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Fault Detection and Diagnosis for Brine to Water Heat Pump Systems

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Abstract

The overall objective of this paper is to develop a data-driven method using principle component analysis for fault detection and diagnosis for ground source heat pumps that can be used by servicemen to assist them to accurately detect and diagnose faults during the operation of the heat pump. Two semi-empirical models for heat pump unit were built to simulate fault free and faulty conditions in the heat pump. Both models have been cross-validated by fault free experimental data. Then the models were used to simulate several faults. Principle component analysis is used to reduce the dimensionality of the system. Then simple clustering technique is used for operation conditions classification and fault detection and diagnosis process. Each fault is represented by four clusters connected with three lines where each cluster represents different fault intensity level. The fault detection is performed by measuring the shortest orthogonal distance between the test point and the lines connecting the faults' clusters. Simulated fault free and faulty data are used to train the model. Then, a new set of simulated data for faults is used to test the model and the model successfully detected and diagnosed all faults type and intensity level of the tested faults for different operation conditions with 98% accuracy. The fault detection and diagnosis method used simple nine temperatures and the electrical power, as an input to the fault detection and diagnosis model. Finally, a user friendly graphical user interface is built to facilitate the model operation by the serviceman.
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Keywords: Fault detection and diagnosis, heat pumps, residuals, brine to water, model based, Principle Component Analysis

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1. Introduction

In Sweden alone, there are approximately more than one million heat pumps already installed. In the current single family houses, the heat pump market share is about 50% while it is nearly 90% in the newly built ones [1]. Therefore, small improvements on the heat pump performance could lead to a significant amount of savings in energy usage thus reducing the Green House Emissions to a large extent.
In heat pumps systems, usually manufacturer set certain operation standards to ensure the best possible performance. But in the installed heat pump systems, it is not unusual for them to operate in different conditions than the standard ones set by the manufacturer. Such a deviation could cause efficiency degradation in the heat pump systems. This deviation can be caused by initial installation error, control devices malfunction or components wearing out over time consequently leading to an overall performance degradation in the heat pump system or ultimately causing components or system failure.
Moreover, over the past recent years, significant amount of failure and faults reports in heat pumps systems were filed to heat pump manufacturers and insurance companies. Among these failure and fault reports, a sizable amount was related to inaccurate installation or fault misdiagnosis by the servicemen [2]. Such a mistake by the servicemen could lead to heat pump system performance degradation, system failure or replacement of unnecessary component. These would lead to needless avoidable additional costs on the manufacturers, insurance companies and end-costumer.
To avoid such costs, a proposed solution is to automate fault detection and diagnosis (FDD) process. Furthermore, producing a Smart Fault Detection and Diagnosis (SFDD) system connected to the heat pump that can assist the servicemen during the installation, operation and maintenance processes to reduce misdiagnosis and assure the highest performance in the heat pump systems.
In the area of fault detection and diagnosis in heat pumps, the aim is to automate the inspection procedure that is done by the servicemen. This help them to find out about faults in the system in an early stage and diagnose them correctly thus avoiding major system performance degradation or system failure [3]. Fault detection and diagnosis systems were initially used in very critical system such as nuclear related application and power plant. But with technology development along the years, enhanced hardware computational capabilities and the reduction in their prices, it became more feasible to integrate fault detection and diagnosis procedures in less critical applications such as automotive [4] and [5], industrial systems [6] and heat pump systems.
For typical operation and maintenance procedures involving FDD system, there are four main steps need to be followed. Fault detection, in which the system evaluates the operation condition and detects if there is any unusual activity (fault). If any abnormal activity is detected, the system runs the diagnosis system to isolate the fault and identify the location of the problem. Following the issue identification, an evaluation of the size of the issue and how significant its impact on the system performance. Finally, based on the fault evaluation results, a decision will be made as system shut down, control reconfiguration, repair request or continue the operation in case of an insignificant effect of the fault. Mainly the first two steps of this procedure form the fault detection and diagnosis model [7], [8].

In literature, there are different methods for fault detection and diagnosis that can be summarized into three categories. These categories are quantitative based methods, qualitative based methods and processed history based methods. The methods were compared based on several desired characteristics in fault detection and diagnosis methods such as response quickness, ability to distinguish between different faults, diagnosis accuracy, and adaptability to change in input parameters or internal structure and modeling requirements [9], [10], [11], [7], [12].

Regarding heat pump FDD, in previous literature, several FDD models have been developed for different applications and different boundary levels. For instances on the component boundary level, a FDD model for

leakage detection in check valves and reversing valves in heat pumps operating in cooling mode using decoupling method was developed by [13].
On the heat pump unit level, [14] have suggested two fault detection and diagnosis method for packaged air conditioners. In the first method, sensitivity ratios were introduced between two different parameters. Each ratio is uniquely sensitive to a certain fault. The second is simple rule based FDD method consisting of temperature limit checking procedure.
In 2002, D. Zogg [15] developed two FDD systems for heat pump units, *FuzzyWatch* and *HeatWatch. FuzzyWatch* system identifies the heat pump characteristics using black-box and gray-box models. Then, in the fault diagnosis process, statistical, fuzzy logic and neural networks techniques were used. Training data for fault free and faulty conditions were obtained from two test benches. In the training stage, several hard and soft clustering methods were considered. Each fault was represented by a cluster during the training phase and a membership grade was introduced which evaluates the measured data and identifies which cluster (fault) they belong to. *HeatWatch* system calculates the heat pump physical characteristics and parameters using a steady state model. The system is initialized by loading fault free data of the heat pump parameters to act as reference values. Then, the fault diagnosis process is based on finding the deviation of the calculated parameters from the reference values. The change in certain parameter or characteristic in the heat pump is interpreted as a fault.

Most fault detection and diagnosis methods developed involve heat pump modeling and FDD modeling. In heat pump modeling, in most cases data driven regression black box model of the heat pump were obtained. Such approaches require large amount of measurements data for training. In addition, the heat pump model is built for a specific heat pump unit and specific range of operation conditions and cannot be used for other units or operation conditions outside the training data range. Likewise, in the FDD model development, in most literature, either simple rule based limit checking or data-driven black-box models were developed. Rule based methods are usually flexible and easy to implement, but lack of fault isolation in fault diagnosis. Data driven models are rather accurate and can distinguish between faults, but inflexible to be used for other types of heat pumps (e.g., ground source heat pumps), demands high computational hardware requirements and usually requires a large amount of training data for fault free and faulty conditions that can be either costly or hard to obtain.
Among the several types of heat pumps (e.g. air to air, air to water and brine to water heat pumps), the brine to water heat pump is the most expensive one. Therefore, implementing a FDD system would be more feasible and convenient in such a system. Thus, ground source brine to water heat pump was considered in this paper.

In this paper, fault detection and diagnosis method for ground source brine to water heat pump is developed. on the heat pump unit boundary level including evaporator, compressor, condenser and expansion valve. In addition to the heat pump unit, the brine and water pumps are included. The main aim of this paper is to develop fault detection and diagnosis model for steady state operation conditions using semi-empirical heat pump models and principle component analysis (PCA) in the FDD modeling to enhance the fault diagnosis accuracy.

2. Methodology

This work was carried out in the following phases:

- Heat pump semi-empirical modelling using Matlab and IMST-ART software and cross validate the models with experimental data.
- Faults simulation in the heat pump model using IMST-ART and trend analysis.
- Obtaining mathematical key performance indicators using principle component analysis (PCA) method.
- Building FDD model using PCA based fault clustering method.

For FDD modelling, a heat pump model was developed first to represent the reference line for a fault free operation. In this step, a semi-empirical vapor compression heat pump cycle model based on the physical principles and experimental data obtained form an operating ground source heat pump unit in different temperature ranges. Two heat pump models are built using Matlab and IMST-ART software. The results from both models were cross-validated against the experimental data.
After obtaining the heat pump models, IMST-ART model is used to simulate different faults in the heat pump unit components in addition to the brine and water pumps.
In the next step, ten variables (nine temperatures and compressor power) were selected to be used for calculating mathematical key performance indicators (KPI) using PCA.
Furthermore, mathematical KPIs are used to build FDD model based on clustering method. The FDD model was tested using simulated data for the different faults using the IMST-ART model.
Finally, user friendly interface was developed for the FDD model that make it more convenient to handle by any technician or serviceman.

3.1 Heat Pump Component

The heat pump unit considered in this work consist of four main components, evaporator, compressor, condenser and an expansion valve. Both evaporator and condenser are Brazed Plate Heat Exchangers (BPHE), the compressor is a hermetic scroll type and the expansion device is thermostatic valve. The main working fluid (refrigerant) is R410A whereas the secondary working fluids are water and brine (mixture of water and ethyl alcohol with 29% fixed concentration) in the condenser and evaporator respectively.
A semi-empirical model was built based on the first principles using empirical measurements obtained from a heat pump operating in nine operating conditions ranging between heat source temperatures of -5, 0 and 5 ºC and heat sink of 30, 40 and 50ºC. Each component of the heat pump unit is modeled based on the physical principles of thermodynamics, energy and mass balance.

3.2 Heat Pump Models in Matlab and IMST-ART

Semi-empirical steady state fault free heat pump model was developed using Matlab. The model was built based on solving a system of equations using energy balance equations applied on the four components, evaporator, compressor, condenser and expansion valve. From the optimization toolbox in Matlab, ***lsqnonlin*** function was used to solve the equation system [16]. The thermodynamic properties are taken from ***CoolProp***. ***Coolprop*** is a C++ library that can be added to Matlab for fluid properties [17].
A second steady state heat pump model was developed using the software IMST-ART developed by the Polytechnic University of Valencia for vapor compression cycles.
The heat pump model was able to predict the normal operation conditions for the unit which can be used later on as a reference line for the FDD model. The relevant parameters are coefficient of performance, heating capacity, compressor power and temperatures across the refrigerant and both secondary working fluids. Both Matlab and IMST-ART model were cross validated with the experimental data. The model results were within ±7% marginal error compared to experimental data. Examples of such variables are heating capacity, compressor power and condensation temperature.

3.3 Faults Simulation

After validation the heat pump models, IMST-ART model was used for fault simulation. In a heat pump unit, seven common faults are considered in this simulation (see Table 1). For each fault, the simulation was done by propagating the faults gradually on eleven steps between the nominal condition and extreme faulty conditions.

Along the eleven steps, three main levels for each fault are introduced as low, medium and high faulty conditions in addition to the nominal operation condition.

Table 1. Fault types, faults simulation and faults levels

Fault type	Fault simulation	Fault level			
		Fault free	Low	Medium	High
Evaporator fouling	Reduction of heat transfer area	00.00%	10.71%	17.86%	35.71%
Condenser fouling	Reduction of heat transfer area	00.00%	12.00%	20.00%	40.00%
Compressor malfunction	Volumetric efficiency reduction	00.00%	15.00%	25.00%	50.00%
Expansion valve malfunction	Increase superheat temperature	00.00%	40.00%	65.00%	130.00%
Water cycle fouling	Increase water mass flow	00.00%	15.00%	25.00%	50.00%
	Decrease water mass flow	00.00%	15.00%	25.00%	50.00%
Brine cycle fouling	Increase brine mass flow	00.00%	15.00%	25.00%	50.00%
	Decrease brine mass flow	00.00%	15.00%	25.00%	50.00%
Refrigerant cycle fouling	Increase refrigerant charge	00.00%	08.00%	12.50%	25.00%
	Decrease refrigerant charge	00.00%	08.00%	12.50%	25.00%

4 Principle Component Analysis Method

Principle component analysis (PCA) approach has been widely used in pattern recognition, performance monitoring, process control and fault detection and diagnosis in industrial process [18], [19]. It has been used in a wide range of application, from component level such as electrical machines [20], and mechanical components such as chillers/heaters [21], to large scale nuclear power plant [22]. PCA approach is a mathematical technique that is used for dimensionality reduction of a multivariable system. PCA is usually used to transform a multivariable space into a new subspace with minimum amount of dimensions that preserve maximum variance (information) of the original variables. The original variables of the system are linearly correlated to calculate a new set of variables known as principle components (PCs) whereas each PC value is a result of a linear correlation of all the original variables. The number of the PCs calculated is equal to the number of the original variable but arranged in descending order based on the variance of the original data along its axis. All the PCs are orthogonal to each other. This means that each PC captures along its axis data variance that is not captured by the other PCs. This allow us to reduce the number dimensions of the original data with preserving most of the original data information. The benefit of this procedure is that it allows us to identify what is the minimum amount of PCs we need to choose to maintain maximum amount of original data information, thus we are able to minimize the system dimensions. Reducing the dimensionality of the data into two or three dimensions allows us to graphically visualize it thus makes it more convenient to recognize certain behaviors or patterns in the data.

4.1 Principle Component Analysis Procedure

To perform PCA, Matlab function ***pca*** was used [23]. The PCA process is carried out in six main steps:

1) *Obtaining training data from the original variables.* In this step the fault free and faulty simulated data of the heat pump are used as the original data system. The original variables (dimensions) used are nine temperature measurements in addition to compressor electrical power input across the heat pump unit

(T_1, T_2, T_3, T_{cond}, T_4, T_5, T_6, T_7, T_8, E_{comp}). This data is represented as matrix X_{nxm}, where *m* is number of columns and *n* is the number of rows. Each column represents an original variable (for example a temperature), whereas each row represents a sample data point of each variable.

2) *Mean normalizing of the original data matrix*. This is done by subtracting the mean of each variable (column) from each data point of that variable where X_{1xm} is a matrix that includes the mean values of each column in X_{nxm}. This produces a new matrix $Xnormalized_{nxm}$ where each element in X_{nxm} is replaced by the mean of that variable (column) subtracted from that element. This means that each column (dimension) of the normalized matrix has a mean have of zero. This is done to facilitate the next step.

3) *Finding the covariance matrix* Σ *of* $Xnormalized_{nxm}$. Each covariance value in the covariance matrix represents the correlation between two variables in $Xnormalized_{nxm}$. A positive, negative or zero covariance value means that they are directly proportional, indirectly proportional or not correlated respectively. The covariance matrix is calculated using Eq. [1].

$$\Sigma = \frac{1}{n-1}\sum_{i=1}^{n}(\boldsymbol{x_i} - \boldsymbol{x_{mean}})\,(\boldsymbol{x_i} - \boldsymbol{x_{mean}})^{\boldsymbol{T}} \tag{1}$$

Since the mean values of the normalized matrix is equal to zero, the formula can be rewritten as shown in Eq. [2]

$$\Sigma = \frac{1}{n-1}\sum_{i=1}^{n}\boldsymbol{x_i}\,\boldsymbol{x_i^T} = \frac{1}{n-1}\,\boldsymbol{X_{normalized}}^{\boldsymbol{T}}\boldsymbol{X_{normalized}} \tag{2}$$

The result covariance matrix will be square symmetrical matrix Σ_{mxm} where the diagonal elements equal the variance of each column (dimension) in $Xnormalized_{nxm}$.

4) *Finding the eigenvectors and eigenvalues of covariance matrix* Σ_{mxm}. The eigenvectors are calculated to identify the directions of the PCs. Each eigenvector represents the direction of one PC. In the other hand, the eigenvalues determine which eigenvector has the maximum variance along its axis, thus representing most of the system information. The higher the eigenvalue more variance the corresponding eigenvector has along its axis. Matlab function ***eig*** is used to find the eigenvectors [24]. This Matlab function returns vector matrix V_{mxm} and diagonal matrix D_{mxm} that include the eigenvectors and eigenvalues respectively.

5) *Choosing the number of dimensions* k *where* $k < m$. In the previous step, all eigenvectors obtained has a unit length. This means that by comparing the eigenvalues in terms percentages of the summation of all eigenvalues (diagonal elements of D_{mxm}), the minimum eigenvectors (dimensions) can be identified while preserving most of the original data information. This is done by using Eq. [3]

$$\boldsymbol{V_{exp,j}} = \frac{\boldsymbol{d_j}}{\sum_{i=1}^{m}\boldsymbol{d_i}} \tag{3}$$

Where (V_{exp}) is the ratio of one eigenvalue with respect to the summation of all eigenvalues. After calculating V_{exp}, usually the first few eigenvectors would represent most information (variance) of the original data.

6) *Projecting the original data into the new selected dimensions.* After choosing the new number k of eigenvectors (dimensions), the original data is projected into the new subspace by multiplying the original data matrix by the chosen eigenvectors as shown Eq. [4]

$$\boldsymbol{A_{n\times k} = X_{n\times m}\, V_{m\times k}} \tag{4}$$

Where A_{mxk} is the projection matrix of the original data into dimensionally reduced subspace with k dimensions (PCs).

4.2 Principle Component Analysis Results

The training data used for PCA included fault free and faulty data of the heat pump. The original data matrix X_{nx10} (dimensions) used are nine temperature measurements in addition to compressor electrical power input across the heat pump unit (T_1, T_2, T_3, T_{cond}, T_4, T_5, T_6, T_7, T_8, E_{comp}). After reforming PCA, ten eigenvectors V_{10x10} and eigenvalues D_{10x10} are found. The result of eigenvalues for each eigenvector is shown in Figure 1a. The eigenvalues of the first, second and third eigenvectors are relatively high compared to the rest of the eigenvectors. This mean that they preserve most of the information about the system.

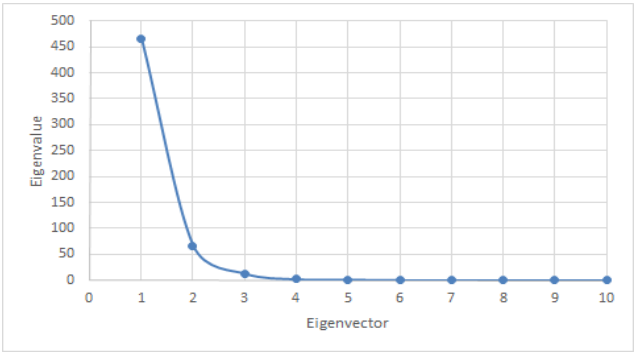


Fig. 1a. The eigenvalues for each eigenvector

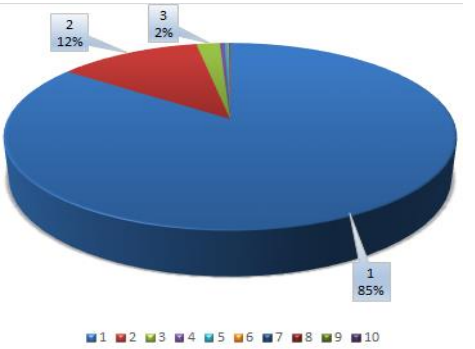


Fig. 1b. Percentage of the variance along each eigenvector

The first three eigenvectors preserve almost 99% of the original variance of the data (Figure 1b). In other words, the first three eigenvectors (PCs) can be used as new axis without missing nearly nothing form the original system information. Therefore, the original ten dimensional space X_{nx10} can be reduced to only three dimensions A_{nx3}. This will make visual presentation of the data possible thus more convenient to identify any pattern or behaviors caused by the faults. These three new variables (PCs) will act as mathematical key performance indicators (KPIs) for the heat pump performance. The result correlation to calculate the principle components is shown in Eq. [5].

$$\boldsymbol{PC_i = p_0\, T_1 + p_1\, T_2 + p_2\, T_3 + p_3\, T_{cond} + p_4\, T_4 + p_5\, T_5 + p_6\, T_6 + p_7\, T_7 + p_8\, T_8 + p_9\, E_{comp}} \tag{5}$$

The coefficients p_0 to p_9 for the first tree PCs are presented in Table 2.

Table 2. Fault types, faults simulation and faults levels

PC	p_0	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9
PC_{1st}	-0.022	-0.031	0.714	0.384	0.307	-0.032	-0.028	0.317	0.380	0.022
PC_{2nd}	0.437	0.481	-0.238	0.150	0.171	0.477	0.432	0.099	0.213	0.012
PC_{3rd}	-0.031	-0.257	-0.530	-0.147	0.561	-0.188	-0.189	0.360	0.339	-0.009

4.3 Fault Detection and Diagnosis Model

After analyzing the projected data, using first PC (PC_{1st}) and second PC (PC_{2nd}) projection of the data in two dimensions, each operation condition appeared to form distinguishable group (cluster). Figure 5 shows the data points groups used in for each operation condition

4.4 Operation condition classification

From the previous analysis, simple two dimensional circular clustering method is used. The clustering is divided into two steps, (PC_{1st}) and (PC_{2nd}) two dimensional clustering and (PC_{2nd}) and (PC_{3rd}) two dimensional clustering. The first step is used to classify the operation condition, whereas the second step is used for fault detection and diagnosis. A minimum of ten data points is used to build each cluster. During the training process, each cluster is identified by a center CC and a radius CR. CC is calculated according to Eq. [6], [7] and [8], while CR is considered to equal the point with the highest distance from corresponding CC.

$$CC_j = [cc_{PC_{1st}} \quad cc_{PC_{2nd}}] \tag{6}$$

$$cc_{PC_{1st}} = \frac{1}{n-1}\sum_{i=1}^{n} PC_{1st_i} \tag{7}$$

$$cc_{PC_{2nd}} = \frac{1}{n-1}\sum_{i=1}^{n} PC_{2nd_i} \tag{8}$$

Where CC_j includes the cluster center in two dimensions, j represent one group of data (operation condition), n number of data points, $cc_{PC_{1st}}$ and $cc_{PC_{2nd}}$ is the average points of that data group along PC_{1st} and PC_{2nd} dimensions respectively. Figure 3 shows the clustering example for the operation conditions results presented in Figure 2.

For the operation condition classification procedure, operation condition cluster ratio (OCCR) is introduced and calculated according to Eq. [9]

$$OCCR_i = \frac{DC_i}{CR_i} \tag{8}$$

Where $OCCR_i$ is the operating condition cluster ratio with respect to a certain cluster i , CR_i is the radius of that cluster and DC_i is the distance between the center of cluster i and the projected data points for the measurements

into two dimensional subspace (PC_{1st} & PC_{2nd} for operation condition classification) subspace. When 0<= $OCCR_i$ <= 1, it means that the measurement point is located inside that cluster (operating condition) and the corresponding operating condition is classified. Whereas if $OCCR_i$ > 1, it means that the measurement point is located outside that cluster and the corresponding operation condition is excluded. Figure 3 shows an example for this concept.

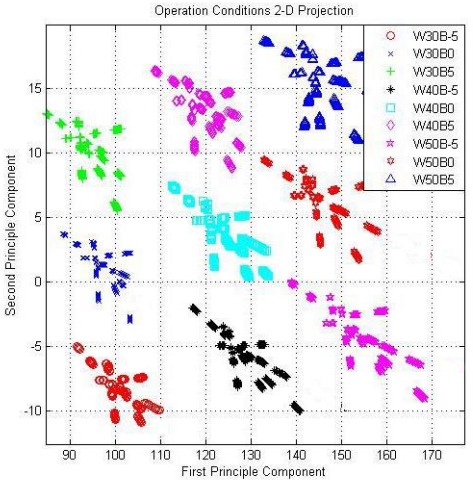


Fig. 2. PC_{1st} *and* PC_{2nd}*projections of operation conditions data*

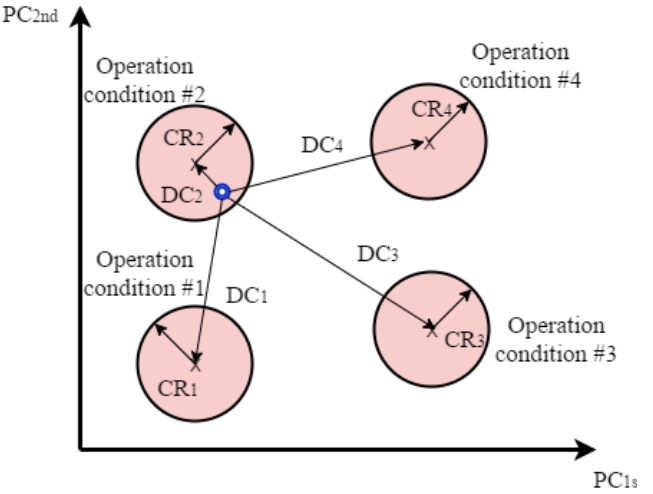


Fig. 3. Example of operation conditions' clusters in CR , DC and OCCR

4.5 Fault type and level classification

After classifying the operating condition using PC_{1st} and PC_{2nd} dimensions, PC_{2nd} and PC_{3rd} subspace is used for the fault classification procedure. During the training stage, each fault was divided into three segments (low, medium and high) each represented by a straight line between two cluster centers. Each fault tends to deviate in a certain direction from the nominal condition data. In the other hand, each fault level of the same fault is deviating in the same direction as the fault but in increasing magnitude. Each fault level data appears to forms group of data points. (see PC_{2nd} and PC_{3rd} projection of faulty data for operation condition water and brine inlet temperatures *30°* and *0°*respectively *W30B0*), each fault level group of points is represented by one point as center of the data points in Figure 4. Each fault is represented by four points (cluster centers), fault free, low, medium and high fault intensity. The low intensity fault line is a line connecting fault free and low fault level clusters. Likewise, Medium and high intensity fault lines are lines connecting low-medium fault level and medium- high fault level clusters respectively. During fault classification stage, the orthogonal distance OD_i between the measurement data point and each fault level line i is calculated. For more details about the formulas used see [25]. The classification process is done by identifying the shortest orthogonal distance OD_i between the test point and fault line segments (intensity levels) and its corresponding projection distance PD_i. PD_i represent the distance between the beginning of the fault intensity level line to the projection of the test point on that line. Figure 5 show an example of this classification procedure in which the fault classification would be of the first fault type with high fault intensity level (the small red dots that are the orthogonal projection distance of the test point on the fault line.

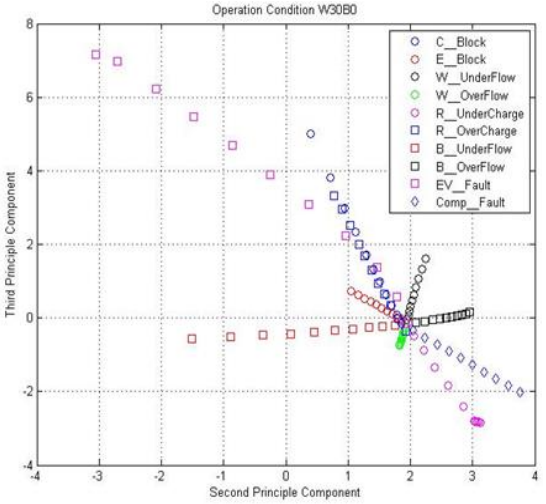


Fig. 4. $\boldsymbol{PC_{2nd}}$ and $\boldsymbol{PC_{3rd}}$ projection of faulty data groups centers in operation condition W30B0

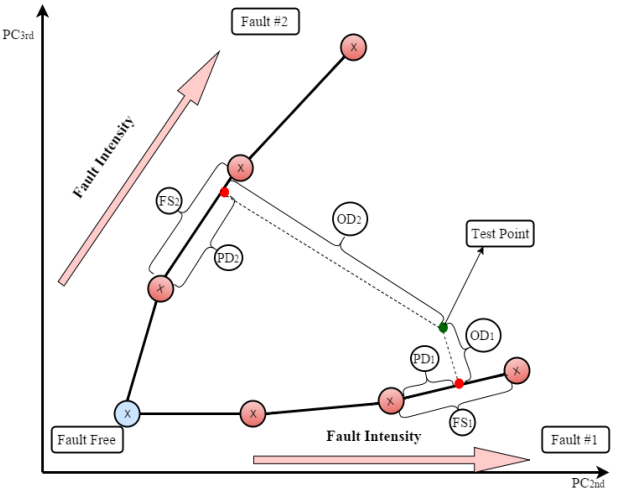


Fig. 5. Example of fault type and level classification concept

After classifying the fault, fault level ratio FLR is introduced as a measure of the intensity of the fault within that fault level. FLR_i has a value between 0 and 10. FLR is calculated according to Eq. [9]

$$\boldsymbol{FLR_i} = \left(\frac{\boldsymbol{PD_i}}{\boldsymbol{FS_i}}\right) \times 10 \tag{9}$$

For medium and high fault levels, FLR_i has a value between 10 - 20 and 20 – 30 respectively. They are simply calculated by adding 10 and 20 respectively to Eq. [9]. In Eq. [9], PD_i is the distance between the projected point PP_i and the point that represent the start of that fault line segment i and FS_i is the length of the fault line segment (see Figure 5).

In case of multi-fault occurring at the same time, fault probability factor (FPF) is introduced for the three faults that have minimum OD values. FPF is calculated according Eq. [10]

$$\boldsymbol{FPF_i} = \left[1 - \left(\frac{\boldsymbol{OD_i}}{\sum_{i=1}^{3} \boldsymbol{OD_i}}\right)\right] \times 100 \tag{10}$$

The higher the value of FPF the more likely that its corresponding fault is occurring. In case of two faults having similar values of FPF , that suggest that both of these faults are occurring.

4.6 FDD model algorithm

Figure 6 below shows the algorithm of the FDD model. This algorithm performs fault detection first. Then in case of faulty conditions, it displays the three faults shortest OD in increasing order in addition to their respective FLR and FPF . (indicating that the lower the OD , the more likely that fault is happening). The algorithm was developed using Matlab.

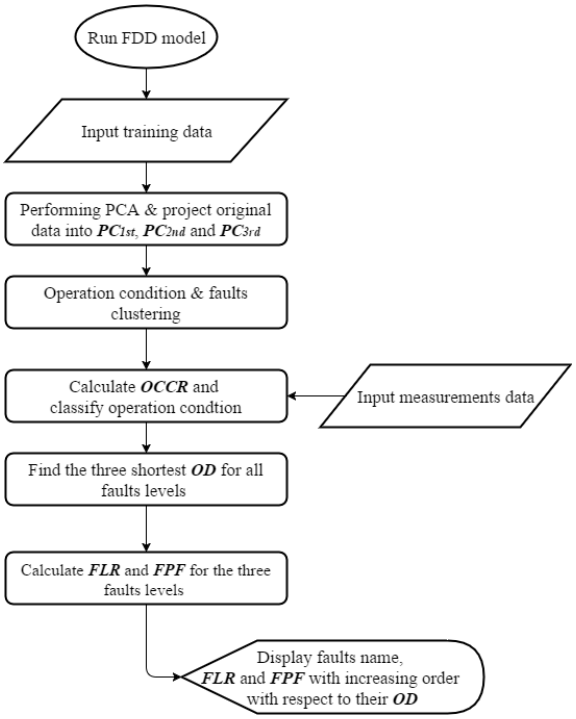


Fig. 6. FDD model algorithm using PCA

4.7 Fault type and level classification

After developing the FDD model, a graphical user interface is built to facilitate the model operation. The GUI requires (T_1, T_2, T_3, T_{cond}, T_4, T_5, T_6, T_7, T_8, E_{comp}) as input and then displays the top three possible faults with their prospective FPF and FLR values (see Figure 7).

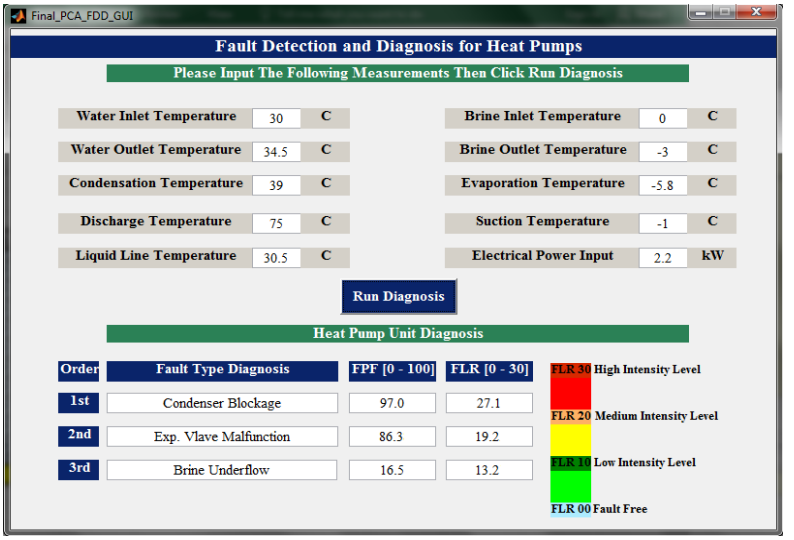


Fig. 7. Graphical user interface for the FDD model

4.8 FDD model algorithm results

For testing the FDD model, a new set of data for fault free and faulty conditions is simulated for each operation condition tested. The FDD accuracy results for each operation condition is presented in Figure 10. The result presented in Figure 10 are for imposing a single fault at a time.

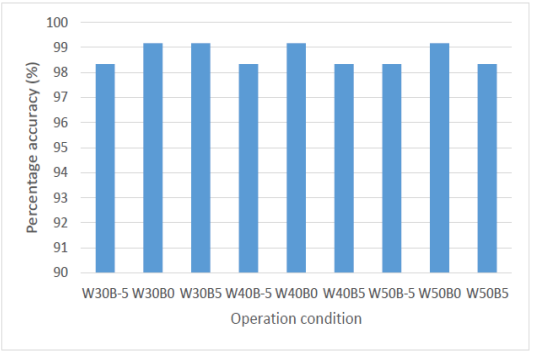


Fig. 8. PCA FDD model accuracy for each operation condition

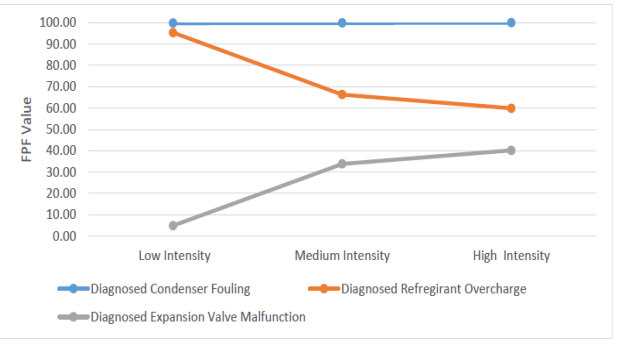


Fig. 9. FPF values for condenser faults with different fault levels at W30B0 operation condition

The results of the FDD model show rather high accuracy in detecting and diagnosing the faults among the operation. In addition to successfully diagnosing the fault type, the model was also able to diagnose the fault intensity level (low, medium or high) successfully. The model layout (as shown in Figure 7) was developed to display the top three possible diagnosis with their prospective FPF and FLR values. In Figure 8, the results that were considered as miss diagnosed only if it was not displayed as a first diagnosis option. During the low intensity fault levels, the difference of values between the shortest three orthogonal distances are rather small

(which lead to very similar FPF values) but still distinguishable by the model. In contrast, the more the fault intensity level progress the higher the difference of values between the shortest three orthogonal distances (larger difference between FPF values) thus making the diagnosis result more accurate and concise. After testing the model, if the difference between the first and second FPF is greater than $\mathcal{7}$, that suggest that the first fault is the correct diagnosis and the second one should be excluded. In Figure 9, we can see that at the lower intensity fault level, the FPF values for both condenser blockage and refrigerant overcharge are very similar but still the correct diagnosis (condenser fouling) is higher. Whereas at high intensities the difference becomes larger thus easier to diagnose.

5 Conclusion

In this paper the aim was develop fault detection and diagnosis method for ground source heat pumps. Data-driven method using principle component analysis was developed using Matlab. Two semi-empirical heat pumps models using Matlab and IMST-ART software were developed to simulate fault free and faulty operation conditions of the heat pump. Both models were validated with fault free experimental data and the result showed sufficient accuracy. Then, different faults were simulated using IMST-ART software. Then, easily measurable performance indicators (temperatures and electric power input) were selected to be used in the next step for PCA. The semi-empirical heat pump model developed in Matlab was used as reference line for fault free operation condition and it was essentially used to identify the operation condition classification. FDD data-driven method using principle components analysis procedure, the data for the faults simulated by IMST-ART was used as training data. After performing PCA, the original ten variables (dimensions) were reduced to three with preserving nearly all (99%) of the system information. This dimensionality reduction made it possible to visualize the system behaviors and patterns during faults. Furthermore, simple clustering methods were used to classify the heat pump operation conditions and each fault intensity level. In each operation condition, each fault was represented by four clusters (fault free, low, medium and high intensity level) and three lines connecting the centers of the clusters to represent different fault intensity levels. For fault diagnosis process, FPF was introduced as a measure of the likelihood of the of a certain fault occurring by comparing the three shortest orthogonal distances between the testing point and nearest fault lines. Additionally, FLR was introduced as measure of fault progression degree between two consecutive fault levels. Finally, a graphical user interface was built to facilitate the model's operation by servicemen. Following are few remarks obtained from the results:

- The FDD model was able to successfully detect and diagnose faults type and fault level of intensity with rather high accuracy despite the proximity of the symptoms of some faults (like condenser blockage and refrigerant overcharge).
- In the case of low intensity fault levels, the difference between FPF values are rather small but still successfully distinguishable by the model. In contrast, the more the fault intensity level progress the higher the difference between FPF values, thus making the diagnosis result more accurate and concise.
- FPF values provide convenient measure in case of two coexistent faults. In such case the two faults will have very similar FPF values.
- The fault detection model was tested using simulated faulty data. Therefore, experimental testing for the faults and validation is needed to be done.

Nomenclature

T_1	Evaporation temperature (°C)	T_{cond}	Condensation temperature (°C)
T_2	Suction temperature (°C)	T_6	Brine outlet temperature (°C)
T_3	Discharge temperature (°C)	T_7	Water inlet temperature (°C)
T_4	Subcooled temperature (°C)	T_8	Water outlet temperature (°C)
T_5	Brine inlet temperature (°C)	E_{comp}	Compressor electrical power input (kW)

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