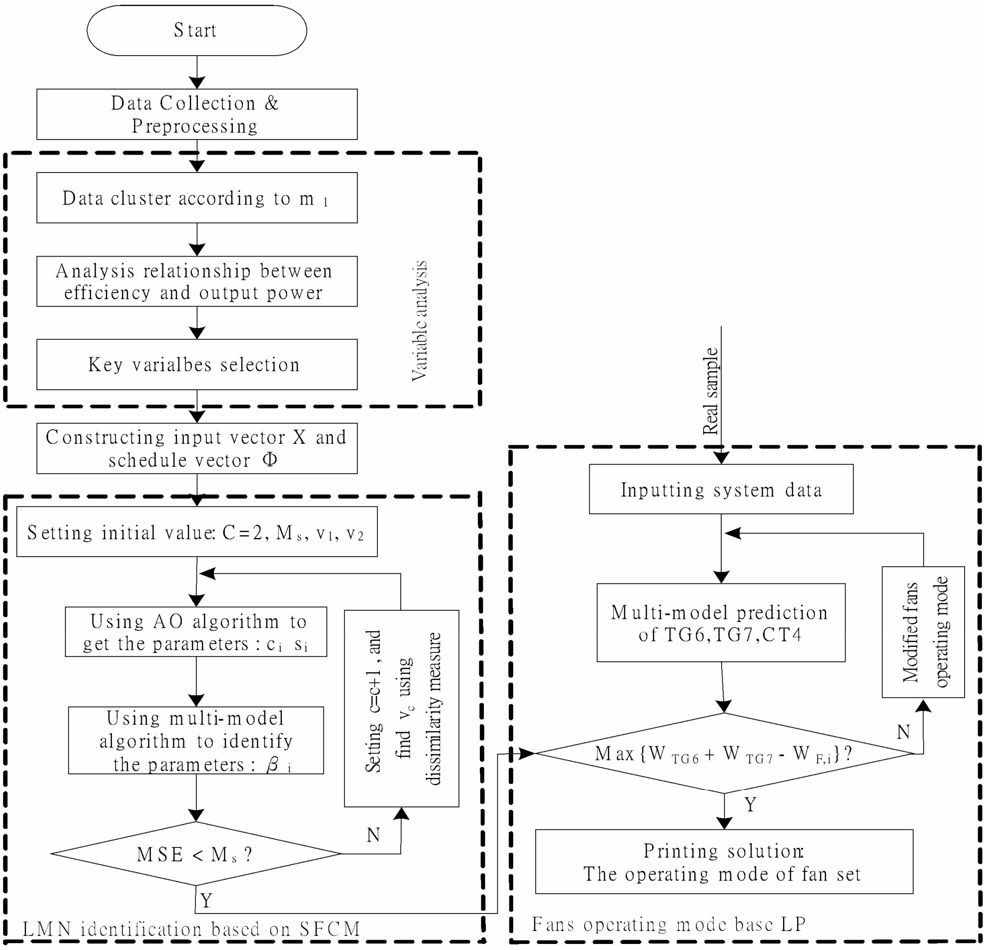

Fig.2. Flowchart of the proposed algorithm.

3. RESULTS AND DISCUSSION

In this section, we present the results and discussion together. The first part of this section focuses on the on-line optimal operation of the cooling tower, and this is then followed by the on-line performance assessment.

3.1 On-Line Optimal Operation

The data used in this study were collected from one of CSC power plants from February 2 to June 30. The sampling frequency of the data is one per minute. There are 1,440 samples per day. The first 6,000 pieces of data are used as a training set; the rest of them are used for testing. With key variables being selected and following the LMN identification algorithm proposed in this study, the results of the predicted MSE of LMN versus cluster number for TG6 are showed in Fig.3(a). The satisfactory number of LMN for this case is 4 (i.e. $c_{TG6} = 4$) and final MSE is 0.02. Then the model is validated by the test data of the next five months (February 2 - March 2, March 4 - March 30, April 1 - April 27, April 28 - May 31, and June 1 - June 30). Figure 3 (b) shows the estimated thermal efficiency against the real thermal efficiency of TG6 in a typical day, April 7. The figures demonstrate that the proposed method have a good modeling performance. The performance of modeling in terms of MSE for all the test data in each month is listed in Table 1.

After reliable models for TG6, TG7 and CT4 system are acquired, the objective functions for this optimal operation problem are rewritten. Since the set of fans operates in seven modes, their power consumption is discretely rated and ranged between 110.4kW and 552kW. The optimal operation problem is solved for each point of sample which is taken at a rate of one sample per minute. In the operation of the studied plant, the operator does not often change the operation mode of the fan set, which needs to be adjusted manually.

Figure 4 shows the operation history of the fan set on a typical day, i.e., April 7. The optimal operation mode of the fan set should be changed in response to the variations of ambient air conditions, and operation loads. After solving the optimal operation problem for this particular day, the suggested operation modes of the fan set are also plotted in Fig.4.

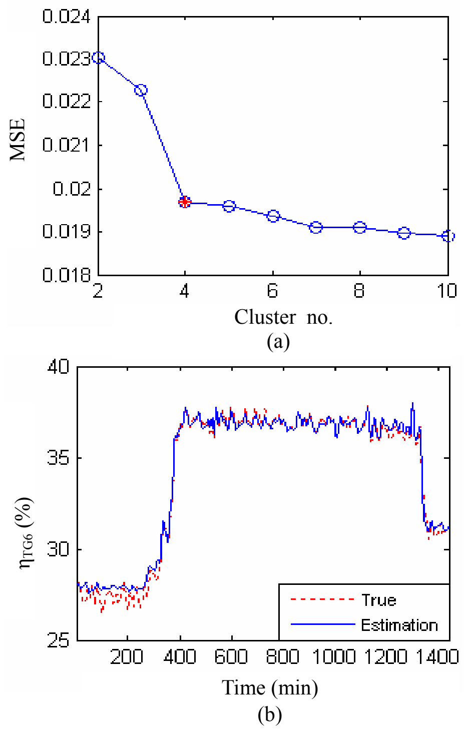

Fig.3. Performance of TG6's LMN.

Responding to the suggested changes of the fan operation modes, the net power gained of CT4 are plotted respectively in Fig.5 for every minute on this particular day. As shown in these figures, the operations of the fan set are suggested to switch to higher speeds during half of this day; the maximum net power gained is about 1.7MW. On average, the net power gained is around 0.5MW. The average approach of the original percentage of net power gained by implementing the proposed optimal operation to the output power generated by TG6 and TG7 is also calculated. Table 2 shows the average power gained in these five months to be between 0.46 and 0.9MW. By summing up the energy saving, the cost saved is about 0.24 million USD per year for the studied plant.

Table 1 Performance of LMN

Date	MSE		
	TG6	TG7	CT4
Feb. 2 - Mar. 2	0.151	0.320	0.054
Mar. 4 - Mar. 30	0.239	0.247	0.1173
Apr. 1 - Apr. 27	0.247	0.1601	0.1512
Apr. 28 - May 31	0.244	0.1355	0.0828
June 1 - June 30	0.229	0.3279	0.1335

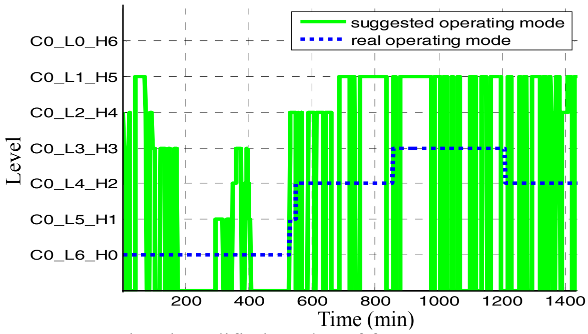

Fig.4. Real and modified modes of fans.

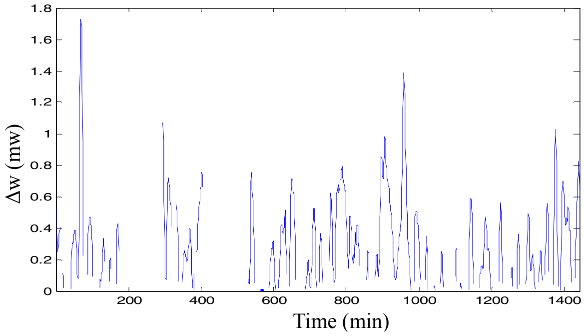

Fig.5. Total net power gain gain according to modified operating mode of fans.

3.2 On-Line Performance Assessment

As mentioned above, it is difficult to do the test under design operating conditions. So, the developed LMN can best be used to investigate the effects of the design input parameters on the outputs.

Figure 6 depicts the predicted values of $T_{CW,out}$ with respect to the operating mode of the fans when the other four input parameters are kept constant at the design values. In this figure, $T_{CW,out}$ is denoted as a function of the water-air mass flow rate ratio L/G. It is seen that, as expected, $T_{CW,out}$ decrease with m_{air} increasing (m_{air} is determined by W_F).

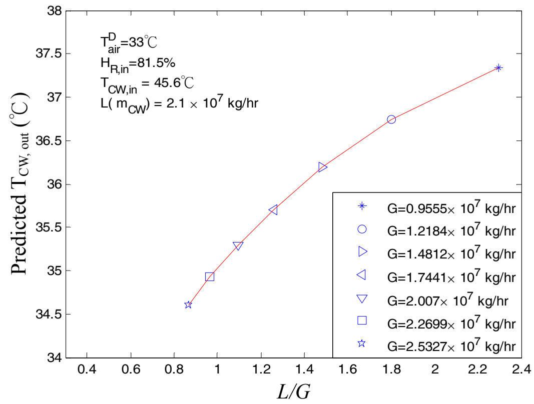

Fig.6. LMN predictions for $T_{cw,out}$ vs. the water/air mass flow ratio.

When the estimated value is below the design input parameters and *L/G*, the tower characteristics *KaV/L* can be calculated by the following equation:

$$\frac{KaV}{L} = \int_{T_{cw,out}}^{T_{cw,in}} \frac{c_{p,w} dT}{h_w - h_a} \quad \text{.................................(15)}$$

where, h_w, h_a are the enthalpy of air-water vapor mixture at bulk water temperature and wet bulb temperature, respectively. In this equation, H_w and H_a are given by the following equations[11]:

$$H_w = \alpha e^{\lambda T} \quad \text{...(16)}$$

$$H_a = H_1 + c_{p,w}(L/G)(T_{CW,in} - T) \quad \text{..........................(17)}$$

where, $\alpha = 20.9$, $\lambda = 0.052$, $H_1 = \alpha e^{\lambda T_{wb}}$ is the enthalpy of moist air at the entry of the tower. Rearranging Eq.16, Eq.17 and Eq.15 yields:

$$KaV/L = \int_{T_{cw,out}}^{T_{cw,in}} \frac{c_{p,w} dT}{\alpha e^{\lambda T} - \left[\alpha e^{\lambda T_{wb}} + c_{p,w}(L/G)(T_{CW,in} - T)\right]}$$

.... (18)

Table 2 Net power gained and the approach

Date	Approach		Net power gained (TG6+TG7)	
	Real (°C)	Suggested (°C)	ΔW (MW/min)	$\sum \Delta W / (W_{TG6} + W_{TG7})$ (%)
Feb. 2 - Mar. 2	10.39	7.12	0.91	0.83
Mar. 4 - Mar. 30	10.03	6.89	0.52	0.35
Apr. 1 - Apr. 27	9.24	7.99	0.90	0.63
Apr. 28 - May 31	9.11	8.25	0.71	0.32
June 1 - June 30	5.22	5.34	0.46	0.17

With the inlet water temperature and water mass flow rate kept constant at the values 45.6°C and 2.1×10^7 kg/h (the design parameters), Figure 7 plots *KaV/L* against water/air mass flow ratio, *L/G*, for inlet air temperatures at 33°C, 35°C, 37°C and relative humidity at 81.5%, 71.0%, 61.7% (the wet bulb temperature is 30°C), respectively.

The three kinds of test conditions result in three similar and close curves. To prove the validity of the proposed approach, the real data (from July 1 - September 30, 2009) which fall in the range of the design input parameters (±5%) are selected to calculate their corresponding *KaV/L*. As shown in Fig.7, the calculated tower characteristics (the green points) based on real data fall on or close to the curves. This demonstrates that the predicted tower characteristic is exactly consistent with the calculated one. Then, the predicted characteristic curve is compared with the design tower characteristic curve to evaluate effectiveness of the cooling tower. Figure 8 reports the details. On the same plot, a condition curve representing the design approach at design range and design wet bulb temperature passes through the two tower characteristic curves.

The condition and design characteristic curves intersect at design $(L/G)_{design}$. In the same way, the intersection of the predicted tower characteristic curve and the design condition curve determines the test $(L/G)_{test}$. The intersection denotes that the tower will produce design cooling water temperature with design range and wet bulb temperature at this point. Then, the effectiveness of cooling tower can be calculated by[10]:

$$\eta = \frac{(L/G)_{test}}{(L/G)_{design}} \times 100\% \qquad (19)$$

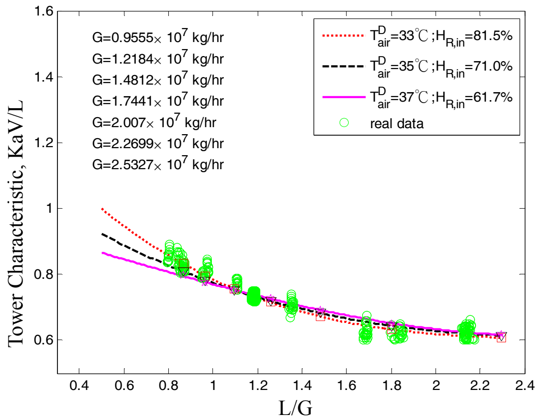

Fig.7. Predicted tower characteristic vs. calculated tower characteristic.

In this studied plant, the current effectiveness is 46.70%. It shows that the thermal performance of the cooling tower is so low that revamping work is necessary in the near future.

4. CONCLUSIONS

In this study, we apply the recently developed LMN to model two TG units and a CT unit; then solve an optimal operation problem which integrates the above acquired models. The proposal algorithm is demonstrated with the real plant data. The study provides a theoretical framework and an example to dem-

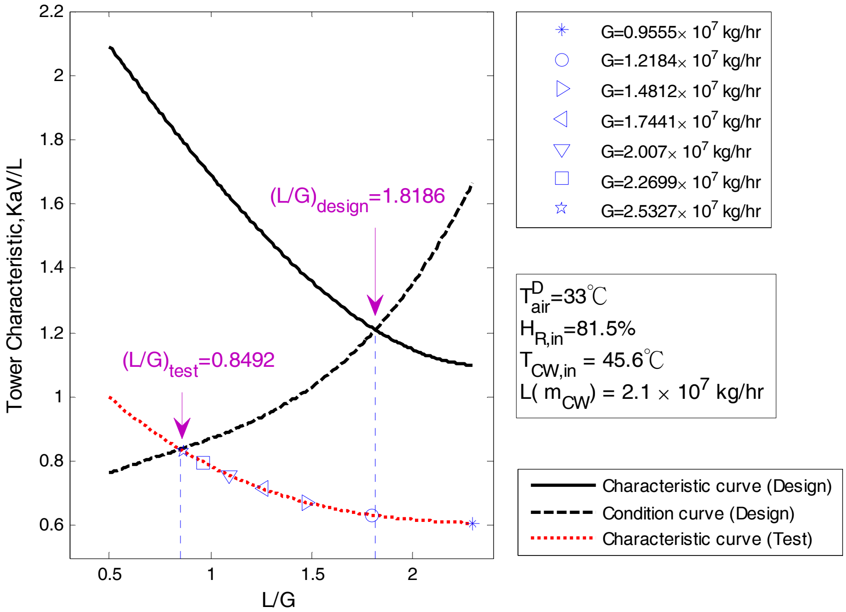

Fig.8. Tower characteristic vs. the water/air mass flow ratio.

onstrate how to achieve the optimal operation in the integration of TG and CT systems. Cooling water temperature is the key linking variable between TG and CT. After solving the optimal problem, the best operation mode of the fan set is suggested. With all mathematical work and without any change in the existing plant, the energy saving is handily accomplished. This study reported an energy saving of 0.4% of the power output of a TG system.

Besides, the effectiveness of an existing cooling tower can be evaluated via the acquired cooling tower operation model. This study reveals that a cooling tower can be modeled using a local-model-network approach within a high degree of accuracy. The proposed approach requires only a limited volume of running data, rather than an exhaustive experimental study, and manufacturers employing this approach in determining the performance of cooling towers can save drastically on both engineering effort and cost. The user in plants can easily uncover ineffective operations of a cooling tower to prevent the wastage of energy and water.

REFERENCES

1. Z.Y. Huang and, R.M Edwards:"Power Generation Efficiency Improvement through Auxiliary System Modifications"; IEEE Transactions on Energy Conversion, 2003, vol. 18, no. 4, pp. 525-529.
2. C.C. Chuang and D.C. Sue:"Performance Effects of Combined Cycle Power Plant with Variable Condenser Pressure and Loading"; Energy, 2005, vol. 30, no. 10, pp. 1793-1801.
3. J.E. Braun and G.T. Diderrich:"Near-optimal Control of Cooling Towers for Chilled-water Systems"; ASHRAE Transactions, 1990, vol. 96, no. 2, pp. 806-813.
4. R.S.J Malcolm,and W.L. James: "Cooling Tower Fan Control for Energy Efficient"; Energy Engineering, 2001, vol. 99, no. 1, pp. 7-31.
5. M.P. Cassidy and J.F. Stack,: "Applying Adjustable Speed AC Drives to Cooling Tower Fans"; presented at the Annual Petroleum and Chemical Industry Conference, 1988, pp. 87-90.
6. A. DeVilliers and P. Bosman: "Optimizing Turbine Cycle Heat Rate Against Cooling Tower Operations"; presented at the American Power Conference, 1999, vol. 61-2, pp. 856-861, Chicago, Illinois, U.S.A.
7. F. Merkel: "Verdunstungskühlung"; VDI-Zeitchrift, 1925, vol. 70, no. 1, pp. 123-128.
8. H. Jaber and R.L. Webb: "Design of Cooling Towers by the Effectiveness-NTU Method"; ASME J. Heat Transfer, 1989, vol. 111, no. 1, pp. 837-843.
9. J.C. Kloppers and D.G. Kroger: "A Critical Cooling Tower Performance Evaluation"; presented at the 12th IAHR Symposium in Cooling Towers and Heat Exchangers, UTS, Sydney, Australia ,2001, pp. 108-115.
10. Cooling Tower Institute, CTI Code Tower, Standard Specifications, Acceptance Test for Water-cooling Towers, Part I, Part II and Part III, CTI Code ATC-105, Revised, February 1990.
11. M. Lemouari, M. Boumaza and I.M Mujtaba: "Thermal Performances Investigation of a Wet Cooling Tower"; Applied Thermal Engineering, 2007, vol. 27 (5/6): pp.902-909. □