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AI and Big Data Analytics for Wafer Fab Energy Saving and Chiller Optimization to Empower Intelligent Manufacturing – Chen-Fu Chien[1,2]

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INTRODUCTION

Chiller machine is one of the most electricity-consuming parts of factory facilities in high-tech industries such as semiconductor and TFT-LCD manufacturing. Indeed, the configuration of chiller machines including the switch of chiller machines and temperature setting for each chiller machine affects the environment of wafer production as well as electricity expense. In reality, operations of chillers seriously rely on engineers' practical experiences. It means that the decisions of switching configuration is not consistent as well as fluctuate consequence [1]. To reduce variability and optimize the chiller allocation, researchers have come up with various solutions, but few of them can indeed be widely adopted due to differences of factory layout, machine types, data collections, etc. Conventionally, the partial load ratio (PLR) of chillers is considered an essential index to evaluate operation efficiency. Engineers usually tend to keep the loading and the performance of the whole chiller system within a particular range to conserve electricity and cost, so-called the average chiller loading method [2]. However, PLR is not adjustable, and it would be influenced by chilled water supply temperature setting, cooling load requirement, outdoor temperature and so on. Besides, using unstable chillers would also affect the overall performance of the chilled water system. The operation efficiency can be further enhanced once those improper chillers are excluded in advance.

This study proposes a solution that integrates big data analytics and machine learning techniques to automatically provide recommendations of chiller optimization for energy saving. The optimal chiller adjustment is defined as the condition that the required cooling load for a wafer fab is satisfied while and the electricity consumption is minimized. In the meantime, those adjustment alternatives considering chiller healthy status to obviate inappropriate combinations. Hence, engineers only need to judge the rationality of these recommendations to adjust chillers so that can guarantee operation effectiveness and efficiency as well as empower intelligent manufacturing. An empirical study was conducted in a leading semiconductor company in Taiwan to demonstrate the validity of the proposed approach.

LITERATURE REVIEW

In the past, researchers used system parameters to form mathematical formulas to estimate total electricity consumption or coefficient of performance (COP). The total electricity consumption stands for the electricity consumed by the overall chiller system. COP is regarded as the cooling capacity of one-unit electricity consumption. In other words, COP can be thought of as the efficiency of the chilled water system. Since data of refrigerant are hard to measure and quantified, and the multi-chiller system accounts for around 60% of the total electricity consumption, most researchers focused on analyzing data from the chilled water side. The representative approaches including Gordon-Ng universal model [3], ASHRAE Guideline 14 [4], Lee's thermodynamic model [5]. Owing to limitations of data and interactions between chillers, this study has taken chiller combinations, dew point temperature, and other operation parameters into consideration to build a new chiller conservation approach. Besides, this study uses the idea of machine health to monitor health conditions of chillers simultaneously. A neuro-fuzzy machine condition prognostic system [6] is developed to monitor the health condition of the gearbox. It forecasts the future states of the fault propagation trend through parameter monitoring. Yan and Gao [7] used Approximate Entropy to monitor the machine health and conduct an empirical study on the bearing test bed. A hybrid model of autoregressive moving average and generalized autoregressive conditional heteroscedasticity was proposed to explain the wear and fault condition of the vibration signal-based machines [8]. Chien, Peng, and Yu [9] proposed a novel index, namely Overall Power Energy Effectiveness (OPE), for measuring overall energy expenditure effectiveness and evaluate energy conservation in a semiconductor fab. Thus, this study proposed an approach to optimize chiller adjustments on condition that the chilled water requirement is satisfied and the proper chillers are operated.

PROPOSED APPROACH

The overall process of the proposed approach is shown in Figure 1. Since either the multi-chiller system operates under low PLR or high PLR would lower the efficiency and consume extra power usage, this study integrates a model for cooling load forecasting and a model for chiller system

PLR prediction model to estimate the best combination of the chiller operation. In addition, considering the health of each chiller, the multi-chiller system can run at the optimal performance.

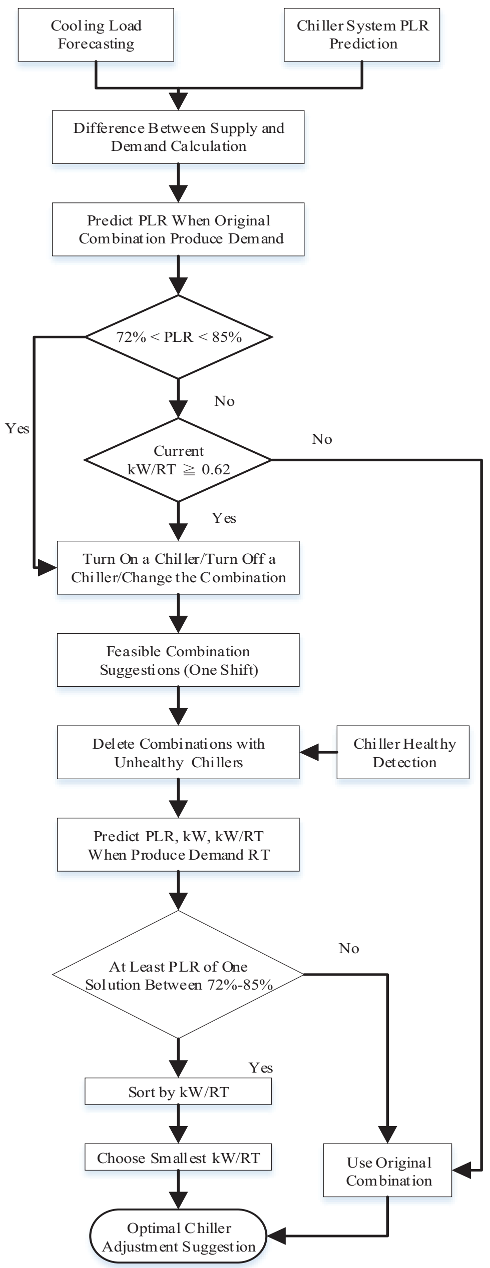

Figure 1. The proposed approach for chiller optimization

Cooling Load Forecasting

This study employed a SARIMAX model [10] for cooling load forecasting and the general form is shown below.

$$(RT_t - C(B)DPT)(1-B^S)\Phi_P^S(B)\phi_p(B)(1-B)^d(1-B^S)^D = \Theta_Q^S(B)\varepsilon_t$$

where RT_t is the cooling load value at period t, s is the period which is 24-hour in this case, DPT is the dew point temperature and C(B) is the model parameter.

The cooling load demand of the following half-day can be derived in advance to ensure the supply is sufficient. Since the cooling load demand has a high positive correlation with the outdoor temperature, the dew point temperature is regarded as an explanatory factor in this model.

Chiller System PLR Prediction

This study employed a multivariate adaptive regression splines (MARS) model [11] for chiller system PLR prediction and the general form is shown below.

$$PLR = \beta_0^{PLR} + \sum_{i=1}^{n} \beta_i^{PLR} CH_i + \sum_{m=1}^{M} \beta_m^{PLR} H_m^{PLR}(x) + \varepsilon_m^{PLR}$$

$$RT = \beta_0^{RT} + \sum_{i=1}^{n} \beta_i^{RT} CH_i + \sum_{m=1}^{M} \beta_m^{RT} H_m^{RT}(x) + \varepsilon_m^{RT}$$

$$kW = \beta_0^{kW} + \sum_{i=1}^{n} \beta_i^{kW} CH_i + \sum_{m=1}^{M} \beta_m^{kW} H_m^{kW}(x) + \varepsilon_m^{kW}$$

where CH_i denotes the operating condition of chiller i, if turned on, CH_i equals 1, otherwise, CH_i equals 0, and n is the number of chillers. PLR stands for partial load ratio of the overall chiller system, it means the real capacity versus the design capacity of chillers, RT is the cooling load, and kW is the electricity consumption of the combination when producing RT.

After either the highest or the lowest cooling load demand is derived from the cooling load forecasting model, the cooling load supply capacity of the current chiller combination would be calculated to see whether another chiller shifts are necessary. To evaluate the overall system performance, kW/RT is explained as the electricity consumption efficiency.

Chiller Healthy Detection

In the factory, chillers are inspected and maintained regularly and repaired when having breakdowns. To cut down on repair fees and extend usage of chillers, this study evaluated the health of each chiller by the change point detection method. In this study, by analyzing current PLR, evaporator refrigerant pressure, oil tank pressure, and high oil pressure of each chiller, the health condition of chillers can be determined in advance to evaluate each feasible solution.

EMPIRICAL STUDY

The proposed approach is implemented in a wafer fab of a leading semiconductor company in Taiwan. The solution provides chiller adjustment recommendation to engineers every morning and evening for decision support. This study collected 11-month data to evaluate the model validity and used kW/RT as the key performance index. As shown in Table 1, the kW/RT reduction rate vary from time to time and the overall result is 2.17%. Generally, most electricity can be conserved in summer. With this approach, the operation efficiency of the system would be enhanced under the same dew point temperature level especially when the dew point temperature is higher than 18 ℃ as shown in Figure 2 and Figure 3.

Table 1. kW/RT reduction rate

Month	Morning	Evening
December	0.53%	0.39%
January	0.50%	0.40%
February	1.84%	2.29%
March	1.87%	2.72%
April	1.35%	2.01%
May	1.72%	2.47%
June	1.50%	2.77%
July	1.37%	2.72%
August	2.74%	3.91%
September	3.08%	3.49%
October	3.48%	4.36%

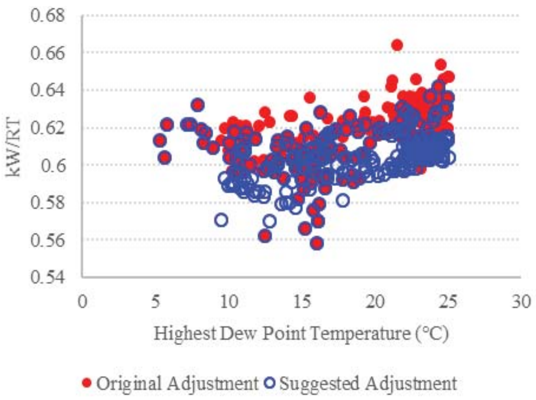

Figure 2. Performance comparison (Morning)

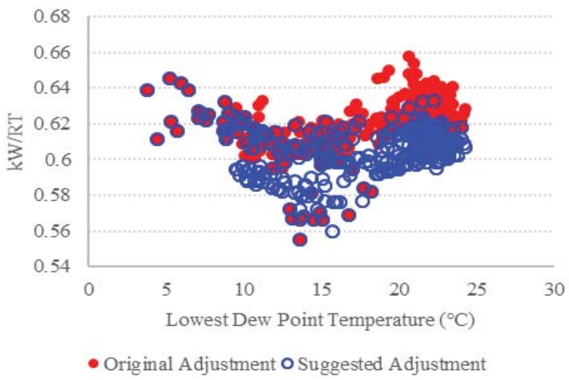

Figure 3. Performance comparison (Evening)

Considering with facility engineers' experience, the average PLR of the entire system is used to evaluate whether to turn on/off an extra chiller or change the chiller combination to enhance operational efficiency. Suggestions provided by this approach can be classified into three scenarios:

(1) When estimated PLR exceeds 85%, one other chiller should be turned on.

(2) When estimated PLR is lower than 72%, one chiller should be turned off.

(3) When estimated PLR is between 72% and 85%, but kW/RT is higher than 0.62, conservations can be achieved by altering the combination.

This study illustrated these cases to show the feasibility of this proposed approach.

Case 1. Estimated PLR≧85%

In this case, the highest dew point temperature in the morning is 22.45 ℃ according to the weather forecasting report. Under this given dew point temperature, the cooling load forecasting model derives the highest cooling load in the following 12 hours would be 7077.5RT. Then, with the chiller system PLR model, it can be obtained that once the current combination produces 7077.5RT, the PLR would be 85.6% which exceeds 85%. Therefore, it is essential to turn on one chiller to maintain the overall performance and the demand. Before the simulate performance of each feasible combination, the health evaluation of chillers would be analyzed through the chiller healthy detection model. The result showed that all the 13 chillers are healthy and adjustable.

As shown in Table 2, the approach would recommend enginers to turn on chiller 7, which can not only lower the PLR and keep the system operate within a proper range but also reduce the kW/RT from 0.622 to 0.619.

Table 2. chiller switching recommendation in case 1

	Chillers													PLR (%)	kW/ RT	Priority
	1	2	3	4	5	6	7	8	9	10	11	12	13			
As-is	V	V	V	V						V		V		85.6	0.622	--
To-be	V	V	V	V			O			V		V		73.8	0.619	1

V: chiller in use
O: recommended turn-on chiller
X: recommended turn-off chiller

Case 2. Estimated PLR≦72%

In this case, the lowest dew point temperature in the evening is 23.13 ℃ according to the weather forecasting report. Under this given dew point temperature, the cooling load forecasting model derives the lowest cooling load in the following 12 hours would be 7010.1RT. Then, with the chiller system PLR model, it can be obtained that once the current combination produces 7010.1RT, the PLR would be 71.8% which is lower than 72%. Therefore, it is essential to turn off one chiller to conserve electricity and enhance the operating efficiency. Considering the usability, chiller healthy detection model indicated that all the 13 chillers are health and adjustable.

As shown in Table 3, the approach would provide three alternatives to engineers. The best one is to turn off chiller 3, which can not only improve the PLR and but also reduce the kW/RT from 0.613 to 0.600. The other two recommendations are also doable since both of them can reduce the kW/RT.

Case 3. Estimated PLR between 72% and 85%

In this case, the highest dew point temperature in the morning is 20.37 ℃ according to the weather forecasting report. Under this given dew point temperature, the cooling load forecasting model derives the highest cooling load in the following 12 hours would be 6180.4RT. Then, with the chiller system PLR model, it can be obtained that once the current combination produces 6180.4RT, the PLR would be 74.3%, which is within the threshold. However, the current kW/RT is 0.621; it would be better to change the combination to conserve more electricity. Considering the usability of each chiller, as listed in Table 4, it seems there are a risk if chiller 5 is operated, thus those combinations with chiller 5 would be deleted.

Table 3. chiller switching recommendation in case 2

	Chillers													PLR (%)	kW/ RT	Priority
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*			
As-is	V	V	V	V		V				V	V			71.8	0.613	--
To-be	V	V	X	V		V				V	V			80.1	0.600	1
	V	V	V	X		V				V	V			80.9	0.601	2
	V	V	V	V		X				V	V			81.4	0.605	3

V: existing chiller
O: additional turn-on chiller
X: additional turn-off chiller

Table 4. chiller usability recommendation in case 3

Chiller	*1*	*2*	*3*	*4*	*5*	*6*	*7*
Usability	Y	Y	Y	Y	N	Y	Y
Chiller	*8*	*9*	*10*	*11*	*12*	*13*	
Usability	Y	Y	Y	Y	Y	Y	

Y: The chiller is adjustable
N: The chiller is not adjustable

CONCLUSION

An empirical study was conducted to validate the validity of the proposed approach. The company has imported this approach into their system to replace with traditional decision-making methods so that the practical revenue can be assessed shortly.

This decision support system is designed to help operators when they encounter inconsistent decision-making. It tends to be passive, i.e., it only works when operators need it. In the future, it can be ameliorated to further assist operators in conducting adjustments at the proper time. Besides, due to the lack of individual flowrate data, the PLR of each chiller is hard to be predicted since there are no ways to validate the model. Once the company installs fluid meters for each chiller, the individual performance can be derived so that engineers can further sort the good chillers from the bad.

With this decision support system, anthropogenic effects can be eliminated, and the stability of the chiller can be well-monitored as well. This approach helps the company conserve electricity usage and cost down, and make the chilled water system run in the best PLR, letting the system work efficiently and eco-friendly.

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APPENDIX

The notations used in this study are listed as below.

Notation	**Definition**
RT	Total cooling load produce by multi-chiller system
DPT	The dew point temperature
kW	Total electricity consumption
RT_t	The cooling load data at period t
CH_i	The operating condition of chiller i (either 1 or 0)
COP	The coefficient of performance (kW/RT)
PLR	Partial load ratio of each chiller or the system
n	Number of chillers