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Improved energy management of chiller systems by multivariate and data envelopment analyses

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ABSTRACT

The operation of chiller systems accounts for the major proportion of electricity consumption in commercial buildings. This paper considers using multivariate and data envelopment analyses to facilitate the energy management of chiller systems. The system studied contains five sets of chillers, pumps and cooling waters and it operates for an institutional building. Based on a huge set of operating data, multiple linear regression was used to correlate the system coefficient of performance (COP) with a set of climatic and operating variables. Data envelopment analysis was then employed to calculate the scale, technical and overall efficiencies. These three efficiencies were further examined to ascertain which controllable variables caused a decrease of system COP. The results show that the existing energy management gives a technical efficiency of 0.76 and fine-tuning the controllable variables could achieve an electricity saving of 5.34% in relation to the existing operation. The significance of this study is to demonstrate a systematic approach to examine which operating variable should be fine-tuned to improve system performance with higher technical efficiency.

1. Introduction

To enhance building energy performance, it is important to develop a systematic tool which helps assess the energy management of building services systems. Among various building services systems in a commercial building, the operation of a chiller system could account for over half of the total electricity consumption and therefore evaluating its energy management opportunities should be prioritized. Simulation and statistical analysis are common methods to analyse the energy performance of chiller systems. The simulation method involves developing a mathematical model with validation by experimental or operating data. The validated models are used to identify the theoretical energy performance under perfect control. The modelling results are compared with the actual performance to see if any fault or improper control causes a decline in the performance indicator—coefficient of performance (COP). COP is defined as the total cooling energy output in kW over the total electric power input in kW of the chillers and auxiliary devices like pumps and cooling towers.

Pure physical simulation models have limited applications in analysing the energy performance of existing systems due to complexity in modelling a large system with sophisticated configuration and difficulty in collecting technical specifications and physical details of system components. Regarding the tools for auditing and benchmarking air-conditioning systems, André et al. [1] addresses the need to use simplified models which are fast to run and not too demanding in terms of parameters identification. The models should be reliable and adaptable to simulate improvements that can usually be brought to a system. Alternatively, grey-box or black box models involving statistical techniques are more common in performance identification and forecast. These types of models draw mainly on operating data rather than the physical characteristics of system components. Lee and Lu [2] demonstrated how to select empirical-based models to predict energy performance of vapour compression water chillers. Yik and Chan [3] developed a comprehensive set of regression-based models for various air-conditioning and refrigeration system components and the modelling tool can be used to evaluate the baseline performance required for a given system design and to explore optimum design options for achieving a higher performance rating of the system.

With the sophistication of building management systems (BMS) and microprocessor control, it is possible to collect a series of operating data over the year at hourly or minutely intervals with the required accuracy. This facilitates the calibration of grey- or black-box models and the development of statistical models for appraising the operating performance of chiller systems. Torrella et al. [4] carried out an on-site real-time evaluation of a direct-fired double effect absorption chiller. They drew on modelling equations based on energy and mass balances with experimental data to ana-

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lyse specific COP by unit of chilled water mass flow rate through the evaporator. Sun et al. [5] drew on operating data of an existing multiple-chiller plant to validate a system model included in the simulation software TRNSYS [6]. The validated model was used to analyse an optimal strategy for operating chillers in steps in response to the changing building cooling loads and to investigate criteria for achieving the optimal control strategy. The Gordon and Ng's thermodynamic model [7] was one of the generic grey-box models used for chiller diagnosis and optimization. It correlates the chiller COP with some temperatures monitored typically at the evaporator and condenser sides and contains some empirical parameters to account for system irreversibility associated with heat leaks. The operating performance of different types of chillers can be characterized by the empirical parameters identified from regression analysis with operating data. Chan and Yu [8] used the operating data of an air-cooled screw chiller system to analyse how the chiller components interact with each other and discussed how the analysis helped implementing floating condensing temperature control to improve chiller performance. They addressed the importance of specifying the upper limit of condensing temperature to enhance the energy efficiency of air-cooled chiller systems. Some studies coupled empirical-based models with genetic algorithms and other advanced techniques to perform optimization on the physical and operating characteristics of chillers [9–11].

The development of aforementioned grey-box models and optimization techniques requires sophisticated knowledge and skills which may not be acquired by most system operators. Furthermore, it may be impossible to draw only on system simulation skills to explain the change of system COP under various combinations of load conditions and controls with climatic influences, considering that chiller systems have various designs and configurations. It is quite difficult to simulate the trade-off between the power of system components when a medium- to large-sized chiller system has various operating modes for many sets of chillers, pumps and cooling towers. It is preferable to carry out pure statistical analysis based on operating data for appraising chiller system performance. Chung [12] reviewed different kinds of statistical methods in developing benchmarking systems for building energy-use performance. The methods involve simple normalization, ordinary least square, stochastic frontier analysis and data envelopment analysis. Wong et al. [13] proposed a simple benchmark using a 5-star rating system for electricity and fuel gas consumption in residential buildings. Survey samples were collected and statistical correlation was examined between the occupant load and the annual water, electricity and fuel gas consumption. The benchmark assigned the 1-star rating to the least sustainable households having electricity and fuel gas consumption in the top 10% of the samples, and the 5-star rating to the most sustainable ones in the bottom 10% of the samples.

In an analysis of climatic influences on the electricity consumption of chiller systems, Lam et al. [14] used the principal component analysis to develop two significant principal components as functions of five climatic variables. A clustering technique was then applied to the two principal components to develop 18-day-types for building energy study. A correlation was examined between the chiller electricity use and the principal components. Three multiple linear regression models were formulated to predict the daily chiller electricity consumption with the day types. The regression analysis was found to be essential for weather normalization and inter-year comparisons when energy saving measures were implemented to a chiller system. Lee [15] used the multiple linear regression method and data envelopment analysis to examine the effectiveness of energy management of office buildings. He introduced the use of scale and technical efficiencies to examine the environmental and management factors affecting the annual electricity consumption of the buildings. Xu et al. [16] performed principal component analysis to identify the correlation between the compressor power, temperatures and pressures at the evaporator and condenser sides. The principal components were used to simulate the systematic variations of chiller energy performance. Wavelet analysis was considered to detect and diagnose faulty sensors and recover measurements and was capable of processing noises and dynamics.

Drawing on statistical methods in the past studies, this paper considers using multivariate and data envelopment analyses to identify energy management opportunities for a chiller system. Different from previous studies, this paper demonstrates how scale, technical and overall efficiencies in the data envelopment analysis (DEA) help classify the impacts of controllable variables on managing system performance. Results of DEA help ascertain the highest achievable performance under operating constraints of an existing chiller system without developing any sophisticated models. A medium-sized chiller system with five sets of water-cooled chillers, pumps and cooling towers will be first described. Statistical methods will be presented to illustrate how to perform multivariate and data envelopment analyses on a huge collection of operating data. A multiple linear regression model will be established which describes the correlation between the COP of the chiller system and a list of climatic and operating variables. Results from the data envelopment analysis will be used to explain how the controllable variables should be set to increase the system COP. The significance of this study is to demonstrate a systematic approach to develop a model which facilitates effective energy management and to estimate COP improvements if energy management opportunities are identified.

2. Methods

2.1. Description of chiller system

A chiller system serving an institutional complex in Hong Kong was studied, as shown in Fig. 1. Table 1 gives the general technical information on the system components. Three centrifugal chillers are designed to cater for the peak building cooling load of 4500 kW. One additional centrifugal chiller is installed as a standby chiller. The screw chiller with a smaller capacity operates only for light duty loads at night to avoid the light load operation of the large centrifugal chillers. The chillers are connected in parallel and operate with their constant speed pumps to deliver the amount of chilled water required to meet the changing building cooling load. With a fixed flow rate of chilled water passing through each chiller, the temperature difference of chilled water is kept at 5 °C at full load and decreases from 5 °C when the chiller load drops. The chilled water distribution system contains a decoupling bypass pipe linking the primary and secondary chilled water loops to balance the flow under part load conditions. The secondary loop chilled water pumps operate in different numbers and speed to deliver the required flow rate of chilled water for the air-side system.

Heat rejection of the chillers is done by five fresh water evaporative cooling towers, each of which provides sufficient heat rejection capacity required for each of the chillers and they are linked together by a common cooling water circuit. The temperatures of the cooling water entering the condenser and leaving from the condenser are designed to be 33 °C and 38 °C, respectively, under the full load conditions. The cooling tower fans are cycled on with high/low speed to control the cooling water entering the condensers at around 33 °C under various operating conditions. Constant speed condenser water pumps are used to provide a fixed cooling water flow rate of 87 L/s for each large chiller and 41 L/s for the small chiller.

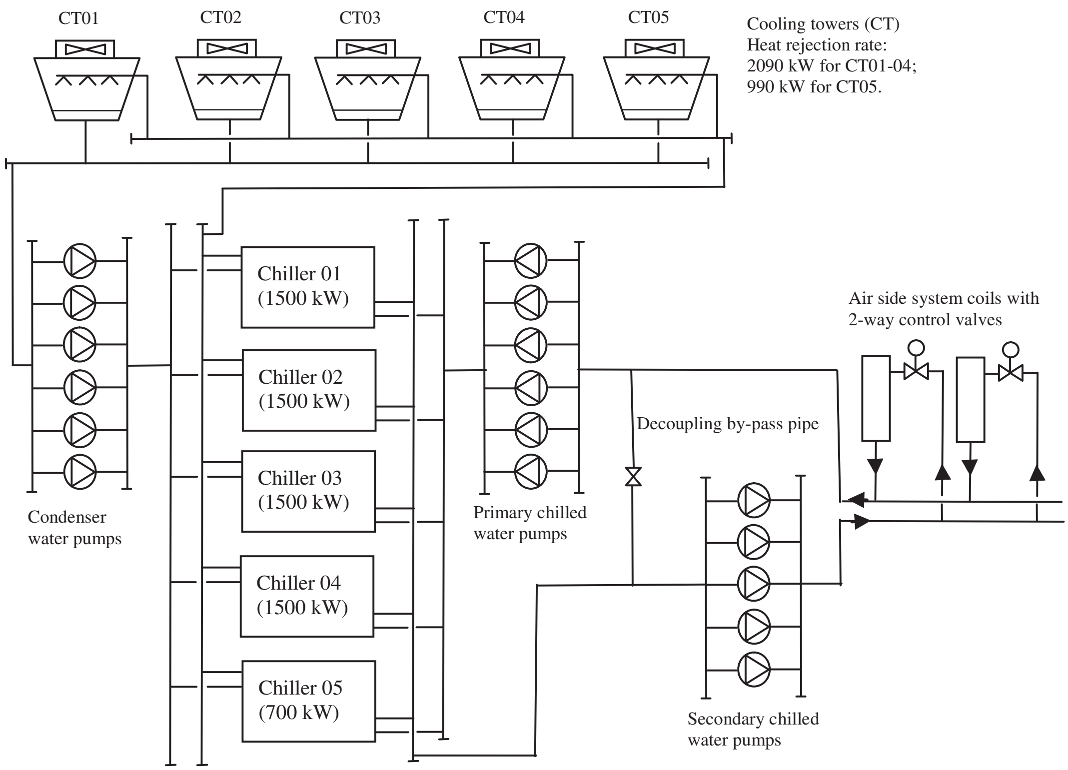

Fig. 1. Schematic diagram of the system.

Table 1
General specifications of system components.

Total cooling capacity (kW)	6700	
For each chiller	4 numbers (3 duty and 1 standby)	1 number
Compressor type	Centrifugal	Screw
Refrigerant type	R134a	R134a
Nominal cooling capacity (kW)	1500	700
Nominal compressor power (kW)	267	138
COP at full load	5.6	5.1
Design chilled water supply/return temperature (°C)	7/12	7/12
Design chilled water flow rate (l/s)	72	33
Design condenser water entering/leaving temperature (°C)	33/38	33/38
Design condenser water flow rate (L/s)	87	41
For each cooling tower		
Heat rejection capacity (kW)	2090	990
Design entering/leaving temperature (°C)	38/33	38/33
Water flow rate (l/s)	87	41
Air volume flow rate (m^3/s)	63	31
Fan motor power (kW)	9	4.5
Design wet-bulb outdoor temperature (°C)	28	28
Rated power of each primary chilled water pump (kW)	16	11
Rated power of each secondary chilled water pump (kW)	53	22
Rated power of each condenser water pump (kW)	25	11

The building management system monitored and logged hundreds of operating variables at 0.5-h intervals. The multivariate analysis focuses on the operating variables listed in Table 2. The system COP (variable 1) constitutes the dependent variable in the development of a regression model. It is calculated by the system cooling load (in kW) over the total power input (in kW) of chillers, primary chilled water pumps, condenser water pumps and cooling tower fans. T_{db} and T_{wb} (variables 2 and 3) are two independent temperatures to reflect climatic influences on the system cooling load and the control of cooling towers. Variables 4 to 11 are the variables involved in the operation and control of the system components. The load factor (variable 4) was used to ascertain if the operating chillers carried their highest load for any given building cooling load. Early staging of chillers commonly observed in many existing systems leads to the low load factor of operating chillers with a low COP. Variables 5–8 are typical temperatures at the evaporator and condenser sides to analyse chiller performance. The chiller system was originally designed to operate with the traditional sequencing control—all the chillers, primary chilled water pumps, condenser water pumps and cooling towers operate in pairs with the same number. Yet different sequencing patterns with non-zeros of D_{pp}, D_{cdp} and D_{ct} (variables 9–11) were observed for a certain building cooling load. They were therefore considered to analyse the trade-off between the power of system components when there were different sequencing patterns. Considering the system with chillers of two capacities, it is worth distinguishing the operation of the small chiller from the large chillers. When one large chiller operates, the number of operating chillers is assigned to be 1 unit. Given that the smaller chiller accounts for around half of the capacity of the large chiller, its operation is represented by 0.5 units. The operation of the pumps and cooling tower of smaller size is also counted as 0.5 units. Regarding variables 9–11, for instance, if one large and one small chillers are running, the number of operating chillers is 1.5. If two large primary loop pumps (2 units) are operating for one large and one small chillers, then D_{pp} is 0.5 (i.e. 2–1.5).

The operating variables were measured from June to November over a year, which accounts for all operating conditions with medium-to-high cooling demand in response to climatic conditions of Hong Kong. Excluding some illogical data due to erroneous measurements, around 6700 sets of operating conditions were gathered and used in this study. Examples of erroneous measurements included zeros or negative values of data archived on some electric

Table 2
List of operating variables.

No.	Variable	Nature	Description
1	COP	Continuous	The system COP, given by the total system load in kW divided by the total electric power in kW of chillers, pumps and cooling tower fans
2	T_{db}	Continuous	Outdoor dry bulb temperature (°C)
3	T_{wb}	Continuous	Outdoor wet bulb temperature (°C)
4	LF	Continuous	Load factor—the total load in kW carried by the operating chiller over their total nominal capacity in kW
5	T_{chws}	Continuous	Temperature of supply chilled water (measured at the main header) (°C)
6	T_{chwr}	Continuous	Temperature of return chilled water (measured at the main header) (°C)
7	T_{cdwe}	Continuous	Temperature of cooling water entering the condenser (measured at the main header) (°C)
8	T_{cdwl}	Continuous	Temperature of cooling water leaving the condenser (measured at the main header) (°C)
9	D_{pp}	Discrete	Number of primary chilled water pumps running subtracted from the number of chillers operating
10	D_{cdp}	Discrete	Number of condenser water pumps running minus the number of chillers operating
11	D_{ct}	Discrete	Number of cooling towers running minus the number of chillers operating

currents and chilled water or condenser water temperatures while the chillers operated properly. The operating variables of the idle system components were set to be zero.

2.2. Multivariate analysis

The form of a typical multiple linear regression model is given by Eq. (1), where y is the dependent variable to be predicted, a is the intercept, $b_1,\ldots,b_n$ are regression coefficients and $x_1,\ldots,x_n$ are significant independent variables. In this study, y is the COP and x_1 to x_{10} are variables 2–11. Commercial statistical software SPSS v16.0 [17] was used to identify a and b_1 to b_{10}, based on around 6700 sets of operating conditions (or observed data). Considering that the variables contain different units and natures, the regression model to be constructed is represented by the standardized independent variables, with the form given by Eq. (2). $x_{i,\text{mean}}$ and S_i are the mean and standard deviation of x_i, respectively. The accuracy of the model was evaluated in terms of R^2 (coefficient of determination) and σ_{est} (the standard error of the estimate). Eqs. (3) and (4) show the formulas used to compute R^2 and σ_{est}, where Y is the actual COP, Y' is the predicted COP of the regression equation and N is the number of sets of operating data. A higher value of R^2 means that the equation is more accurate and that a higher percentage of the total variation in COP can be estimated by the predicted COP. σ_{est} is analogous to the root-mean-square error of the predicted COP and a smaller σ_{est} means a more accurate regression model.

$$y = a + b_1x_1 + b_2x_2 + \cdots + b_nx_n \quad (1)$$

$$\text{COP}_{\text{predicted}} = a + b_1x_1^* + \cdots + b_{10}x_{10}^* = a + \sum_{i=1}^{10} b_i\left(\frac{x_i - x_{i,\text{mean}}}{S_i}\right) \quad (2)$$

$$R^2 = 1 - \frac{\sum(Y' - Y)^2}{\sum(Y - \sum Y/N)^2} \quad (3)$$

$$\sigma_{est} = \sqrt{\frac{\sum(Y - Y')^2}{N}} \quad (4)$$

2.3. Data envelopment analysis (DEA)

Fig. 2 illustrates the concepts of using the DEA to analyse optimal efficiencies over the datasets. Each data point (P_1–P_7) is regarded as a decision making unit (DMU). Based on the plots, under-estimation occurs at P_1, P_4, P_5, P_6 and P_7 as their outputs (predicted values) are smaller than the corresponding inputs (observed values). On the other hand, over-estimation occurs at P_2 and P_3. DEA draws on a linear programming technique to assess the efficiencies of DMUs. The line segment joining P_1, P_2, P_3 and

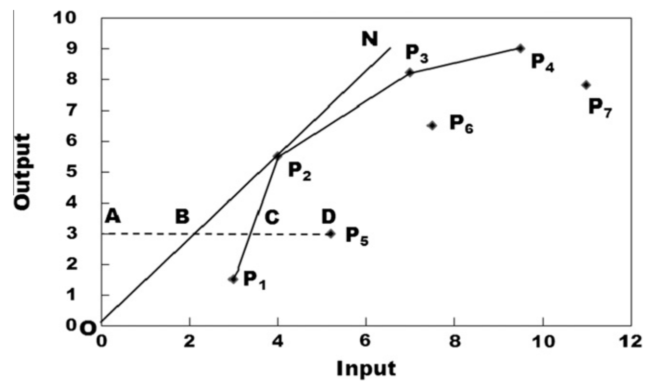

Fig. 2. Plot for explaining the overall, scale and technical efficiencies in DEA.

P_4 is a non-parametric piecewise envelope (or frontier) which owns the optimal efficiency over the datasets for a comparative efficiency measurement. Among the points P_1, P_2, P_3 and P_4, P_2 gives the highest ratio of the output to input. Any data lying on the line joining the origin and P_2 (line ON) means that the overall efficiency is equal to one, while any data lying on the frontier means the technical efficiency is equal to one. Scale efficiency is used to relate the technical efficiency with the overall efficiency, and it is given by the overall efficiency divided by the technical efficiency. For any data point not lying on the frontier or the line MN (taking P_5 as an example), the calculation of its overall, scale and technical efficiencies is given by Eqs. (5)–(7). Scale efficiency was used to capture climatic influences on the system COP. This analysis focuses on how technical efficiency can be increased to improve the system COP if the controllable operating variables attain their optimal settings. The DEA computer program version 2.1 developed by Coelli [18] was used to evaluate the efficiencies for each DMU (one set of operating conditions).

$$\textit{Overall efficiency} = AB/AD \quad (5)$$

$$\textit{Scale efficiency} = AB/AC \quad (6)$$

$$\textit{Technical efficiency} = AC/AD \quad (7)$$

3. Results and discussion

3.1. Multiple linear regression model

A summary of statistical results of the variables is shown in Table 3. The actual system COP varied from 0.08 to 5.22 with a mean of 3.78, given that the total power input involves not only chillers, but also pumps and cooling tower fans. If the compressor power was considered only, the COP of the chillers varied from 0.17 to 9.15 with a mean of 4.89, which complies with the manufacturer's

Table 3
Summary of statistical results of the variables.

	Variable	Minimum	Maximum	Mean ($x_{i,\text{mean}}$)	Standard deviation (S_i)
y	COP	0.08	5.22	3.78	0.39
x_1	T_{db}	9.31	35.98	27.09	4.05
x_2	T_{wb}	9.27	29.83	24.05	3.72
x_3	LF	0.02	1.2	0.73	0.14
x_4	T_{chws}	7.04	17.83	8.11	1.07
x_5	T_{chwr}	9.97	19.34	12.33	0.95
x_6	T_{cdwe}	25.11	40.75	30.16	1.48
x_7	T_{cdwl}	27.56	44.66	33.75	1.86
x_8	D_{pp}	−2	2	0.05	0.21
x_9	D_{cdp}	−1	2	0.04	0.22
x_{10}	D_{ct}	−3	2	-0.30	0.68

performance data in general. Using the built-in regression analysis of the software SPSS v16.0, the regression model of predicting the system COP was constructed and is given by Eq. (8). The t-statistics of the variables are shown in the small parentheses under the coefficients. The values of R^2 and σ_{est} are 0.8286 and 0.1617, respectively. This implies that the accuracy of the model is quite good and exceeds 80% (actually 82.86%) of the actual change of system COP can be predicted within 95% confidence level.

$$\begin{aligned}\text{COP}_{\text{predicetd}} = {} & \underset{(1907.15)}{3.7775} + \underset{(9.28)}{0.0459}\left(\frac{T_{db}-27.09}{4.05}\right) - \underset{(-4.24)}{0.0245}\left(\frac{T_{wb}-24.05}{3.72}\right) \\ & + \underset{(114.55)}{0.3485}\left(\frac{LF-0.73}{0.14}\right) - \underset{(-51.77)}{0.1992}\left(\frac{T_{chws}-8.11}{1.07}\right) \\ & + \underset{(34.91)}{0.1594}\left(\frac{T_{chwr}-12.33}{0.95}\right) + \underset{(8.25)}{0.0259}\left(\frac{T_{cdwe}-30.16}{1.48}\right) \\ & - \underset{(-38.58)}{0.1362}\left(\frac{T_{cdwl}-33.75}{1.86}\right) - \underset{(-8.09)}{0.0433}\left(\frac{D_{pp}-0.05}{0.21}\right) \\ & - \underset{(-2.18)}{0.0116}\left(\frac{D_{cdp}-0.04}{0.22}\right) - \underset{(-17.59)}{0.0443}\left(\frac{D_{ct}+0.30}{0.68}\right) \end{aligned} \quad (8)$$

Some typical and unique operating features of the system are identified from the impact of significant factors on the COP. The load factor (LF) is the most significant factor with the highest t-statistics magnitude. The positive regression coefficient of LF indicates that operating chillers at higher loads would increase the system COP. This conforms with the operating performance of centrifugal chillers with the highest COP at around full load and a general situation where the proportion of the pump power and cooling tower fan power becomes lower when the chiller operates at higher loads. According to general knowledge, an increase in the temperature of supply chilled water (T_{chws}) generally results in an increased chiller COP. Yet considering the system COP with the total power of chillers, pump and tower fans, a negative regression coefficient between T_{chws} and system COP was identified from the regression model. One reason for this unexpected correlation is that the rise of T_{chws} was associated with the operation of extra chilled water pumps to deliver additional flow of chilled water to the chillers. The operation of an additional chiller was prolonged by allowing the running chillers to be slightly overloaded. Yet this operating strategy caused an unfavourable trade-off between the chiller power and pump power, giving negative coefficients to T_{chws} and D_{pp}. Indeed, the misalignment of the chiller-pump numbers with non-zeros of D_{pp} and D_{ct} weakens the conventional correlation between the system COP and T_{chws}. If T_{chws} is controlled perfectly at its designed level of 7 °C (below the mean of 8.11 °C) without operating unnecessary chilled water pumps (i.e. reinstating $D_{\text{pp}} = 0$), the system COP could be improved based on the regression model. Although T_{chwr} is not a controllable variable for a chilled water distribution system with constant flow, it is expected to be an important operating variable influencing the system COP, given a positive correlation between T_{chwr} and LF.

The regression model complies with general knowledge that a decrease of the cooling water leaving from the condenser (T_{cdwl}) could improve the system COP. For a given chiller load, a drop in T_{cdwl} occurs when the heat rejection effectiveness is enhanced inherently at a lower wet bulb temperature. If an attempt is made on increasing the heat rejection effectiveness by operating extra cooling towers (with a positive D_{ct}), the extra fan power would cause a drop on the system COP. The controllable variable—the temperature of cooling water entering the condenser (T_{cdwe})—has a slight impact on the change of system COP as reflected from its lower t-statistics magnitude of 8.25 and the correlation coefficient of +0.0259. This is probably due to the use of a fixed set point for all operating conditions. Indeed, according to the existing operation of the system, fewer condenser water pumps and cooling towers were staged at a higher T_{cdwe}. The lesser pumping and fan power could outweigh the increased compressor power at a higher T_{cdwe}, resulting in a net power reduction and hence an increased system COP. The regression model helps characterize the change of system COP due to the interdependence between T_{cdwe}, D_{cdp} and D_{ct} if a misalignment of chiller-pump-tower numbers occurs.

Overall the regression model could suggest the following ways to increase the system COP:

- operate the chillers at higher loads as far as possible but do not overload the chillers with extra operation of chilled water pumps,
- maintain the temperature of supply chilled water at a design level of 7 °C instead of trying to raise it at above 8.11 °C,
- operate the chillers, chilled water pumps and condenser water pumps at the same number and in pairs and avoid running extra pumps,
- operate fewer number of cooling towers while ensuring the temperature of cooling water leaving from the cooling tower at below 33.75 °C.

3.2. Data envelopment analysis findings

Fig. 3 gives a plot of all operating data for the data envelopment analysis. The results of the efficiencies against the actual system COP are given in Figs. 4–6. As Fig. 4 illustrates, the overall efficiency is the lowest at the smallest COP of 1.0 and it increases with the COP in various degrees. The overall efficiency scatters in a wider range when the actual system COP is between 2.5 and 4, within which the scale efficiency is very high, in the range of 0.82–1. This suggests the wide variation of the technical efficiency and the potential of improving the control strategy in the COP range of 2.5–4. It is interesting to see that the convex variation in scale efficiency. It rises from 0.5 starting from a COP of 1 and reaches 1 at the COP of 3.5 and then drops gently. Indeed, the scale efficiency increases when the outdoor temperature drops, regardless of how heavy the load carried by the chillers and the control of the temperatures at

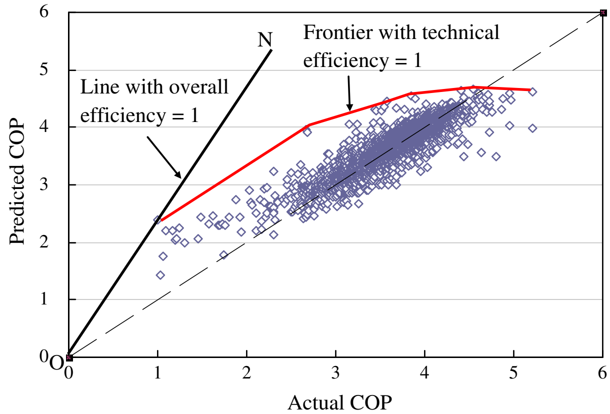

Fig. 3. Plot of operating data for data envelopment analysis.

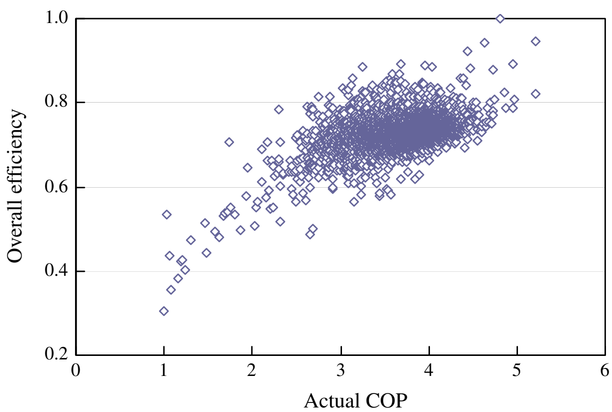

Fig. 4. Overall efficiency against the actual system COP.

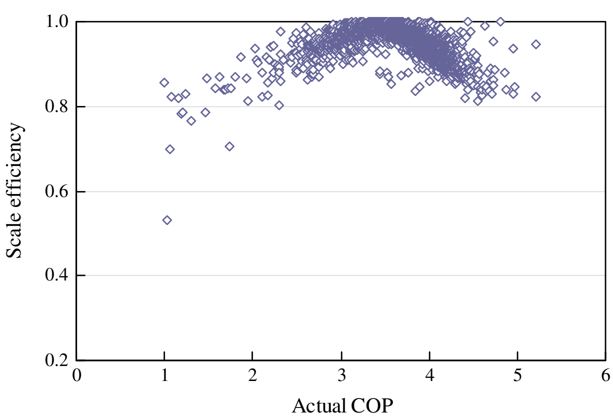

Fig. 5. Scale efficiency against the actual system COP.

the evaporator and condenser sides. This confirms with general knowledge that a lower ambient temperature can enhance chiller system performance, even if a fixed set point is used in the cooling water temperature.

Excluding the effect of climatic influences, technical efficiency can be used to explain whether the system operates with the highest possible efficiency or not. It is expected that the technical efficiency increases generally with the COP and its degree of scattering suggests an opportunity to improve the COP. It is interesting to see a virtual lower boundary showing the cut-off of 0.6 to 1 in technical efficiency when the COP increases from 3 to 5. This could serve as a measure to control the minimum allowable COP by setting the lower limit of technical efficiency.

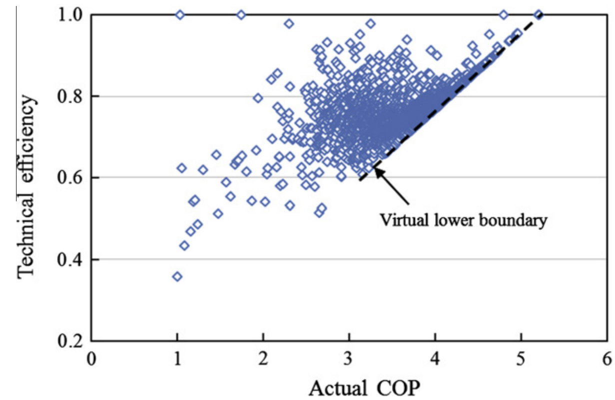

Fig. 6. Technical efficiency against the actual system COP.

Using the regression model, it is possible to predict the improved system COP for a given system load and ambient temperature when optimal set points are applied to the temperatures of chilled water and cooling water and when sequencing control is implemented to the chillers along with pumps and cooling towers. Sequencing control means that the chillers operate according to the schedule in Table 4 in order to ensure their high load operation as frequent as possible. The screw chiller under sequencing control would be a normal duty chiller and run for 52% of the total operating time. Fig. 7 shows a plot of the predicted COP under the improved control against the original COP. Comparing Fig. 3 with Fig. 7, there is an increase (or upward shift) in the predicted COP for most operating conditions. This COP improvement could reduce the electricity consumption by 5.34% or 121,001 kWh over the per-

Table 4
Chiller operating schedule under sequencing control.

System load, Q (kW)	Number of chillers operating		Range of load factor
	Small/screw	Large/centrifugal	
$0 < Q \leqslant 700$	1	0	0–1
$700 < Q \leqslant 1500$	0	1	0.47–1
$1500 < Q \leqslant 2200$	1	1	0.68–1
$2200 < Q \leqslant 3000$	0	2	0.73–1
$3000 < Q \leqslant 3700$	1	2	0.81–1
$3700 < Q \leqslant 4500$	0	3	0.82–1

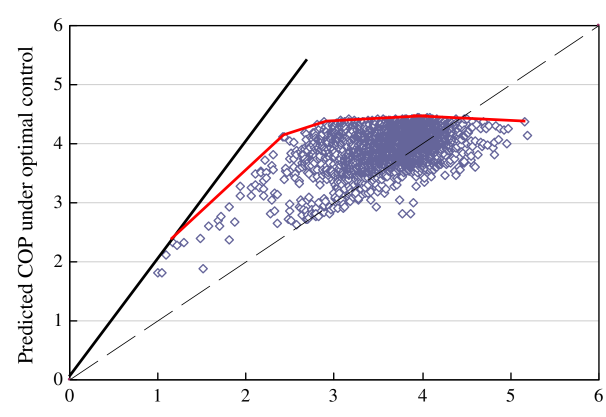

Fig. 7. Plot of predicted COP under improved control against the actual COP.

Table 5
Frequency distribution of technical efficiency under improved control of the chiller system.

Range	Frequency
0–0.2	0
0.2–0.4	0
0.4–0.6	123
0.6–0.8	2204
0.8–1	4352

iod studied. Table 5 gives the frequency distribution of the technical efficiency at different ranges when the improved control is applied to the system. The average technical efficiency rises from 0.76 to 0.81. 65.2% of the total COP data have a technical efficiency of above 0.8.

Overall the data envelopment analysis helps quantify climatic and operational factors influencing the change of system COP. Scale efficiency can be used to identify system performance due to climatic influences while technical efficiency can be used to assess the system's energy effectiveness subject to control and operating strategies. When formulating a benchmark performance for chiller systems, it is important to exclude the effect of climatic influences and so technical efficiency serves to identify the baseline COP and analyse the extent to which the COP can increase with improved operation and control of systems.

4. Conclusions

This study demonstrates how multivariate and data envelopment analyses can be used to facilitate energy management of chiller systems. Using built-in analytical tools in the statistical software SPSS v16.0, a linear multiple regression model was constructed for a chiller system containing five sets of chillers, pumps and cooling towers. The model was used to examine the degree of correlation between climatic and operating variables and the system coefficient of performance (COP). Based on the t-statistics results, the three most significant variables are the load factor, the temperature of supply chilled water and the temperature of cooling water leaving the condenser. Improved settings for the controllable variables were proposed based on the model equation. Data envelopment analysis was then employed to calculate the overall efficiency, scale efficiency and technical efficiency. Scale efficiency increases when the dry bulb and wet bulb temperatures drop. This shows how the system COP varies with the climatic factors. Technical efficiency, on the other hand, reflects the change of system COP resulting mainly from control and operational factors while excluding the effect of climatic variables. The average technical efficiency of the system studied was found to be 0.76 and implementing improved control and operation could reduce the electricity consumption by 5.34% in relation to the existing operation.

The significance of this study is to demonstrate a systematic method to assess the energy effectiveness of chiller systems. Further investigation will be conducted on how the technical efficiency in data envelopment analysis can complement the system COP to explain the control and operating characteristics. It is hoped that multivariate and data envelopment analyses would form a standard tool to assess periodically the operating performance of chiller systems and help to formulate a benchmark for chiller retrofit or improvement work.

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