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Optimization Method for the Chiller plant of Central Air-conditioning System Parameters on Association Rules Analysis for Energy Conservation

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ABSTRACT

More than 50% of the total energy consumption of central air-conditioning system is consumed by the chiller plant. It is crucial to optimize the operational parameters of chiller plant to improve its operational efficiency, reduce its energy consumption, and enhance the overall energy saving of HVAC. The regular methods of chiller plant optimization could be divided into three categories: Engineering method, mechanism modeling and artificial intelligence modeling. In recent years, with the development of the internet of things, the monitor and control platform for HVAC provides mass ground truth data for data mining of chiller plant optimization. Compared with the other methods, the data mining method is more simple, wide applicable and practical. In this paper, the association rule data mining method is utilized to optimize the operational parameters of the chiller plant. One of the chillers of the chiller plant in a large-scale shopping mall in Guangzhou is taken as the case study. After historical data pre-processing, e. g data cleaning, selection of optimization parameters and discretization, a number of association rules are discovered between the optimal energy efficiency and the operational parameters of the chiller plant under various operational conditions by Apriori algorithm. Finally, the simulation result shows that the total energy consumption of the chillers reduced 13.33% and 11.6% than previous result in the transition season and summer respectively by adopting the association rules. The simulation results verify the validity of the mining rules. This method excavates the energy saving potential of chiller plant from the point of view of Engineering practice, which is suitable for the chiller plant with a big sets of operation data. Furthermore, this method could be also used for optimization of HVAC.

1. INTRODUCTION

Above 40% of the total building energy consumption is consumed by HVAC in large-scale public buildings, which has become the top concern of energy-saving retrofit of buildings [1]. In some studies, energy consumption of HVAC varied significantly between similar buildings, highlighting the potential effect of optimal operation strategy of HVAC [2]. And among the various equipment of HVAC, the energy consumption of the chiller plant accounts for nearly 50% of the energy consumption of HVAC especially in the tropical area. It is of great significance to optimize the operating parameters of the chiller plant to improve its operating efficiency, reduce the energy consumption and promote the overall energy conservation of HVAC.

By far, the operational parameter optimization methods could be generally grouped into three classes: empirical model(white box), semi-mechanism models(gray box) or artificial intelligence model(black box). The general idea is using some optimization algorithm to optimize the operational parameters of the chiller plant to get the highest energy efficiency or reduce energy consumption as far as possible under the given constraint conditions.

Some studies by Chan et al. [3] and Chen et al. [4] used neural networks (NN) to establish the energy consumption model of the chillers, and optimize the load distribution of chillers by Genetic algorithm (GA) and the particle swarm optimization (PSO) algorithm respectively. Zhang et al. [5] established a semi-empirical energy consumption model of the chillers, which considered the chilled water supply temperature and the condenser water supply temperature. SLR (surrogate Lagrangian relaxation) and SQP (sequential quadratic programming) methods were used to solve the model of chillers. Powell et al. [6] applied a mixed-integer nonlinear programming technique to optimize the chilled water plant for a campus cooling network by using a semi-empirical chiller performance model. Kusiak et al.[7] utilized eight data-mining algorithms to model the nonlinear behavior of the chiller plant performance from experimental data. The resultant model is used to minimize plant energy consumption adopting the particle swarm optimization algorithm by regulating the supply air temperature set point and static pressure set point of the air-handling unit (AHU) served by the chiller plant. Wei et al. [8] used the data-driven method to derive the black box model of the chiller plant based on the characteristics of the chiller plant and proposed a two-layer intelligence algorithm to solve the optimization problem. The model was tested on two different date sets and the result showed that this method can reduce the energy consumption by 14%.For a chiller plant with multiple chillers and thermal energy storage, Deng et al. [9] adopted MPC to thermodynamic models derived for this plant, and a receding-horizon optimal scheduling solution is obtained to minimize the total energy consumption. Mu et al. [10] proposed a model-free optimization strategy based on multivariate Extremum Seeking Control (ESC) with penalty terms for maximizing the energy efficiency of the chiller plant. The cooling tower fan airflow, chilled water flow, and chilled water supply temperature were selected as optimization variables to improve and maximize chiller plant energy efficiency.

Such ensemble researches all involve the phases of modeling, constraint setting, parameters optimization and so on. The optimization result depends on the accuracy of modeling. Due to the attenuation of equipment performance and the changing operational conditions, it’s difficult to ensure the accuracy of model whose wide Engineering applications are also not so easy.

In recent years, with the development of Internet of Things, the monitor and control platform of HVAC provides massive ground truth data for data mining of chiller plant. Data mining is an advanced technology for discovering interesting knowledge hidden in big data by various of algorithms. Association rule mining (ARM) is one of the most powerful data mining analyzing method which has the ability to extract associations among variables and express knowledge discovered in a rule format.. As a conventional ARM algorithm, Apriori algorithm is always used to discover frequent patterns from categorical and cross-sectional data. Although ARM has been applied in building energy management fields, there are fewer studies on chiller operational optimization.

In this paper, based on a large amount of actual operating data of the chiller plant, many controllable operational parameters which have strong correlation with energy consumption are selected by the association rule method, and the association rule method are applied to extract associations rules between the operational parameters and different cooling load rate. These rules could be easily used in the actual Engineering project to reduce energy consumption of chiller plant.

2. Association rules mining and Apriori algorithm

2.1 Association rules mining

Association rule mining (ARM) is an unsupervised learning process. It was firstly applied to perform the "market basket analysis", which aims to identify customer purchase behaviors. Later, ARM has been widely used to analyze large datasets in various fields, such as retail, bioinformatics and sociology [11].

ARM is used to discover the knowledge frequently-occurring and describe the interrelatedness of data items from a given data set *I*. The discovered knowledge is called an association rule. ARM usually deals with discrete and categorical data; therefore, during the mining process of association rules, the attributes of continuous values are usually divided into a limited number of intervals using discrete and statistical methods. Each interval corresponds to a category, and then the discrete data are analyzed by ARM. [12].

Usually an association rule is defined as: $A \rightarrow B,(S,\ C)$. Where: A and B are subsets of disjoint data, s and c are respectively the support and confidence of the rule. In general, association rules are derived by defining these two parameters, i.e., the minimum thresholds of support and confidence. The support and confidence respectively describe the usefulness and reliability of the association rules. The support of a rule is the joint probability of the antecedent and consequent, as defined in Eq.(1). The confidence of a rule is the conditional probability of the consequent, given the antecedent, as defined in Eq.(2).

$$S = Support(A \rightarrow B) = P(A \cup B) \tag{1}$$

$$C = Confidence(A \rightarrow B) = \frac{P(A \cup B)}{P(A)} \tag{2}$$

If the support for itemset $A \cup B$ is greater than or equal to the minimum support, then $A \cup B$ is a frequent itemset. If the support and confidence of the association rule $A \rightarrow B$ is greater than or equal to the given minimum support and minimum confidence respectively, the association rule $A \rightarrow B$ is a strong association rule. In this paper, the ultimate goal of ARM algorithm is to discover the strong association rules between operational performance index and operational parameters of the chiller plant.

2.2 Apriori algorithm

Apriori algorithm is designed to identify the frequent individual item in the database and extending them to larger and larger item sets as long as those item sets appear sufficiently often in the database. Apriori uses a "bottom up" approach, where frequent subsets are extended one item at a time (a step known as candidate generation), and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found. It consists of two steps: join and pruning[13].

3. Case Study

3.1 Description of building, systems and operational data

This methodology is applied to analyze a set of operation data of one chiller retrieved from the central air-conditioning chiller plant of a large-scale shopping mall in subtropical area. This building is a typical commercial complex with a total floor area of 52,000 m^2, which contains a 3-storey basement for parking and a 5-storey block for shopping. The chiller plant of the HVAC system in this building consists of 4 water-cooled chillers(denoted as CH1 to 4), 6 chilled water pumps(denoted as CHP1 to 6), 6 cooling water pumps(denoted as CWP 1 to 6) and 2 cooling towers with 8 pumps(denoted as CTP 1 to 8). The design specifications of main chiller plant components are summarized in Table 1. The average annual operating time of HVAC is above 3500 hours and the total capacity is 10,500 kW (about 3000 rt).

Table 1: Specification of the chiller plant

	Components	**Number**	**Remarks**	**Power(kW)**
chillers	CH1/CH2	2	Cooling capacity: 3517kW	647
	CH3/CH4	2	Cooling capacity: 1758.5kW	322
Chilled water pumps	CHP1~3	3	Flow: 600m3/h	75
	CHP4~6	3	Flow: 300m3/h, head 32m	37
Cooling water pumps	CWP1~3	3	Flow: 850m3/h, lift 28m	90
	CWP4~6	3	Flow: 400m3/h, head 31.5m	45
Cooling tower	CTP1~4	4	Flow: 200 m3/h	5.5
	CTP5~8	4	Flow: 400 m3/h	7.5

The monitor and control system for the chiller plant has been installed since October 30th, 2013. Besides power consumption data, a large number of measurements are also recorded at the interval of 150 seconds, such as chilled water supply and return temperature, cooling water supply and return temperature.

3.2 Discovering associations in operational data of chiller plant

3.2.1 Selection of Optimal Performance Index

The coefficient of performance of the chiller plant (COP_{cp}) is defined as Eq. (3):

$$COP_{cp} = Q / W \tag{3}$$

$$Q = C_p M_e (T_{chwr} - T_{chws}) \tag{4}$$

Where Q is the output cooling energy, kW; W is the total power consumption of the chiller plant, kW; C_p is the specific volume of chilled water, J/(kg•°C); T_{chwr} is the chilled water return temperature, °C; T_{chws} is the chilled water supply temperature, °C; M_e is the chilled water mass flow, kg/s. COP_{cp} is a ratio of useful cooling provided to work required, and represents the cooling efficiency of the chiller plant. Therefore, COP_{cp} is selected as the performance index.

3.2.2 Selection of Operational parameters

There are two principles for the selection of operational parameters: (1) the parameters should closely related to COP_{cp}; (2) the parameters are easy to regulate or control during the operation.

In this paper, four operational parameters are chosen as the optimizing object for ARM, including chilled water supply temperature T_{chws}, pressure difference between the supply and the return line of chilled water ΔP_{chw},cooling water return temperature T_{cwr}, temperature difference of the supply and return chilled water ΔT_{chw}. Furthermore, the actual cooling capacity, outdoor dry bulb temperature T_{odb}, outdoor relative humidity H_{or} are selected as the external parameters for operation condition division. The chiller partial load rate (PLR) is not selected as one of the operational parameter of Apriori algorithm, because it isn't easy to directly control, and its influencing factors are comprehensive and complex.

4. Chiller plant operation optimization strong association rules mining application

The historical data of the central air-conditioning chiller plant collected by the mall's data collection system was used to mine strong association rules. The process is shown in Figure 1.

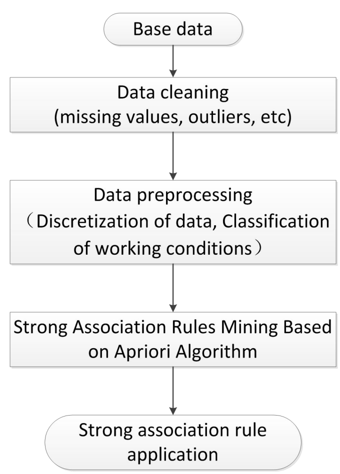


Figure 1: The general process for Strong association rules mining

4.1 Data Sets

Four-year data from 12pm on August 14, 2013 to 11 pm on October 25, 2017 are used for analysis at the interval of 150 seconds. 855,860 sets of data were recorded in the database in total, but only 302,966 pieces of data just when one chiller is switched on and only 144,792 pieces of data for the operational condition that multiple chillers are switched on at the same time. Because the cross combined operation problem should be taken into consideration for multiple chillers and the massive base data demand of ARM, just a single chiller operational condition is analyzed by ARM in this paper. CH2 is chosen to be the research object for strong association rules mining and there are 58,524 pieces of record for it.

4.2 Data Cleaning

During the process of acquisition, transportation and storage, the data are easily affected by many factors such as noise interference, sensor failure, communication interruption and other various factors, which may lead to many abnormalities like missing data, unreasonable data. The existence of abnormal data will affect the result of energy usage pattern mining seriously [15]. Thus, identification and processing method for abnormal data is an important part of ARM. In this paper, unreasonable data are mainly detected by some simple judgement, such as $T_{chws} > T_{chwr}$, $T_{odb} = 0$, $H_{or} = 0$ and so on. The total number of data records is 58,524 before data cleaning. If there is one missing or abnormal data or more in one record, this record would be removed. Then, 12,628 records were removed, and the number of remaining records is 45,896.

4.3 Data pre-processing

4.3.1 Discretization

Since the ARM only works with categorical variables and operation data of chiller plant are mostly numeric, discretization is necessary. The operational data of chilled plant usually have their own characteristics, so their discretization is a challenging problem. The common approach on discretization of numerical variables is to partition the rang with continuous properties into several non-overlapping groups according to the priori knowledge which contains two methods for grouping: equal-width binning and equal-frequency grouping. In this paper, equal-width binning is used to discretize the work conditions to keep the distribution characteristics of the original working conditions as much as possible for engineering applications, such as outdoor dry bulb temperature and ambient relative humidity. Meanwhile, the other parameters are discretized by equal-frequency grouping method, because large difference in the numbers of data points among groups may negatively effect on the extraction of association rules.

Parameters' grouping is time-consuming and it is usually done by trial and error. For the demand of control accuracy, the final binning of equal-width group, Table 2 summarizes the discretization method for CH2.

Table 2: Operational parameters discretization of CH2

Equal-width binning grouping		
External parameters for operation condition division	**group interval**	**variation range**
Actual cooling capacity /kW	200	2200-4000
Outdoor dry bulb temperature /℃	5	20-35
Outdoor relative humidity	20%	20%-100%
Equal-frequency grouping		
Operational parameters	**group number**	**variation range**
Chilled water supply temperature /℃	15	9.1-15.3
Differential pressure of chilled water /kPa	15	76-300
Condenser water supply temperature /℃	15	20.5-34.0
Differential temperature of condenser water /℃	10	1.9-11.2
COPc	15	2.90-6.40

4.3.2 Typical conditions definition

After partition of operating conditions, it's necessary to optimize the operational parameters of the chiller plant under different conditions. But the data distribution is unevenly distributed under different conditions, so the working conditions with data size greater than 200 is defined as a typical operating condition according to the data set size of CH2. Finally, 54 typical operation modes for CH2 are defined after the outliers removed from the data set by 3σ principle.

4.4 Strong Association Rules Mining Based on Apriori Algorithm

The Apriori algorithm is used to discover strong association rules for each typical operating condition here. However, a smaller support threshold may lead to a dramatic increase in the association rules obtained, which makes the rules lacks of representation and a larger support threshold may cause that none of the rules could be found. For the setting of confidence threshold, it's the same.

As mentioned before, Equal-width binning may lead to a large difference of the data size under different conditions, so different minimum support threshold for different typical conditions was set according to the data size. In this paper, according to the amount of data for each working condition, the minimum support was set in segments shown as Table 3. By trial and error, the minimum confidence c was finally chosen to be 70%.

Table 3: Minimum Support Distribution

Data Volume (N)	Minimum support (s)/%
$500 > N \geq 200$	0.7
$1000 > N \geq 500$	0.5
$N \geq 1000$	0.2

By Apriori algorithm, parts of the strong association rules are listed in Tables 4 under the typical working conditions of the chiller plant when only CH2 is running. The meaning of the strong association rules is that under different condition (cooling capacity, Outdoor dry bulb temperature, ambient relative humidity), the operational parameters including chilled water supply temperature, differential pressure of chilled water, condenser water supply temperature, and the differential temperature of condenser water are set to the optimized values in Table 4, which could ensure the probability of optimized *COPc* is not less than 70%.

Table 4: Strong association rules of the chiller plant for CH2 running alone under different operating conditions

Cooling capacity /kW	Outdoor dry bulb temperature /℃	Ambient relative humidity /%	Chilled water supply temperature /℃	Differential pressure of chilled water /kPa	Cooling water supply temperature /℃	Differential temperature of condenser water /℃	COPc
2200	20-25	80-100	10.5	244	25.55	2.7	3.67
2200	25-30	60-80	10.9	213	27.5	2.7	3.67
2400	20-25	80-100	11.5	182	22.55	4.4	4.07
2400	25-30	60-80	11.1	244	25.55	3.6	4.01
2600	20-25	60-80	11.1	163	22.55	2.7	4.34
2600	25-30	20-40	10.9	182	25.55	2.7	4.24
2800	20-25	80-100	11.3	182	22.55	4.7	4.59
2800	25-30	40-60	10.9	182	24.95	3.6	4.59
3000	25-30	40-60	11.3	193	26.6	3.6	4.54
3000	25-30	60-80	10.7	213	27.1	3.85	4.34
3200	20-25	80-100	10.5	213	24.95	4.4	4.59
3200	25-30	40-60	11.2	154	26.05	4.25	4.59
3200	25-30	60-80	10.7	172	24.95	4.7	4.59
3200	30-35	40-60	9.4	285	29.5	4.4	4.34
3400	25-30	20-40	10.9	213	25.55	3.85	5.19
3400	25-30	40-60	10.7	227	24.95	4.25	4.89
3400	25-30	60-80	9.8	182	24.95	4.4	4.59
3400	30-35	40-60	10.3	244	32.15	2.7	4.59
3400	30-35	60-80	11.8	285	33.3	4.1	4.34
3600	25-30	20-40	10.9	227	25.55	3.85	5.59
3600	25-30	60-80	11.8	202	27.5	5.05	5.39
3600	25-30	80-100	9.8	182	28.65	2.7	5.19
3600	30-35	40-60	9.4	285	27.9	4.7	4.59
3600	30-35	60-80	9.8	213	28.3	4.1	5.19

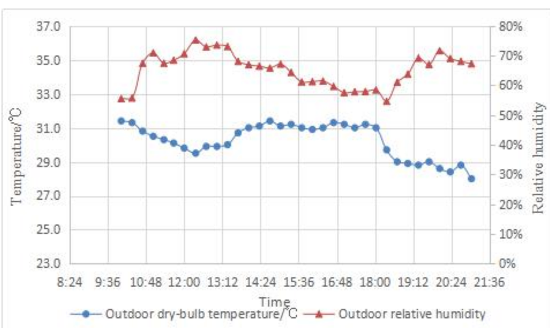
The rules in Table 4 indicate that, the chilled water supply temperature could be set above 9℃ to improve the energy efficiency under different conditions.

5. Simulation and Analysis

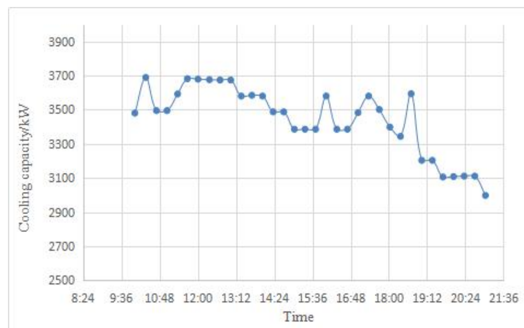
One day in summer is chosen for CH2 running alone to verify the effective of the discovered rules and the actual COPc of chiller plant was compared with the simulation value with the application of rules. Fig. 2 presents the profiles of ambient temperature, relative humidity and cooling capacity.

Fig. 3 displays the time series graph of actual COPc of chiller plant (the blue one) and optimizes COPc(the red one). The COPc of chiller plant before optimization ranges from 3.51 to 4.70 while the COPc after optimization varies from 4.34 to 5.39. It's obvious that the COPc of chiller plant after optimization is significantly higher than that before optimization.

However, from Fig.4, it was shown that the average COP of CH2 after optimization is slightly lower than the actual COP. The range of COP of CH2 before optimized is 5.80 to 6.72, and the range is 5.59 to 6.86 after optimization. That is to say, although the performance of CH2 is effected, the performance of the chiller plant is significantly improved. The actual power consumed by chiller plant is 5583.0kWh while the power consumption after optimization is 4935.6kWh, and the overall energy consumption of the chiller plant is reduced by 11.60% mainly due to the power reduction consumed by chilling water pump and cooling water pump. From Fig.2, the cooling capacity is on the decline on June 9th, 2017 due to the decrease of outdoor dry-bulb temperature. With two drops of outdoor temperature in two periods of time (from 10:00 to 14:20, from 18:00 to 21:00), the big differences between the actual COPc of chiller plant and optimization take place while the difference for COP of CH2 is not obvious. The reason behind is that optimized parameters are more effective to improve the whole energy efficiency of chiller plant under the part load conditions.



(a) Outdoor dry bulb temperature and relative humidity



(b) Cooling capacity

Figure 2: Operational conditions on June 9th, 2017

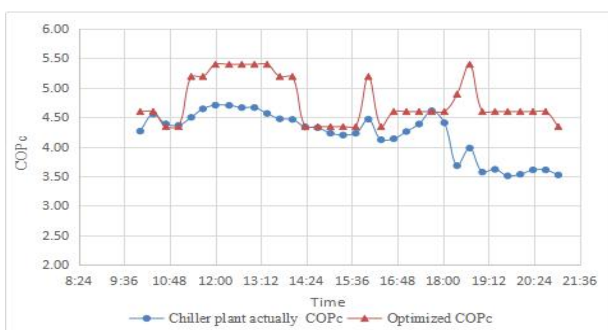


Figure 3: Comparison of actual value and optimized one for COPc of chiller plant

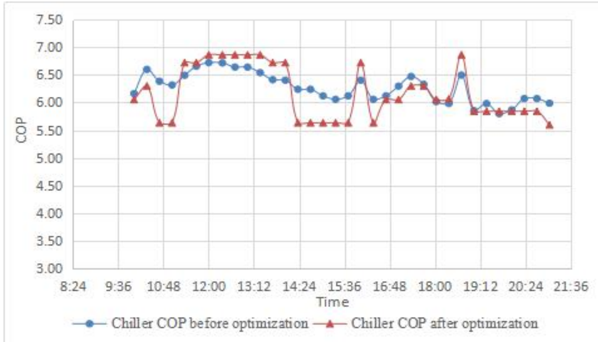


Figure 4: Comparison of actual value and simulation one for the COP of CH2

6. Conclusion and discussions

Operational data of HVAC are in essence multivariate time series data. So far, few studies focus on temporal knowledge discovery and applications in big operational data. This paper presents a case study for discovering the strong association rules of operational parameters for chilling plant by Apriori algorithm based on four-year historic operational data. On the basis of domain knowledge, experience and historic data, working conditions and operational parameters with continuous numeric characteristic are discretized. 54 typical operating conditions are found for CH2 and the minimum supports were sets by segment. The simulation result shows that the improvement of chiller plant depends on the coordinated operation of all the equipment and main parameters optimization, not only the improvement of energy efficiency for one single device (whether it is a chiller or a pump or a cooling tower).

It's a non-trivial task to apply the big data analysis to the energy saving field of HVAC. It not only requires that researches are fully familiar with the operation of HVAC with good judgement of the abnormal data, but also could skillfully use the data mining algorithm and data processing methodology. Data quality is also crucial for the application of DM technology on this field. In this paper, the operational conditions with just one chiller on are just taken into consideration. It's much more complex for multiple chillers to optimize the parameters than single chillers by data mining because load distribution of multiple chiller, the optimized combined operation of different chillers, limited data for all combined operation pattern under different conditions and so on are all involved. It would be the focus of our future research directions.

ACKNOWLEDGEMENT

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