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Cost-sensitive and sequential feature selection for chiller fault detection and diagnosis

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ABSTRACT

Fault detection and diagnosis (FDD) plays an essential role of maintaining large-scale heating ventilation air conditioning (HVAC) systems for industrial usage. The process of selecting important features is a crucial step for FDD methods of HVAC components, such as chillers. A suitable feature selection method selects the minimum number of features to save the number of installing sensors, and simultaneously maximizes the FDD accuracy. According to the surveyed related works, it is found that most existing works only focus on maximizing the classification accuracy, and miss two important points. First, the misclassification costs of false positive and false negative are different for chiller FDD. Second, the selected feature subsets must be sequential for real-world applications. In this study, a cost-sensitive and sequential feature selection algorithm for chiller FDD is proposed to select the most important features using a back-tracing sequential forward feature selection (BT-SFS) algorithm. The ASHRAE dataset collected by project number 1043-RP is utilized. Support vector machine (SVM), which is proved to be one of the most effective FDD classification method for chillers in existing works, is employed for accuracy measurement. This work fills in the gap between theoretical HVAC FDD methods and real-world HVAC FDD applications.

1. Introduction

Heating ventilation air conditioning (HVAC) system is an important electronic and computerized device for both industrial and residential buildings (Kim et al., 2008). It consumes over 50% of the total building energy consumption all over the world (Omer, 2008). In industrial areas, maintaining indoor air quality is a crucial and complex task that requires the HVAC system to be fully functioning (Yu et al., 2009). In recent years, automatic fault detection and diagnosis (FDD) of HVAC components in buildings, attracts wide attention while possible faults can be detected and diagnosed in the early stage to prevent further damage.

Among all components of the HVAC system, chiller is probably the most important part, which consists of condenser, evaporator, refrigeration subsystems and etc. (Gordon et al., 1995). Recent studies show that the automatic chiller FDD accuracy rates can reach over 90% in most of the cases, with false alarm rates less than 5% (Han et al., 2011b; Li et al., 2015; Yan et al., 2014; Zhao et al., 2013). The main types of chiller faults include: reduced condenser water flow, reduced evaporator water flow, condenser fouling, non-condenserables in refrigerant, refrigerant leakage, refrigerant overcharged and excess oil (Comstock et al., 1999). The internal structure of the chiller is complex with various aged devices. Consequently, most chiller faults do not occur instantly; they usually lose their functions gradually with improper maintenance. FDD approaches install various remote sensors to different parts of the chillers and record time series data, such as temperature, humidity, air pressure and electricity consumption. The recorded data is stationarized, analyzed and modeled to form thresholds for fault alarms. When abnormal data signals are generated, the FDD system automatically throw alarms with possible diagnosis report.

Selecting an optimal subset of features is a crucial step in the process of chiller FDD. The benefits of selecting the minimal number of features include correlation removal, computational complexity reduction as well as optimizing the number of remote sensors to be installed. However, the optimal subset of features to be used in the FDD system still remains as an arguable question in the literature. Existing related works in the literature always focus on

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selecting the feature subsets for maximizing the individual/overall classification accuracy, and leave out two important points:

- *Different misclassification costs.* It is noted that for fault detection and diagnosis problem, the cost of false positive (identifying a faulty sample as a normal sample) should be much higher than the cost of false negative (identifying a normal sample into faulty sample). The false negative situation might be easily verified by manual checking, whereas the false positive case may cause serious damage to the HVAC system.
- *Sequentially selecting features*. In most existing related works, such as Han et al. (2011b); Yan et al. (2014); Zhao et al. (2013); Zhou et al. (2009), the selected feature subsets are not sequential. For example, suppose S_6, S_7, ..., S_{16} are the selected feature subsets consisting of 6, 7, ..., 16 features, respectively. Sequential feature selection methods require $S_6 \subset S_7 \subset \ldots \subset S_{16}$. The sequential way of selecting important features impacts the literature on two crucial aspects: first, it provides a clue for the building management system (BMS) to utilize minimal budget and achieve reasonable performance for chiller FDD by selecting the most important sensors to install. Second, more sensors can be added to improve the FDD performance without abandoning any existing sensors.

In this study, the chiller dataset collected by Comstock et al. (1999) is revisited; and the above two problems are tackled. The goal of this study is to sequentially calculate the most effective feature subsets for cost-sensitive FDD. The sequential forward feature selection (SFS) method is employed to select the most suitable feature subsets. A back-tracing SFS (BT-SFS) algorithm is designed to overcome the local extreme problems. Since the SFS is a wrapper style feature selection method, an appropriate machine learning model must be utilized for accuracy measurements. Most existing works demonstrate high FDD classification accuracy using support vector machine (SVM) (Han et al., 2011b; Liang and Du, 2007; Yan et al., 2014). Therefore, a cost-sensitive SVM is designed and selected to be the base model for the SFS method. In the experimental section, the FDD accuracy rates as well as the misclassification costs are shown for the selected subset of features. The current work is a significant add-in to the literature to close the gap between theoretical HVAC FDD algorithms and real-world chiller HVAC FDD applications.

2. Related works

2.1. Feature selection methods for chiller FDD

Feature selection is a well-studied topic in machine learning. In general, feature selection methods can be divided into two categories, namely, wrapper based approach and filter based approach. Traditionally, wrapper based approaches are able to provide more optimal solutions than filter based approaches with higher computational costs compared with filter based approaches. The wrapper based approaches involve sequential forward feature selection (SFS), sequential backward feature selection (SBS), genetic algorithm (GA) and etc (Chandrashekar and Sahin, 2014; Lazar et al., 2012).

In the chiller FDD problem, feature selection is also an important pre-processing step, which was included in almost all existing FDD solutions. In the ASHRAE project report indexed by 1043-RP, (Comstock et al., 1999) concluded twelve features that were most sensitive to the faults tested in the project. Zhou et al. (2009) revisited the same dataset and implemented the chiller FDD solution using a fuzzy neural network. Zhou et al. reduced the size of the feature subset to eight using sensitivity tests with performance indices. Han et al. (2011b,c) published a series of works and introduced the most important sensors for FDD of chillers, combining generic algorithm and SVM. The classification accuracy achieves higher than 99% with 6 to 10 features selected. There are two shortcomings of their works. First, the false positive and false negative cases were not distinguished. The two cases are under completely different scenarios in real-world applications. Second, the selected feature subsets in Han et al. (2011b,c) with numbers of features from 6 to 10 are not sequentially selected. Zhao et al. (2013) and Li et al. (2015) categorized the most important features for chiller fault detection into two groups, consisting of 8 and 16 features, respectively. The feature selection was done in sequence; and the 8 features were included in the 16 feature subset. However, the application of their works is only on fault detection with SVDD. More concise work for chiller FDD is demanded. Yan et al. (2014) showed that, with as few as six features, the FDD approach can achieve reasonable detection and diagnosis accuracy for chillers. The features selected algorithm in Yan et al. (2014) was not proved optimal, since the algorithm is a filter based approach.

Table 1 lists a summary of all existing works. From the literature survey, it was found that although different feature subsets were selected from different works, there are in general some agreements from the state-of-art works. First, due to the efficiency and economical aspect of consideration, all feature selection methods agree that the number of selected features should be in between of six to sixteen. The less number of features leads to inaccurate classification results; and the larger number of features results in high installation and computational complexities. Second, the support vector machine (SVM) is the most appropriate classifier with fast learning speed and reasonable classification accuracy for chiller FDD. Third, selected subsets of features must be sequential. Suppose there are two selected feature subsets: S_6 and S_7 that contain 6 and 7 features, respectively. It is more flexible for the users to make the choice of installing 6 or 7 sensors for FDD, if $S_6 \subset S_7$ is satisfied. Last, *TCI* and *TEO* are features always included in the most important feature subsets for chiller FDD, such as in Han et al. (2011b,c); Yan et al. (2014); Zhao et al. (2013); Zhou et al. (2009).

2.2. Cost-sensitivity learning

The cost-sensitivity learning keeps to be one of the most active research topics in the field of machine learning, which attracts attentions from a broad range of scientists (Elkan, 2001). The problem of analyzing misclassification costs arises while the real-world costs of false positive and false negative are drastically different. For example, in a cancer diagnosis system, a false positive classification may falsely diagnose a patient carrying cancer to be a normal patient, causing fatal results. Lu et al. (2016) proposed a cost-sensitive rotation forest for cancer diagnosis. Liu et al. (2016) extended the work in Lu et al. (2016) and designed a cost-sensitive ensemble learner to classify gene expression data. Fenton et al. (2001) pointed out that cost-sensitivity embedded diagnostic tools can be a future research trend for industrial FDD studies. Sun et al. (2007) embedded the concept of cost-sensitivity into boosting classifiers for imbalanced data classification. Sahin et al. (2013) introduced a cost-sensitive decision tree model to detect fraud. While the costs were directly associated with financial costs, the cost-sensitive classifier can easily identify the most costly transactions, reducing the overall financial loss. Persello et al. (2014) studied the cost-sensitive active learning algorithms and applied the concept of cost-sensitivity in remote sensing data classification to reduce the overall classification cost. Cao et al. (2016) designed a cost-sensitive ranking SVM to classify multi-labeled data and justified their algorithm on a number of benchmark datasets. Yan et al.

Table 1
Feature subsets used in various works.

Reference	Main objective	Selected features	Important insufficiency
Comstock et al. (1999)	Collecting the original dataset for chiller FDD	kW, PRC, TRC_sub, TCA, TCO, TCI, kW/ton, PRE, Tsh_dis, TEA, TEO, TEI	Features were selected by a simple sensitivity test.
Zhou et al. (2009)	Chiller fault detection and diagnosis	PRC, TRC_sub, TCA, TCO, TCI, TEO, TEI, TO_sump	Old sensitivity tests were used.
Han et al. (2011b,c)	Selecting most imporatant features for chiller FDD	**6 features**: TCI, EvapTons, PRE, TR_dis, TO_feed, PO_feed; **7 features**: TEI, TEO, TO_sump, PO_feed, TWI, TWO, FWB; **8 features**: TEO, TCO, FWC, TRC, TR_dis, PO_feed, VE, TWI; **9 features**: kW, FWE, TCA, TRC_sub, T_suc, PO_feed, VC, TWI, THI; **10 features**: TWEO, TBO, EvapTons, kW, TRC_sub, P_lift, TO_feed, PO_feed, TWI, FWB	False positive and false negative cases were not distinguished; and features were not selected in sequence.
Li et al. (2015); Zhao et al. (2013)	Chiller fault detection	**8 features**: TEO, TCI, TCO, TEA, TCA, TRC_sub, TR_dis, TO_sump;**16 features**: TEO, TCI, TCO, TEA, TCA, TRC_sub, TR_dis, TO_sump,TEI, kW, TRE, TRC, T_suc, Tsh_suc, Tsh_dis, PO_feed	only fault detection is targeted.
Yan et al. (2014)	Chiller fault diagnosis	kW, TCO, TEI, TCI, TEA, EvapTons	A filter based approach is used.

Table 2
The confusion table. Positive class refers to normal condition; and negative class refers to faulty condition.

Two-class	Prediction positive	Prediction negative
Positive (normal) sample	*True positive (TP)*	*False negative (FN)*
Negative (faulty) sample	*False positive (FP)*	*True negative (TN)*

Table 3
Cost matrix.

Two-class	Prediction positive	Prediction negative
Positive sample	*0*	C_{01}
Negative sample	C_{10}	*0*

(2017) applied a cost-sensitive ensemble learner to fault diagnosis for air handling units (AHUs) of HVAC systems. The cost-sensitive learners are verified to provide more reliable diagnosis decisions in various fields with higher classification accuracy and lower misclassification costs.

3. Cost-sensitive classification accuracy measurements

The traditional classification accuracy can be optimized to involve cost sensitivity, referring to the misclassification costs in the literature (Parambath et al., 2014). The difference between traditional classification accuracy (TCA) and cost-sensitive classification accuracy (CSCA) is that CSCA embeds misclassification costs into the classification accuracy. For real-world applications, such as the chiller FDD problem, the CSCA reflects the actually demanded fault detection and diagnosis accuracy rates for engineers. In this section, the definition of CSCA that will be used as the measurement criterion to select the most important features for chiller FDD is explained.

3.1. Misclassification costs

The misclassification cost was defined while the scientists found that the situations differ greatly for various false classification cases. For a two-class classification problem, as an example, Table 2 shows the four situations of true positive, false positive, true negative and false negative classification cases. In this study, i.e., for the chiller FDD problem, positive class of samples are always referred to normal conditional samples; and negative class of samples are faulty conditional samples. Suppose the misclassification costs for true positive and true negative are both 0. The misclassification costs of false negative and false positive are denoted as C_{01} and C_{10}, respectively; and the cost matrix is shown in Table 3.

3.2. Embedding the misclassification cost into the classification accuracy

Traditional classification accuracy (TCA) calculates the overall classification accuracy using the total number of corrected classified samples over the number of all samples. It can also be calculated by one excluding the falsely classified rates (Eq. (1)).

$$TCA = \frac{N_{TP}+N_{TN}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}} = 1-\frac{N_{FN}+N_{FP}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}}, \quad (1)$$

where the terms N_{TP}, N_{FN}, N_{TN} and N_{FP} denote the number of samples that belong to true positive, false negative, true negative and false positive categories, respectively. The term $N_{TP}+N_{FN}$ denotes the total number of all positive samples in the testing dataset; and the term $N_{TN}+N_{FP}$ denotes the number of all negative samples in the testing dataset. For traditional classification accuracy calculation, Eq. (1) can be expanded further by separating false positive rate and false negative rate:

$$TCA = 1-\Bigg(\frac{N_{TP}+N_{FN}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}}\cdot\frac{N_{FN}}{N_{TP}+N_{FN}} + \frac{N_{TN}+N_{FP}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}}\cdot\frac{N_{FP}}{N_{TN}+N_{FP}}\Bigg),$$

where the term $\frac{N_{FN}}{N_{TP}+N_{FN}}$ denotes the misclassification rate of positive samples, or, in other words, false negative rate. Similarly, the term $\frac{N_{FP}}{N_{TN}+N_{FP}}$ denotes the false positive rate. It is easy to verify that $\frac{N_{TP}+N_{FN}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}} = \frac{N_{TN}+N_{FP}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}} = \frac{1}{2}$, given the condition that $N_{TP}+N_{FN} = N_{TN}+N_{FP}$. In the definition of cost-sensitive classification accuracy (CSCA) calculation, the two coefficients are replaced by α and β:

$$CSCA = 1-\Bigg(\alpha\cdot\frac{N_{FN}}{N_{TP}+N_{FN}}+\beta\cdot\frac{N_{FP}}{N_{TN}+N_{FP}}\Bigg), \quad (2)$$

where TCA is a special form of CSCA, where $\alpha = \frac{N_{TP}+N_{FN}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}}$ and $\beta = \frac{N_{TN}+N_{FP}}{N_{TP}+N_{FN}+N_{TN}+N_{FP}}$. In Eq. (2), by adapting the cost matrix to the classification accuracy calculation, α is defined as: $\alpha = \frac{C_{01}}{C_{01}+C_{10}}$; and β is defined as: $\beta = \frac{C_{10}}{C_{01}+C_{10}}$. It can be easily justified that the

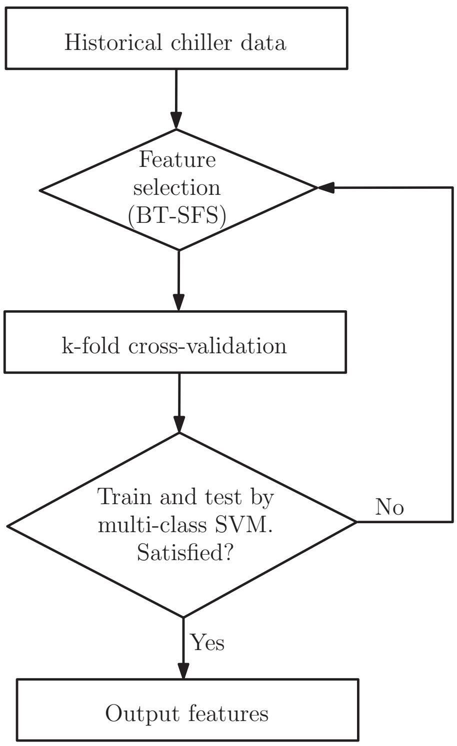

Fig. 1. The overall flowchart of selecting suitable subset of features for a given set of historical data.

summation of α and β always equals to 1; and the symbols α and β introduce a linear interpolation between the values of $\frac{N_{FN}}{N_{TP}+N_{FN}}$ and $\frac{N_{FP}}{N_{TN}+N_{FP}}$. Since both $\frac{N_{FN}}{N_{TP}+N_{FN}}$ and $\frac{N_{FP}}{N_{TN}+N_{FP}}$ are values in between of 0 and 1. The value of CSCA is also always between 0 and 1.

The CSCA expression shown in Eq. (2) reflects the impact of the misclassification costs in real-world application scenarios. For example, while the misclassification cost of false positive is greater than the misclassification cost of false negative, i.e., $C_{10} > C_{01}$, the false positive rate ($\frac{N_{FP}}{N_{TN}+N_{FP}}$) will be emphasized in the calculation of CSCA, since $\beta > \alpha$. The value of CSCA decreases faster while the false positive rate becomes larger, which is consistent with the original formulation purpose of CSCA.

4. The proposed method selecting most important features for chiller FDD

The general flowchart of the feature selection algorithm can be described in Fig. 1. For a given historical dataset, the selection of feature subsets is evaluated by *k*-fold cross-validation with multi-class SVM. The selection process is repeated until the classification accuracy is acceptable. In this study, the way of sequentially selecting the optimal feature subsets for chiller FDD is tackled. The proposed method is named as back-tracing sequential forward feature selection (BT-SFS).

The main methodology is described in this section. The target of this study is to find the optimal sequentially selected feature subsets for FDD of chillers. All selected features will be ordered in a sequential way according to their importance in chiller FDD. Seven different chiller faults are considered, which cover the main types of chiller faults in the real-world applications.

A real-world scenario is considered, where any types of the seven main chiller faults can happen at any time. On one hand, an accurate automatic FDD system requires adequate number of sensors to be installed; on the other hand, the limited budget demands to remove less significant sensors to cut the cost. The importance order of all features provides a clue for the building management system (BMS) to balance the tradeoff between the number of sensors and the limited budget, i.e., with a limited budget, the BMS can always choose the top important sensors to capture the main possible faults for chillers. Moreover, when the budget increases, the existing sensors can still be used with additional sensors purchased. In contrast, if the important features are not selected sequentially, such as the works in Han et al. (2011b); Yan et al. (2014); Zhao et al. (2013); Zhou et al. (2009), the old sensors can hardly be re-used, since most of the features are different for various selected feature subsets (Table 1).

In this study, based on a pre-defined minimal feature subset suggested by existing works in the literature, an extended SFS algorithm is performed base on cost-sensitive SVM classification results. The selected feature subsets are therefore sequential, and correspond the highest cost-sensitive classification accuracy.

4.1. Chiller data

The chiller data is employed from experiments performed by ASHRAE Project RP-1043 (Comstock et al., 1999). A 90-ton (316 kW) centrifugal chiller is used to simulate seven different types of faults with four sever levels. The lab setup consists of five water flow loops, including an evaporator water loop, a condenser water loop, a hot water loop, the city water supply loop and the steam supply loop. Sixty-four features were captured in 2 min time interval. Among the sixty-four features, sixteen of them were calculated values (a full list of the nomenclatures can be found in Appendix A). The rest forty-eight features were directly measured by various physical sensors, including twenty-nine temperature features, five pressure features, five flow rate features, seven valve position features and etc. The main tested faults include: refrigerant leak/undercharge (F1), condenser fouling (F2), reduced condenser water flow (F3), non-condensables in refrigerant (F4), reduced evaporator water flow (F5), refrigerant overcharge (F6) and excess oil (F7). Each fault involves four degrees of sever level. The whole dataset contains 158,506 data samples with 15,333 normal samples and from 5111 to 5115 faulty samples for each sever level, i.e., 20,444–20,460 samples per fault.

4.2. Chiller FDD and multi-class cost matrix

The problem of data-driven chiller fault detection and diagnosis is usually converted to multi-class classification problem, by considering the normal condition as class 0 and F1, F2, ..., F7 as class 1, 2, ..., 7 (Han et al., 2011a; Yan et al., 2014). Therefore, the chiller FDD problem described in ASHRAE Project RP-1043 can be viewed as a eight-class classification problem by ignoring the four degrees of sever level.

The particular cost matrix for chiller FDD utilizing the data collected by ASHRAE Project RP-1043 can be generalized to an 8×8 matrix as shown in Table 4. For a particular C_{ij}, if $i = 0$, where the normal samples were misclassified into faulty cases (false negative), the misclassification cost is assumed to be equal: $C_{01} = C_{02} = \cdots = C_{06} = C_{07}$. It is reasonable in a real-world scenario, since the costs of manual checking of different false alarms are close. For false positive cases, it is assumed that: $C_{10} = C_{20} = \cdots = C_{60} = C_{70} > C_{0j}$, since a false fault detection of a faulty case causes more damage than a false fault detection of a normal case.

4.3. Multi-class cost-sensitive classification accuracy

For any fault, suppose the corresponding misclassification rate of C_{ij} is θ_{ij}. It is noted that θ_{ij} represents the number of samples belonging to class *i*, which is misclassified to class *j*, over the total number of samples in class *i*. The cost-sensitive classification

Table 4
Cost matrix for the chiller FDD problem utilizing data collected by ASHRAE project 1043-rp.

	Pred. norm.	Pred. F1	Pred. F2	Pred. F3	Pred. F4	Pred. F5	Pred. F6	Pred. F7
Norm.	0	C_{01}	C_{02}	C_{03}	C_{04}	C_{05}	C_{06}	C_{07}
F1	C_{10}	0	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}
F2	C_{20}	C_{21}	0	C_{23}	C_{24}	C_{25}	C_{26}	C_{27}
F3	C_{30}	C_{31}	C_{32}	0	C_{34}	C_{35}	C_{36}	C_{37}
F4	C_{40}	C_{41}	C_{42}	C_{43}	0	C_{45}	C_{46}	C_{47}
F5	C_{50}	C_{51}	C_{52}	C_{53}	C_{54}	0	C_{56}	C_{57}
F6	C_{60}	C_{61}	C_{62}	C_{63}	C_{64}	C_{65}	0	C_{67}
F7	C_{70}	C_{71}	C_{72}	C_{73}	C_{74}	C_{75}	C_{76}	0

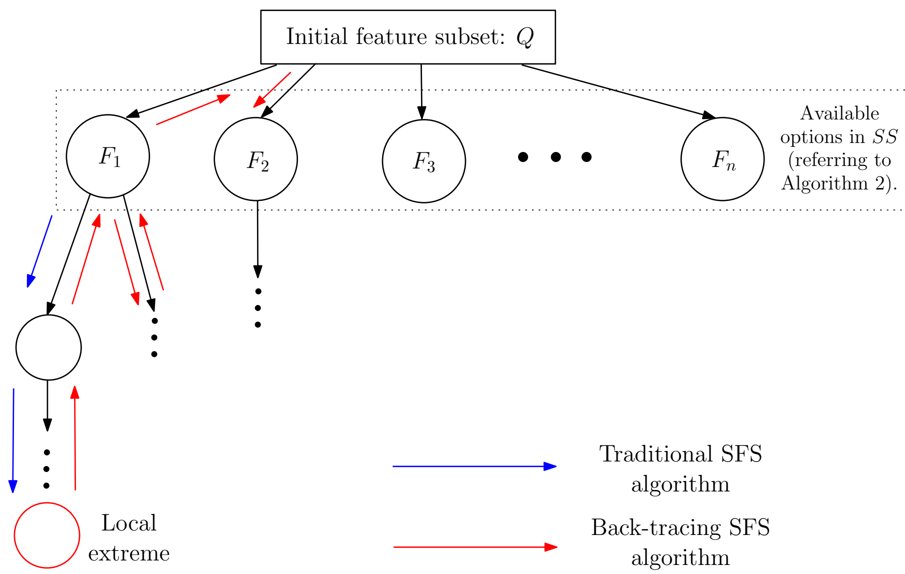

Fig. 2. The comparison of traditional SFS algorithm and the proposed BT-SFS algorithm.

accuracy in Eq. (2) is expanded to:

$$CSCA = 1 - \left(\sum_{i=0}^{n} \sum_{j=0}^{n} \alpha_{ij} \cdot \theta_{ij} \right),$$

where $n = 7$ in this study. Furthermore, to force CSCA to be in between of 0 and 1, it is denoted that:

$$\sum_{i=0}^{n} \sum_{j=0}^{n} \alpha_{ij} = 1, \tag{3}$$

$$\alpha_{ij} = \frac{C_{ij}}{\sum_{i=0}^{n} \sum_{j=0}^{n} C_{ij}}. \tag{4}$$

4.4. Multi-class support vector machine

The traditional support vector machine (SVM) only supports two-class classification. However, in chiller FDD, the SVM is required to distinguish multiple classes samples. The one-against-all approach is adopted to implement the multi-class SVM (Liu and Zheng, 2005). The detail steps of the training and testing processes of a multi-class SVM can be described as follows:

- *Training Phase*. For a eight-class (one normal class and seven faulty classes) classification problem, eight base binary SVMs will be used. The radial basis function (RBF) kernel is selected; and the two parameters C and γ are tuned in the experiments. In turn, each class was re-labeled as '+1' with the rest classes as '−1' to train a base binary SVM.
- *Testing Phase*. In the testing phase, each testing sample X will be classified by the trained eight base binary SVMs. Each base binary SVM classifier provides a confidence level for X belonging to each base classifier's '+1' class. The final label of X is determined by the highest confidence level among all base SVMs.

4.5. Back-tracing sequential forward feature selection

The proposed BT-SFS method utilizes the multi-class SVM as the base classifier and selects the most important features in a sequential manner. As a wrapper-based approach, the traditional SFS algorithm is famous in providing extremely high classification accuracy and has been applied in various areas, such as industrial applications, medical diagnosis, biometric identification and etc. (Dietterich, 2002). An overview of the SFS algorithm is summarized in Algorithm 1.

By selecting one feature variable at one time, the traditional SFS algorithm advances one step further towards the 'optimal' classification accuracy. However, the searching of the 'optimal' classification accuracy is local, which can be stuck at the local extremes (Fig. 2).

In this study, the traditional SFS algorithm has been extended by adding a back-tracing scheme. At each node of the search tree, all options towards obtaining higher classification accuracy are recorded, by maintaining a heap (sorted priority queue) ordering the unvisited features according to the cost-sensitive classification accuracy. While a local extreme is reached, the BT-SFS algorithm back traces the searching branch and looks for alternative options until the maximum number of features is reached (Algorithm 2).

Algorithm 1 Traditional sequential forward feature selection algorithm.

Input: all features available (P).
Output: selected feature subset (Q).

Initialization: $Q =$ pre-defined minimal feature subset.
Implement Q using the Stack data-structure.
while the number of features in $Q <$ pre-defined maximal number of features **do**
  best fit value (BFV) = 0.
  selected feature (SF) = 0.
  for each feature F in P but not in Q **do**
    $Q' = Q \cup F$.
    if the classification accuracy Eval(Q') $> BFV$ **then**
      $BFV =$ Eval(Q').
      $SF = F$.
    end if
  end for
  $Q.push(SF)$.
end while

Algorithm 2 Back-tracing sequential forward feature selection algorithm.

Input: all features available (P).
Output: selected feature subset (Q).

Initialization: $Q =$ pre-defined minimal feature subset.
Implement Q using the HEAP data-structure.
while the number of features in $Q <$ pre-defined maximal number of features **do**
  stored feature subset for the current node (SS) = 0.
  for each **unvisited** feature F in P but not in Q **do**
    $Q' = Q \cup F$.
    if the (cost-sensitive) classification accuracy Eval(Q') $>$ Eval(Q) **then**
      $SS = SS \bigcup F$.
    end if
  end for
  if $SS \neq \phi$ **then**
    Randomly select $F' \in SS$.
    Mark F' as **visited**.
    $Q.push(F')$.
  else
    Back trace the parent node.
    $Q.pop()$.
  end if
end while

5. Experimental results

5.1. Experiment setups

The sequential forward feature selection algorithm is applied to the AHSRAE 1043-rp dataset. Based on the existing feature selection works for chiller FDD that were surveyed (Table 1), several bases were worked out for the experiments performed in this study:

1. A reasonable range for the number of selected features should be in between of six and sixteen. The less number of features leads to inaccurate classification results; and the larger number of features results in high installation and computational complexity for FDD.
2. TCI and TEO are two important features that should always be included in the selected feature subsets for chiller FDD.
3. The selected feature subsets must be sequential for real-world chiller FDD applications.

Recall the cost matrix in Table 4, assuming $C_{0j} = w$, existing works in the literature suggest C_{i0} to be around $5w$ (Liu et al., 2016; Lu et al., 2016; Yan et al., 2017). Partitioning the cost elements into two categories: C_{i0} and C_{0j} to be false fault detection cases; C_{ij}, where $i \neq 0$ and $j \neq 0$, are false fault diagnosis cases.

Table 5
Feature subsets used in various works.

Ind.	3	4	5	6	7	8	9
Feat.	PO_feed	TCO	EvapTons	TEI	TCA	TO_sump	PRE
$CSCA_1$	0.9388	0.9529	0.9653	0.9733	0.9867	0.9918	0.9919
$CSCA_2$	0.9357	0.9503	0.9610	0.9704	0.9839	0.9907	0.9913
$CSCA_3$	0.9416	0.9617	0.9679	0.9775	0.9910	0.9923	0.9924
	10	11	12	13	14	15	16
Feat.	THI	TWEO	FWC	PRC	FWE	TWCO	TRC_sub
$CSCA_1$	0.9928	0.9937	0.9940	0.9945	0.9948	0.9955	0.9960
$CSCA_2$	0.9920	0.9928	0.9935	0.9939	0.9941	0.9947	0.9953
$CSCA_3$	0.9931	0.9939	0.9942	0.9948	0.9951	0.9957	0.9964

Table 6
Feature subsets used in various works with the highest cost-sensitive classification accuracy.

Ref.	Sel. feat. subsets	Group1	Group2	Group3
Comstock et al. (1999)	12 features	0.9667	0.9646	0.9721
Zhou et al. (2009)	8 features	0.9747	0.9738	0.9791
Han et al. (2011b,c)	6 features	0.9702	0.9654	0.9759
	7 features	0.9521	0.9513	0.9527
	8 features	0.9909	0.9897	0.9919
	9 features	0.9846	0.9839	0.9857
	10 features	0.9759	0.9685	0.9783
Zhao et al. (2013) and Li et al. (2015)	8 features	0.9687	0.9644	0.9697
	16 features	0.9891	0.9849	0.9921
Yan et al. (2014)	6 features	0.9174	0.9135	0.9179

Table 7
Nomenclature.

Var.	Description
kW	Instantaneous input power
PRC	Condenser pressure
TRC_sub	Subcooling temperature
TCA	Condenser approach temperature
TCO	Temperature of condenser water out
TCI	Temperature of condenser water in
kW/ton	Chiller efficiency
PRE	Evaporator pressure
TEA	Evaporator approach temperature
TEO	Temperature of evaporator water out (RTD)
TEI	Temperature of evaporator water in
TO_sump	Temperature of oil in sump
T_suc	Refrigerant suction temperature
Tsh_suc	Refrigerant suction superheat temperature
Tsh_dis	Refrigerant discharge superheat temperature
PO_feed	Pressure of oil feed
TO_feed	Temperature of oil feed
FWB	Condenser water bypass rate
EvapTons	Evaporator cooling rate
TWI	Temperature of city water in
TWO	Temperature of city water out
FWC	Condenser water flow rate
FWE	Evaporator water flow rate
VE	Evaporator valve position
VC	Condensor valve position
THI	Temperature of hot water in
TWEO	Temperature of evaporator water out (Thermistor)
TBO	Temperature of building water out
P_lift	Pressure lift across compressor

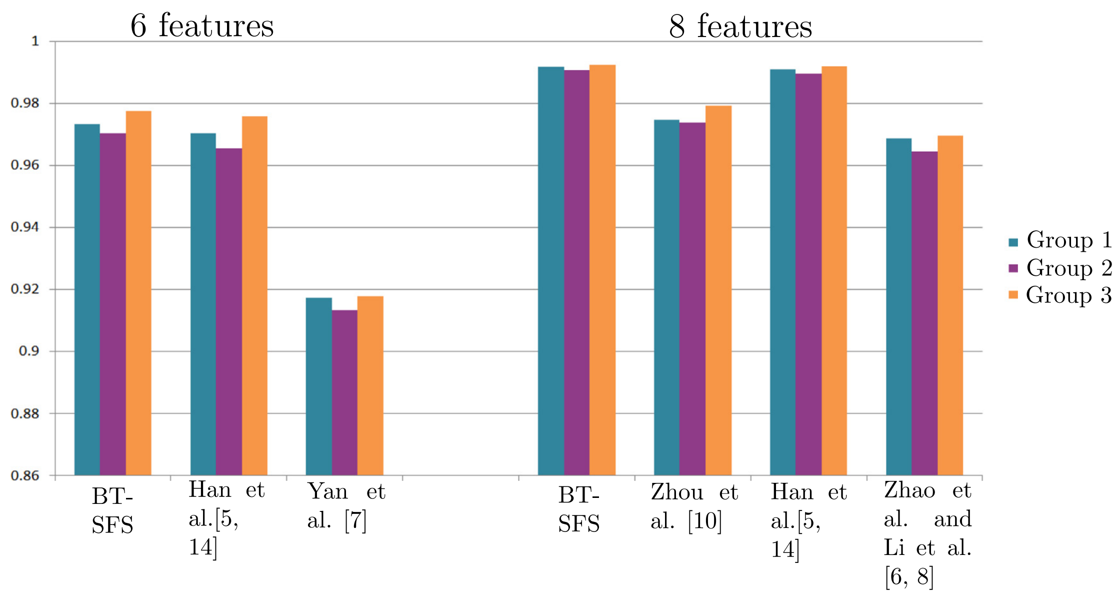

Fig. 3. The comparison of cost-sensitive classification accuracy for 6 and 8 features between BT-SFS and selected existing works. For example, on the left side, the CSCA results with 6 features from different works are compared. Utilizing the same dataset as described in Section 4.1, with five-fold cross-validation, the CSCA using the six features selected by the proposed BT-SFS is higher than the CSCA of the features selected by the other two works.

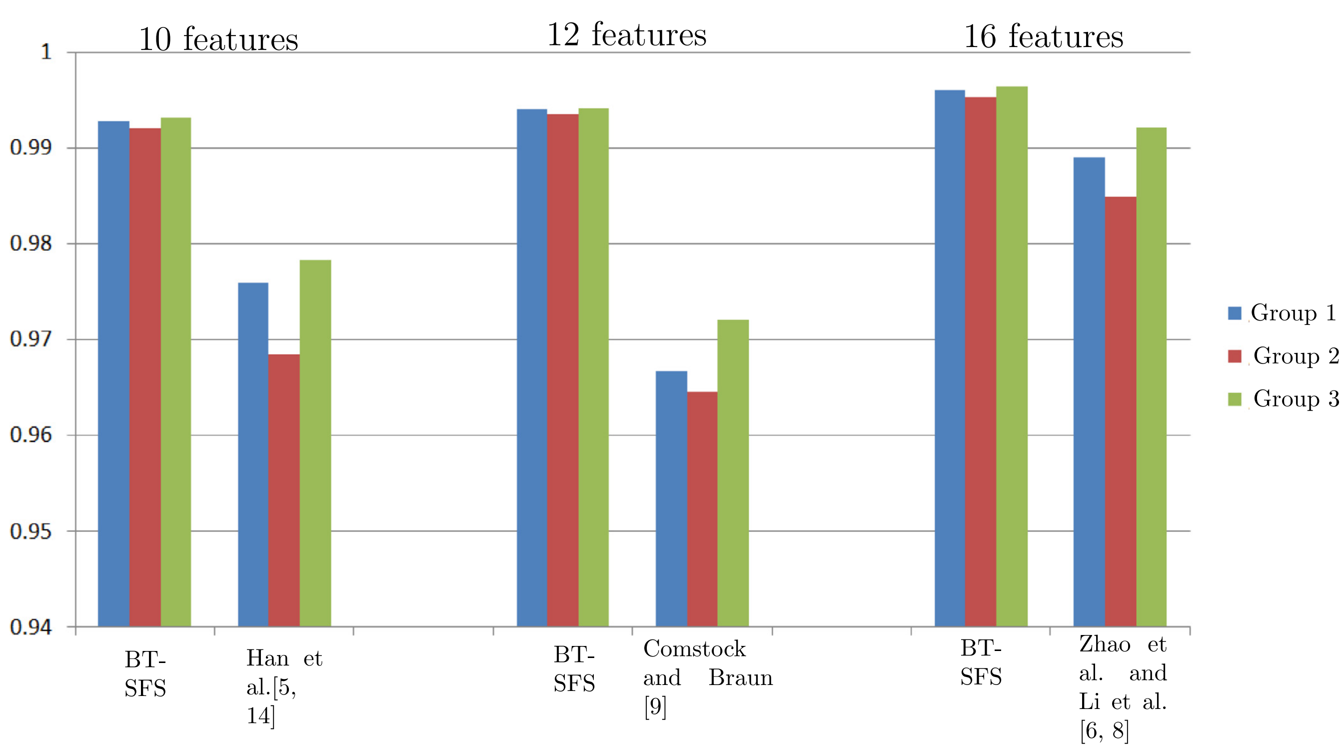

Fig. 4. The comparison of cost-sensitive classification accuracy for 10, 12 and 16 features between BT-SFS and selected existing works.

Three groups of proportions are assigned to the cost matrix elements in Table 4:

- *Group 1*: $C_{0j} = w$; $C_{i0} = 5w$; and $C_{ij} = 3w$ for $i \neq 0$ and $j \neq 0$.
- *Group 2*: $C_{0j} = w$; $C_{i0} = 8w$; and $C_{ij} = 4w$ for $i \neq 0$ and $j \neq 0$.
- *Group 3*: $C_{0j} = w$; $C_{i0} = 3w$; and $C_{ij} = 2w$ for $i \neq 0$ and $j \neq 0$.

For each proportion group, the values of α_{ij} can be easily calculated according Eqs. (3) and (4). The actual formula of CSCA can be derived to Eqs. (5)–(7) for the three proportion groups, respectively:

$$CSCA_1 = 1 - \left(\frac{1}{168} \sum_{j=1}^{7} \theta_{0j} + \frac{5}{168} \sum_{i=1}^{7} \theta_{i0} + \frac{3}{168} \sum_{i=1}^{7} \sum_{j=1}^{7} \theta_{ij} \right). \tag{5}$$

$$CSCA_2 = 1 - \left(\frac{1}{231} \sum_{j=1}^{7} \theta_{0j} + \frac{8}{231} \sum_{i=1}^{7} \theta_{i0} + \frac{4}{231} \sum_{i=1}^{7} \sum_{j=1}^{7} \theta_{ij} \right). \tag{6}$$

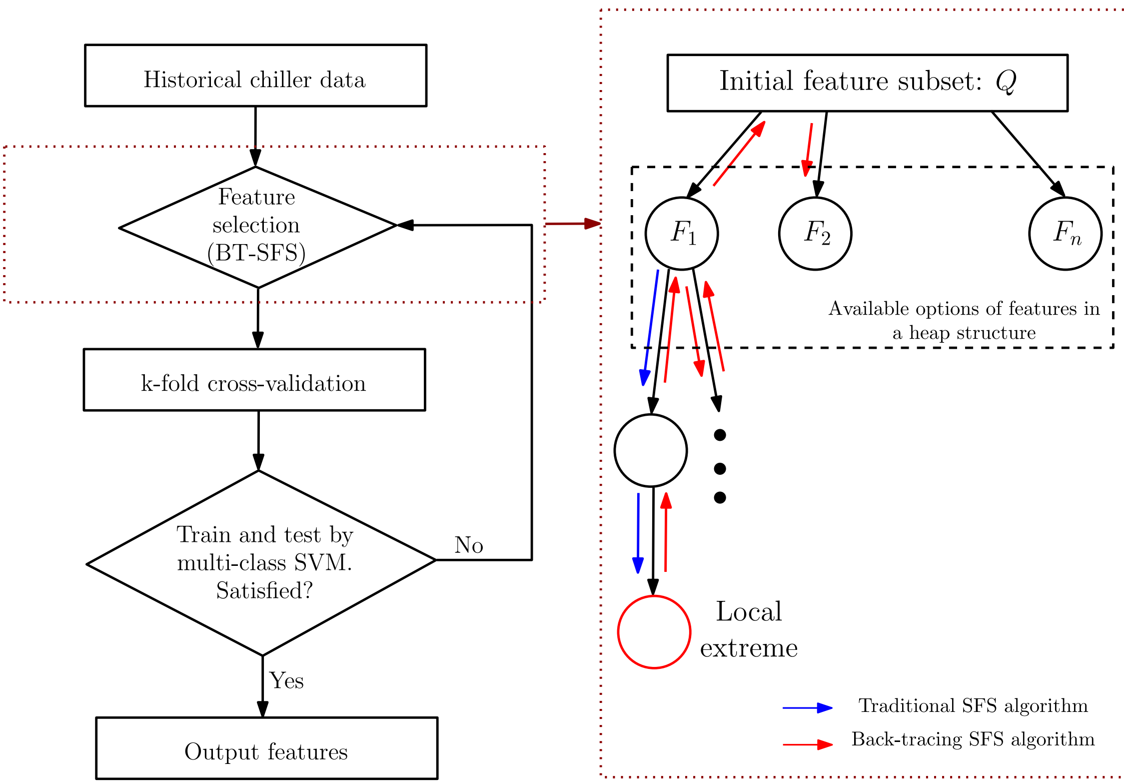

Fig. 5. The graphical abstract of the proposed BT-SFS method. This study proposes a cost-sensitive FDD algorithm for chillers that sequentially selects the most important features using a back-tracing sequential forward feature selection (BT-SFS) algorithm.

$$CSCA_3 = 1 - \left(\frac{1}{112} \sum_{j=1}^{7} \theta_{0j} + \frac{3}{112} \sum_{i=1}^{7} \theta_{i0} + \frac{2}{112} \sum_{i=1}^{7} \sum_{j=1}^{7} \theta_{ij} \right). \tag{7}$$

5.2. Experiment results

It is noted that the set of *TCI* and *TEO* are used as the pre-defined minimal feature subset (Algorithm 2) for the BT-SFS algorithm. The evaluation of the selected feature subsets is based on cost-sensitive multi-class SVM classification results. The cost-sensitive multi-class SVM is implemented using LibSVM and Matlab (Chang and Lin, 2011). All three groups of misclassification costs are tested; and the experimental results are listed in Table 5. The optimal feature sequence selected by BT-SFS for general chiller FDD is (from most important to least important): TCI, TEO, PO_feed, TCO, EvapTons, TEI, TCA, TO_sump, PRE, THI, TWEO, FWC, PRC, FWE, TWCO and TRC_sub.

It is recalled that the cost-sensitive classification accuracy (CSCA) is designed to evaluate the overall FDD accuracy of seven most important faults for chillers, including refrigerant leak/undercharge, condenser fouling, non-condensables in refrigerant and etc. The CSCAs listed in Table 5 are calculated based on 5-fold cross-validation of eight classes with 158,506 data samples (as described in Section 4.1). While various faults might happen for complex equipment, such as the chiller, the order proposed in this study provides an important clue for the BMS to automatically detect possible chiller faults.

From the results in Table 5, the CSCA keeps increasing until the maximum number of features is reached. The BT-SFS is utilized avoiding local maximum that stops the traditional SFS algorithm collecting useful features. For comparison purposes, all feature subsets suggested from existing works listed in Table 1 are also tested using the three groups of misclassification costs. The highest cost-sensitive classification accuracy for each fault type is listed in Table 6. It is noted that both parameters of the SVM, i.e., C and γ, are optimized using the tuning method (Wang et al., 2017). The highest cost-sensitive classification accuracy comparison between the proposed BT-SFS work and existing works is visualized in Figs. 3 and 4. For example, in Fig. 3, on the left side, the CSCA results with 6 features from different works are compared. The six features are: (TCI, TEO, PO_feed, TCO, EvapTons, TEI) for BT-SFS method, (TCI, EvapTons, PRE, TR_dis, TO_feed, PO_feed) from Han et al.'s (2011b, 2011c) work and (kW, TCO, TEI, TCI, TEA, EvapTons) from Yan et al.'s (2014) work. Utilizing the same dataset as described in Section 4.1, with five-fold cross-validation, the CSCA using the six features selected by the proposed BT-SFS is higher than the CSCA of the features selected by the other two works. Similarly, the CSCA rates are compared for 8, 10, 12 and 16 features selected by BT-SFS and the same number of features selected by existing works in the literature. The closest work to the BT-SFS is the genetic algorithm (GA) based approach, proposed by Han et al. (2011b,c), where the highest CSCA of eight features reaches 99.19% for Group 3 cost settings, only 0.04% lower than the BT-SFS results. However, the features selected by GA based approaches are not sequential, which is less useful in real-world scenarios.

In overall, the experimental results show that after embedding the misclassification cost into the accuracy calculation and enforcing the selection of important features to be sequential, the cost-sensitive classification accuracy utilizing the proposed BT-SFS algorithm is still higher than all existing works for the same number of selected features. From the experimental result, it can be seen that while the cost difference between false positive and false negative increases, the cost-sensitive classification accuracy decreases. This means that, the cost sensitivity embedding is necessary for better interpretation of the chiller FDD results. To conclude, the proposed BT-SFS method provides a more flexible installation sequence of sensors for BMSs, a more accurate way of calculating the classification accuracy and a series of more important feature subsets for chiller FDD.

6. Conclusion

The purpose of this study is to search for an optimal subset of features for chiller FDD. Compared to existing works, the features selected in this study by an extended sequential feature selection algorithm are sequential and cost-sensitive. The sequential way of selecting important features impacts the literature on two crucial aspects: first, it helps the building management system (BMS) to balance the tradeoff between the number of sensors to be installed and limited budget. Second, while the budget increase, the sequential order of the feature importance provides a clue to purchase more sensors, utilizing the full set of existing sensors. It gives the BMS the flexibility to choose the number of sensors according to specific situations; and more importantly, it gives the scientists a clear guidance for important feature selection for chiller FDD in future studies.

In this study, a cost-sensitive scheme is carefully designed to distinguish the difference between false positive and false negative. The cost-sensitive scheme is then embedded into the multi-class SVM to build be base classifier for BT-SFS. The proposed BT-SFS algorithm is an extension of the traditional SFS algorithm. It overcomes the difficulty of getting rid of local extremes as in the traditional SFS problems. As a result, the cost-sensitive BT-SFS successfully selects 16 important features, from most important to least important, for the chiller FDD problem. Experimental results show that the selected features are able to provide higher cost-sensitive classification accuracy comparing with existing works results under the same of selected features. This work provides two important contributions to the literature: (1) it demonstrates the importance of embedding cost-sensitivity for better interpretation of the chiller FDD results; (2) it shows an algorithm of selecting important features in a sequential way for chiller FDD.

Authors' Contributions

Providing the original idea: Ke Yan, Wen Shen and Zhiwei Ji
Paper writing: Ke Yan, Lulu Ma and Yuting Dai
Experiments: Ke Yan, Lulu Ma, Yuting Dai and Dongqing Xie
Providing suggestions to improve the paper: Dongqing Xie.

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