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# Evaluation of Chiller Power Consumption Using Grey Prediction

Tien-Shun Chan, Yung-Chung Chang, Cheng-Yu Chu, Wen-Hui Chen, Yuan-Lin Chen, Shun-Chong Wang, and Chang-Chun Wang



***Abstract*—**98% of the energy needed in Taiwan has been imported. The prices of petroleum and electricity have been increasing. In addition, facility capacity, amount of electricity generation, amount of electricity consumption and number of Taiwan Power Company customers have continued to increase. For these reasons energy conservation has become an important topic. In the past linear regression was used to establish the power consumption models for chillers. In this study, grey prediction is used to evaluate the power consumption of a chiller so as to lower the total power consumption at peak-load (so that the relevant power providers do not need to keep on increasing their power generation capacity and facility capacity).

In grey prediction, only several numerical values (at least four numerical values) are needed to establish the power consumption models for chillers. If PLR, the temperatures of supply chilled-water and return chilled-water, and the temperatures of supply cooling-water and return cooling-water are taken into consideration, quite accurate results (with the accuracy close to 99% for short-term predictions) may be obtained. Through such methods, we can predict whether the power consumption at peak-load will exceed the contract power capacity signed by the corresponding entity and Taiwan Power Company. If the power consumption at peak-load exceeds the power demand, the temperature of the supply chilled-water may be adjusted so as to reduce the PLR and hence lower the power consumption.

***Keywords*—**Gery system theory, grey prediction, chller.

## I. Introduction

SINCE Taiwan is located in a subtropical area, and has an extremely hot and humid climate in summer, there has been a great increase in demand for air conditioning equipment. Air conditioning equipment used in Taiwan includes window-mounted air conditioners, package-type air conditioners, indoor ventilators, and central air conditioning systems; as a whole, these types of air conditioning equipment account for 30% of Taiwan's total summertime power consumption, and as much as 40% of power consumption at peak load times. The most important part of a central air conditioning system is the chiller which accounts for more than 60% of central air conditioning system power consumption. As a consequence, increasing chiller energy efficiency and thereby reducing air conditioning power costs and easing summertime peak load growth is a key issue in the field of air conditioning. The principal goal of this study is to apply grey prediction– instead of the conventional linear regression model– to establish a model for the chiller power demand, and use this model to predict chiller power consumption. By forecasting chiller power demand during peak load periods and thereby adjusting chiller operating status, users can prevent power consumption from exceeding power demand and reduce operation costs for the customer, while also helping the power company to ease the relentless trend toward increasing installed capacity.

Many researchers have proposed various methods for predicting power consumption of both water-cooled and air-cooled central air conditioning systems, using both chiller power consumption models and air conditioning system overall power consumption models:

(1) Hittle (1977) used the BLAST software to create models for reciprocating and centrifugal chillers, and thereby facilitate the calculation of power consumption during chiller operation [1].

(2) Stoecker (1982) proposed a compressor energy consumption model that can be expressed as a model with condensation temperature and evaporation temperature as independent variables, in which the regression coefficient is derived by fitting using data provided by the chiller manufacturer [2].

(3) Strand (1994) proposed an energy analysis model for direct and indirect ice storage systems that takes into consideration the six factors of ice storage chiller condensation temperature, evaporation temperature, condensation pressure, evaporation pressure, compressor capacity, and reference temperature (300K) when calculating the power consumption of a chiller operating at full load [3].

(4) Solati (2002) used the ASHRAE Toolkit software in

T. S. Chan is with the Department of Energy and Refrigerating Air-Conditioning Engineering, National Taipei University of Technology, Taipei, Taiwan, ROC ( e-mail: james@ntuh.gov.tw).

Y. C. Chang was with the Department of Energy and Refrigerating Air-Conditioning Engineering, National Taipei University of Technology, Taipei, Taiwan, ROC ( e-mail: ycchang@ntut.edu.tw).

C. Y. Chu is with the Department of Energy and Refrigerating Air-Conditioning Engineering, National Taipei University of Technology, Taipei, Taiwan, ROC

W. H. Chen is with the Graduate Institute of automation technology, National Taipei University of Technology, Taipei, Taiwan, ROC

Y. L. Chen is with the Department of Electrical Engineering, Ming chi university of technology, Taipei, Taiwan, ROC

S. C. Wang is with the Department of Electrical Engineering, Lunghwa University of Science and Technology, Taoyuan County ,Taiwan , ROC

C. C. Wang is with the Department of Energy and Refrigerating Air-Conditioning Engineering, National Taipei University of Technology, Taipei, Taiwan, ROC ( e-mail: ccwang@ntut.edu.tw).

conjunction with operating data provided by the manufacturer to establish a power consumption model for screw-type ice water chillers [4].

(5) Chen (2004) proposed used regression analysis to derive equations describing the relationships between chiller power consumption and the variables of cooling tower power consumption and cooling water temperature, chilled water supply temperature, cooling load, and external air wet bulb temperature, and then added the coefficients of identical variables in the equations to obtain a power consumption model for the chiller and cooling tower [5].

(6) Chan (2004) used the TRNSYS program to model the power consumption of an air-cooled chiller, and took into consideration the seven external factors of external air temperature, partial load ratio, chilled water flow, chilled water supply temperature, condensation supercooling, evaporation superheating, and preset compressor temperature when performing iterated calculation of chiller power consumption [6].

(7) Tai (2006) investigated the chiller evaluation methods in ASHRAE Guideline 14, and developed a model able to accurately predict and assess chiller power consumption. This model can be used as a performance model prior to energy conservation improvement, and can also be employed to predict chiller operating efficiency under certain circumstances after improvement [7].

While many methods are currently used in Taiwan and abroad to predict air conditioning power consumption and load, there have been few attempts thus far to apply grey prediction air conditioning systems research; the following are the principal studies in the literature:

(1) Lan (2001) used the grey prediction to develop a grey prediction fuzzy controller able to accelerate air conditioning system response and thereby shorten warm-up time while maintaining an indoor temperature on the preset temperature. This system can also effectively control overshoot, ensuring that the fuzzy controller does not waste energy through overcompensation. The system is extremely stable and also offers clear energy-saving benefits [8].

(2) Jiang (2003) employed the grey prediction model GM(1,1) to predict the COP variation of an air-cooled chiller at different periods of time. The fact that the predicted values matched measured values extremely closely demonstrated that grey prediction can be effectively applied to HVAC systems [9].

(3) Chen (2006) employed the data format needed in grey prediction and performed α-value learning, and then used a modeling program to predict cooling load curves on the next day. The ice storage control system operating model can be adjusted on the basis of the air conditioning equipment's efficiency index to achieve the goal of reducing operation cost [10].

## II. Grey System Theory

Prof. Deng Julong first proposed grey system theory with the publication of his article "The Control Problems of Grey System" [11] in an international journal in March 1982, and also presented the first Chinese-language paper on grey control systems at China's Huazhong University of Science and Technology during the same year. After more than a decade of elaboration by Prof. Deng and other domestic and foreign grey system researchers, grey system theory had grown increasingly mature, and had been applied to ten or more fields, including life science, agriculture, environmental protection, electricity, and manpower. Researchers in Taiwan have issued numerous papers concerning the application of grey system theory to such areas as information, electronics, electrical machinery, mechanical engineering, automation, aerospace, civil engineering, industrial engineering, industrial education, transportation, and business management, and the field is still growing rapidly in Taiwan.

Grey system theory encompasses the following six research methods [12]:

(1) Grey generating:

Generating refers to data processing in order to provide supplementary information, so as to cause regularities and characteristics emerge from disorderly data sets. In other words, we can use grey generating to reduce the randomness and increase the orderliness of data. Commonly used generating methods include the following:

a. Accumulated generating operation (AGO) accumulates data according to sequence.
b. Inverse accumulated generating operation (IAGO) performs accumulated generating in reverse order.
c. Differential generating: Apart from accumulated generating and inverse accumulated generating, differential generating employs existing data and customary mathematical methods to establish data.

(2) Grey relation analysis:

Grey relation analysis is a testing method used to determine the degree of correlation between discrete sequences. Since grey relation analysis can analyze situations where there is little data and many factors, it can make up for the disadvantages of statistical regression analysis.

(3) Grey models:

Generated data can be used to establish models consisting of a set of grey differential equations and grey pseudo-differential equations. These so-called grey models generally consist of the following types:

a. GM(1,1): a first order differential equation with one input variable, typically used for forecasting.
b. GM(1,N): a first order differential equation with N input variables, typically used for dynamic factor analysis, and not for forecasting. However, in the common situation where a system has inertia and a control time lag exists, and it is therefore necessary to assess or judge the effect of behavioral factors on the system's future development, this model must be used for forecasting.
c. GM(0,N): a zero order differential equation with N input variables, typically used for multidimensional correlation analysis.

(4) Grey prediction:

Grey prediction employs the GM(1,1) model to perform predictions from the existing data. The prediction process actually consists of finding the future dynamic state of each median element in a group of sequences. There is generally considered to be four types of grey prediction:

a. Data prediction: Sequence prediction of data size.

b. Abnormality prediction: Prediction of whether an abnormality will occur within a certain period of time.

c. Topological prediction: Existing data is used to make a pattern, which is then used to predict the pattern's development.

d. System prediction: Combines GM(1,1) and GM(1,N); used to predict multiple variables in a system, and understand their mutual influence.

(5) Grey decision making:

When a certain event occurs, grey decision making is used to select the most appropriate of multiple strategies with differing effects to deal with the event. The selected strategy is then combined with the GM (1,1) model to achieve grey decision making.

(6) Grey control

Grey control uses system behavior data to search for behavioral develop patterns that can be used to predict future behavior. When a predicted value is obtained, this predicted value is fed back to effect control, yielding a new control rule formed through an evolutionary process.

Conventional prediction methods typically use continuous function fitting to perform extrapolation, but this approach requires large amounts of known data. Predictions often cannot be made when only a small quantity of data is available, however. Grey prediction can be used in situations where there is little data, and is therefore better than conventional methods under these circumstances.

## III. Definition of the GM(1,N) Model [12]

According to the definitions in grey system theory, the grey differential equation used in the GM(1,N) model is as follows:

$$\frac{dx^{(1)}}{dt} + a x_1^{(1)} = \sum_{i=2}^{N} b_i x_i^{(1)}(k) \tag{1}$$

Where *a* is the development coefficient, *b* is the grey control variable, $x_1^{(1)}(k)$ is the standard sequence, and $x_i^{(1)}(k)$ is the comparison sequence. Assuming that the original sequence as follows:

$$\begin{aligned} x_1^{(0)} &= \{x_1^{(0)}(1), x_1^{(0)}(2), \ldots, x_1^{(0)}(k)\} \\ x_2^{(0)} &= \{x_2^{(0)}(1), x_2^{(0)}(2), \ldots, x_2^{(0)}(k)\} \\ x_3^{(0)} &= \{x_3^{(0)}(1), x_3^{(0)}(2), \ldots, x_3^{(0)}(k)\} \quad k = 1,2,3,\ldots,n \\ &\vdots \\ x_N^{(0)} &= \{x_N^{(0)}(1), x_N^{(0)}(2), \ldots, x_N^{(0)}(k)\} \end{aligned} \tag{2}$$

In the sequence $x_i^{(0)}(k), i = 1,2,3,\cdots,n$, $x_1^{(0)}(k)$ is the system's chief behavior, and in $x_2^{(0)}(k), x_3^{(0)}(k)$, $x_4^{(0)}(k), \cdots, x_N^{(0)}(k)$ are the chief influencing behavioral factors. After performing an AGO to the original sequence, we obtain:

$$\begin{aligned} x_1^{(1)} &= \{x_1^{(1)}(1), x_1^{(1)}(2), \ldots, x_1^{(1)}(k)\} \\ x_2^{(1)} &= \{x_2^{(1)}(1), x_2^{(1)}(2), \ldots, x_2^{(1)}(k)\} \\ x_3^{(1)} &= \{x_3^{(1)}(1), x_3^{(1)}(2), \ldots, x_3^{(1)}(k)\} \quad , k = 1,2,3,\ldots,n \\ &\vdots \\ x_N^{(1)} &= \{x_N^{(1)}(1), x_N^{(1)}(2), \ldots, x_N^{(1)}(k)\} \end{aligned} \tag{3}$$

According to the form of GM(1,N), the post-AGO sequence can be rearranged as:

$$x_1^{(0)}(k) + a z_1^{(1)} = \sum_{i=2}^{N} b_i x_i^{(1)}(k) \tag{4}$$

Where

$$z_1^{(1)}(k) = 0.5 x_1^{(1)}(k) + 0.5 x_1^{(1)}(k-1),\ k = 2,3,4,\ldots,n$$

Using equation (4), substituting the data resulting from generating yields:

$$\begin{aligned} x_1^{(0)}(2) + a z_1^{(1)}(2) &= b_2 x_2^{(1)}(2) + \ldots + b_N x_N^{(1)}(2) \\ x_1^{(0)}(3) + a z_1^{(1)}(3) &= b_2 x_2^{(1)}(3) + \ldots + b_N x_N^{(1)}(3) \\ x_1^{(0)}(4) + a z_1^{(1)}(4) &= b_2 x_2^{(1)}(4) + \ldots + b_N x_N^{(1)}(4) \\ &\vdots \\ x_1^{(0)}(n) + a z_1^{(1)}(n) &= b_2 x_2^{(1)}(n) + \ldots + b_N x_N^{(1)}(n) \end{aligned} \tag{5}$$

The differential equations in (4) can be transformed into an array with the following form:

$$\begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \ldots & x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \ldots & x_N^{(1)}(3) \\ & \vdots & & \\ -z_1^{(1)}(n) & x_2^{(1)}(n) & \ldots & x_N^{(1)}(n) \end{bmatrix} \begin{bmatrix} a \\ b_2 \\ \vdots \\ b_N \end{bmatrix} \tag{6}$$

Using the least squares method,

$$\hat{a} = \begin{bmatrix} a \\ b_2 \\ \vdots \\ b_N \end{bmatrix} = (B^T B)^{-1} B^T Y_N \tag{7}$$

Where B and YN are:

$$B = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \ldots & x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \ldots & x_N^{(1)}(3) \\ & \vdots & & \\ -z_1^{(1)}(n) & x_2^{(1)}(n) & \ldots & x_N^{(1)}(n) \end{bmatrix}, Y_N = \begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(n) \end{bmatrix}$$

This yields the relationships between the chief behavioral factors and each subfactor. The GM(1,N) model thus performs a comprehensive analysis of system outputs and inputs, and yields the weights of each factor relative to the standard sequence $x_1$.

The following equation can be used to perform residual comparison of the values predicted by the model and the original values:

$$e(k) = \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\% \quad (8)$$

When the desired $\hat{a}$ is substituted into equation (9), we can obtain a solution to the white equation, and use this solution to perform predictions.

$$\hat{x}_1^{(1)}(n+1) = \left( x_1^{(1)}(1) - \sum_{i=2}^{N} \frac{b_i}{a} x_i^{(1)}(n+1) \right) e^{-an} + \sum_{i=2}^{N} \frac{b_i}{a} x_i^{(1)}(n+1) \quad (9)$$

$k = n+1$, and k is the number of desired number of periods. Since, however, an AGO has been applied to the foregoing equation, an IAGO must now be applied in order to obtain predicted values for the original data:

$$\hat{x}_1^{(0)}(k) = \hat{x}_1^{(1)}(k) - \hat{x}_1^{(1)}(k-1) \quad (10)$$

## IV. Case Analysis

This study employed empirical data from the air conditioning system of an optoelectronic manufacturing plant. Grey relation analysis was used to find the weights of the chiller energy consumption factors, and grey modeling and a multiple regression equation then used to establish a power consumption model for the chiller, enabling power consumption under different types of load situations to be predicted and compared with actual power consumption. Since the compared data needed to be on the same basis, and because calculations could be made using linear regression only when there are more than ten data items, ten data items were taken when the chiller was operating with a partial load ratio (PLR) of 0.73-0.82 (see Table 1). The data includes chiller power consumption, chilled water supply temperature, chilled water return temperature, cooling water supply temperature, and cooling water return temperature. These also happen to be the most easily measured data items. The last five items in the table are considered to be important factors affecting chiller power consumption. Grey relation analysis is first performed to find the weights of the five power consumption factors, and then grey modeling and a multiple regression equation are used to establish a power consumption model for the chiller; this model is used to predict power consumption and perform comparisons with the empirical data.

Employing the results of grey relation analysis, after taking the absolute value of array $\hat{a}$, we abnormal $b_{PLR} > b_{Tchs} > b_{Tcwr} > b_{Tchr} > b_{Tcws}$. It is therefore known that, in order of their weights, the factors affecting chiller power consumption are: PLR, chilled water supply temperature, cooling water return temperature, chilled water return temperature, and cooling water supply temperature. We therefore set:

TABLE I
OPERATING DATA FROM A HIGH-TEMPERATURE CHILLED WATER CHILLER

| Time | Power consumption (kW) | PLR | Chilled water return temperature (℃) | Chilled water supply temperature (℃) | Cooling water return temperature (□) | Cooling water supply temperature (℃) |
|---|---|---|---|---|---|---|
| 2006/6/29 05:20 | 540.15 | 0.73 | 19.50 | 15.00 | 27.44 | 30.72 |
| 2006/6/29 04:50 | 547.07 | 0.74 | 19.50 | 15.00 | 27.44 | 30.72 |
| 2006/6/29 17:30 | 557.80 | 0.75 | 19.76 | 15.00 | 27.45 | 31.11 |
| 2006/8/4 04:10 | 557.00 | 0.76 | 19.44 | 15.11 | 26.78 | 30.66 |
| 2006/8/4 01:30 | 575.06 | 0.77 | 19.44 | 15.11 | 27.44 | 31.20 |
| 2006/8/10 04:30 | 586.50 | 0.78 | 19.50 | 15.05 | 27.48 | 31.33 |
| 2006/7/1 06:50 | 595.72 | 0.79 | 19.83 | 15.00 | 27.39 | 31.17 |
| 2006/8/15 08:30 | 618.44 | 0.80 | 19.83 | 15.05 | 29.11 | 32.92 |
| 2006/8/14 02:10 | 621.21 | 0.81 | 19.83 | 15.05 | 28.44 | 32.44 |
| 2006/8/15 12:10 | 653.63 | 0.82 | 19.83 | 15.05 | 30.11 | 34.11 |

$X =$ cooling water return temperature - chilled water supply temperature

$Y = PLR$

The multiple regression equation can now be written as:

$$P_{ch} = a_0 + a_1 X + a_2 X^2 + a_3 Y + a_4 Y^2 + a_5 XY \quad (11)$$

Applying multiple regression analysis to the data in Table 1 yields the regression coefficients, which are respectively:

$a_0$ = -328.62, $a_1$ = 93.73, $a_2$ = 4.56, $a_3$ = -297.42, $a_4$ = 2910.44, $a_5$ = -257.27, after adjustment, the coefficient of determination $R^2$=0.997.

It can be seen from the Fig. 1 that there is an extreme difference between the models during the initial period. This is chiefly due to the error resulting from the conversion of $x_1^{(1)}$ in equation (1) from a continuous function to a discrete function. The predicted errors by the grey model are approximate to those by the linear regression from PLR=0.78 to PLR=0.82, Table II is given to evaluate these two predicted models.

TABLE II
OPERATION DATA FOR TESTING PREDICTED MODEL

| Time | PLR | Chilled water return temperature (℃) | Chilled water supply temperature (℃) | Cooling water return temperature (℃) | Cooling water supply temperature (℃) |
|---|---|---|---|---|---|
| 2006/6/29 05:20 | 0.83 | 19.78 | 15.00 | 27.55 | 31.55 |
| 2006/6/29 04:50 | 0.84 | 20.11 | 15.11 | 30.46 | 34.57 |
| 2006/6/29 17:30 | 0.85 | 20.16 | 15.00 | 28.22 | 32.55 |
| 2006/8/4 04:10 | 0.86 | 20.11 | 15.11 | 32.21 | 36.41 |

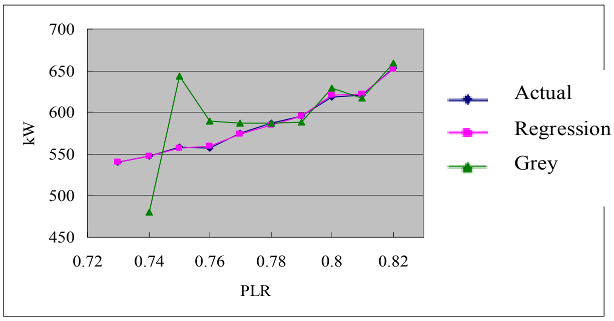


Fig. 1 Residual test of the grey model and regression analysis model

Fig. 2 shows the power consumption values predicted predictions obtained using the established chiller model, and compares them with the actual values. Obviously, the predicted errors by both models are similar.

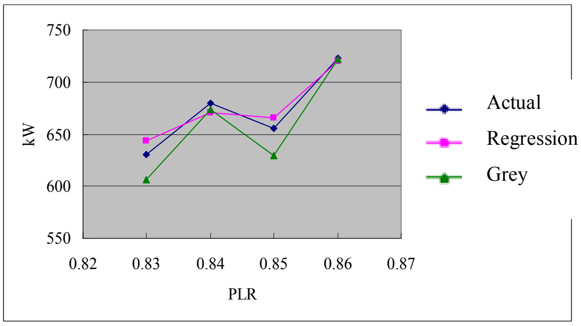


Fig. 2 Result for testing predicted models

It can be seen from Table I that the five main factors affecting chiller power consumption are PLR, chilled water supply temperature, cooling water return temperature, chilled water return temperature, and cooling water supply temperature. If a quadratic regression equation is used with ten data items to establish a chiller model with at least three factors, there will be insufficient data, and the model cannot be implemented. But if the data items are used in grey modeling, since there will be little effect on calculations, predictions are performed in this section when three, four, and five factors are considered simultaneously, and comparisons are made with the two-factor model in the previous section. The effect of the number of factors on prediction error is summarized in Table III.

The prediction error of two-factor linear regression analysis was 1.340%, and the error of two-factor grey modeling was 2.236%. The error of three-factor grey modeling was 1.142%, the error of four-factor modeling was 1.005%, and the error of five-factor modeling was 0.945%. Grey prediction has the advantages of requiring only a small quantity of data and being able to simultaneously consider multiple factors, and can reduce error to less than 1%. In contrast, the use of linear regression analysis is hampered by insufficient data, and cannot yield predictions when there are more than three factors. Because of this, when existing data is insufficient, the results of grey prediction are more accurate than those of regression analysis.

TABLE III
COMPARISON OF PREDICTION ERROR

| Prediction type | Average error of grey prediction (%) |
|---|---|
| Two-factor linear regression prediction | 1.340 |
| Two-factor grey prediction | 2.236 |
| Three-factor grey prediction | 1.142 |
| Four-factors grey prediction | 1.005 |
| Five-factors grey prediction | 0.945 |

## V. CONCLUSION

Chillers are the main energy-consuming equipment in air conditioning systems. Although the efficiency of new chillers has increased in recent years, the effect of different piping layouts and the reduced compressor motor efficiency that occurs after prolonged operation make it impossible to obtain actual power consumption from data provided by the manufacturer. As a consequence, it is necessary to establish a new power consumption model of chillers. This study applied grey theory to the prediction of the power consumption of chillers operating at different PLRs and under different external conditions, and took advantage of the fact that grey prediction only requires a small quantity of data (a minimum of four data items). A program was written to establish a chiller GM(1,N) model that could be used in predictions. The five influencing factors of PLR, chilled water supply/return temperatures, and cooling water supply/return temperature were taken into consideration in this model. The prediction results were very accurate, and achieved an accuracy of over 99% compared with the actual power consumption in short-term predictions (four prediction steps). This method can be used to forecast chiller power consumption when operating at peak load, and whether this value will exceed the power demand. In addition, adjusting chiller chilled water supply temperature will allow a lower PLR and achieve the goal of reducing power consumption. Grey theory is consequently well worth employing as an air conditioning chiller power consumption prediction method.

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