FAULT DETECTION AND DIAGNOSIS ON HVAC VARIABLE AIR VOLUME SYSTEM USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Abrupt faults on HVAC components as blocked dampers or broken fan belt can be successfully detected by methods based on logic rules. On the other hand, those method are less efficient to detect fouling on coil or scaling in tubes that are progressively decreasing the energy efficiency and are long-lasting phenomena. Previous work on simulation data shows that methods based on artificial neural networks (ANN) are adapted to solve this problem. Model method consists in comparing real behavior of the HVAC plant to a normal behavior given by ANN trained during a preliminary phase.

The main difficulty of using ANN for fault detection is to produce the training data. Indeed, the performance of the detector is linked to the quality of these data. The procedure of using real data obtained after a recommissioning is really problematic.

An alternative way using a physical model is tested to produce training data for the cooling coil. This model of cooling coil requires only a rating point to be characterized.

ANN performance with training on simulation data is evaluated on a VAV system. Artificial faults are introduced in the real plant to simulate standard faults occurring in building HVAC system.

INTRODUCTION

Non residential building HVAC equipment failures unavoidably lead to inefficient use of energy, uncomfortable working environment and have negative environmental impacts. To avoid this, the building operator must continuously monitor the performance of the equipment. When operating a complex building it is beneficial to provide the operator with decision making tools which lead to optimal equipment operation and quick recovery from faulty operations.

why focus on the cooling coil?

Moreover, some components are more important for a consumption point of view because the frequency of their fault occurring and the importance of their impact of energy consumption. We choose to focus on one of these critical and fussy components for FDD on HVAC system: the chilled water cooling coil.

Indeed, even if the considered plant is really well protected from dust by filtration, fouling on air-side occurs. to have a idea of the importance, we can calculate the amount of dust accumulated on the cooling coil of a 4.000 m^3/h VAV system during one year. Considering an urban air containing $300*10^6$ particules/m^3 , the air carry 5 kg of dust per year. If the central station air handling unit is well designed, the unit is equipped by F7 filter (EN 779 standard, or Eurovent 4/5 EU7), which means a real efficiency of 70%. The very well build solution leads to an accumulation of 0.6 kg of dust on cooling coil considering that the coil have an induced filtration efficiency of 40%.

The standard French solution (French Code du travail Article R235.2.6) following the law obligation (equipping air handling unit for office by G4 filter (EN 779 standard, or Eurovent 4/5 EU4), leads to 1.9 kg of dust accumulated.

Thus, without speaking of abrupt faults, the cooling coil is constantly under time-scaling performance degradation. It appears really cost-effective to build some tools to optimize the maintenance of the cooling coil.

requirements of the FDD tools

The objective of this work is to construct a tool which the following characteristics:

- plug and play for the users: no additional operation required,
- no complex additional sensor on the air handling unit needed.

The tool is tested and implemented in a real VAV system air-handling unit presented hereafter.

EXPERIMENTAL VAV SYSTEM

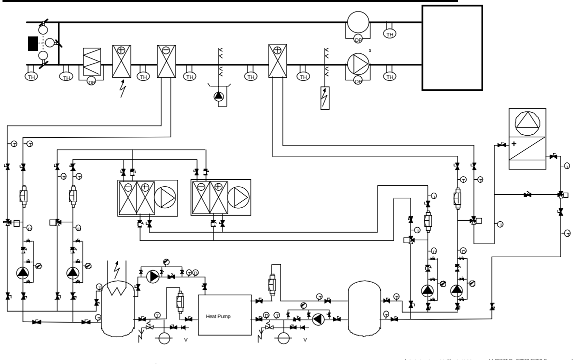

fig 1- experimental VAV system

The informations concerning the cooling coil are the following:

- inlet and outlet air humidity (ε_{ai} ε_{ao} in %) and temperature (T_{ai} T_{ao} in °C),
- inlet and outlet water temperature (T_{wi} T_{wo} in °C),
- fan signal control (C_a in %),
- chilled water valve signal control (C_w in %).

The sensors used are typical from an industrial plant, and their accuracies are respectively ±0.5°C on temperature sensor and ±5% on relative humidity. Those values must be taken into account to determine the threshold of fault detection.

Commonly, there are no sensor inside the air handling unit but this add is easy and not too expensive (around 2,000 FF for 4 sensors, 300 ∈).

Data acquisition is realized with common BEMS product. The sensors are from Landis & Staefa and the supervisor is a PRV commonly used in such VAV systems. At the stage of the project, all algorithms (training of ANN and FDD) are processed off line.

In the following, only the operation with water and fan signal controls over than 0.3 are taken into account. Under this value, flow rates of air and water include unacceptable imprecision.

ARTIFICIAL NEURAL NETWORKS

Previous work on simulation data [DUMITRU, 1996] shows that methods based on artificial neural networks (ANN) are adapted to fault detection, including long-lasting degradation of the performance. Model method consists in comparing real behavior of the HVAC plant to a normal behavior given by ANN trained during a preliminary phase.

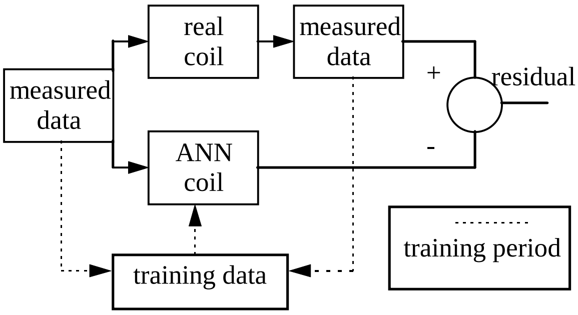

fig 2- fault detection process with training with real data

The residual on air temperature and humidity are calculated as following

$$r\,(T_{ao}) = T_{ao}^{ANN} - T_{ao}^{mes}$$

$$r\,(\varepsilon_{ao}) = \varepsilon_{ao}^{ANN} - \varepsilon_{ao}^{mes}$$

The main advantage of the ANN is the adaptability to all kind of information of the data. Indeed, it is not necessary to evaluate the absolute value of airflow rate. The control signal is enough because the ANN includes in the training the relationship between signal and absolute value.

The previous work on data simulation leads to an optimal architecture of the network with an hidden layer with 4 neurons as shown by the following figure. This architecture is a compromise between performance on training set and performance on test set to prevent from over-fitting and under-fitting.

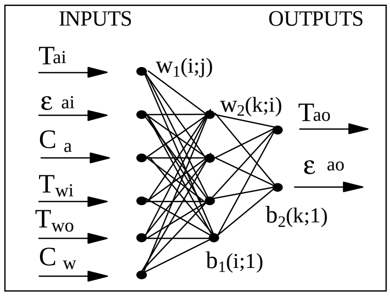

fig 3- architecture of the ANN

The ANN described above is characterized by 2 biases vectors $b_1(i;1)$ and $b_2(k;1)$ and two weights matrix $w_1(i;j)$, $w_2(k;1)$. j is the number of inputs neurons, i is the number of neurons in the hidden layer and k is the number of outputs neurons.

The neural network toolbox of MATLAB [MathWorks, 1994] provides the ANN used. The training algorithm used is back propagation algorithm with Levenberg-Marquardt approximation. The different existing training algorithms are compared for the same error result in term of number of iterations:

- back propagation: 450 iterations,
- back propagation with variable momentum: 73 iterations,
- back propagation with Levenberg-Marquardt approximation: 4 iterations.

The comparison to the cooling coil between simple back-propagation and back-propagation with Levenberg-Marquardt approximation leads to 600,000 iterations for the first one and 300 iterations for the second one.

The training process consists on calculating biases and weight which lead to a predetermined goal error, considering that the goal error is defined as the sum-squared of difference between the target and the evaluated value, considering all points of the training data set.

The performance of an ANN as an FDD tools is directly linked to the training data; which leads to 3 main difficulties. Indeed, the network learns the phenomenon occurring in training data. These difficulties are:

- first, if the training data are collected on a faulty air handling unit, the detector will never detect the fault. A commissioning is necessary to produce training data.
- Second, if the training data file is not exhaustive, the new configuration will appears as a faulty operation. For instance, if the training data includes no condensation, when condensation will appear, the ANN will detect a fault.
- Third, the ANN cannot extrapolate values, all the range of variation of each inputs must be in the training data.

So, it is necessary for the training data to be the most exhaustive as possible. The procedure of using real data obtained after a recommissioning is really difficult and restrincting:

- because of the time and staff required,
- because all the system operation layout have to be included in the training data.

An alternative way of producing training data is to use simulation. To be plug and play, this model could be parameterized from measurements and then used for training the ANN.

DIMENSIONLESS PHYSICAL MODEL OF THE COOLING COIL TO PRODUCE TRAINING DATA

why using physical model to train the ANN?

The artificial neural network is a mathematical tool. His main advantage is to be a universal approximation-maker requiring less data than the others. If the ANN is trained on the physical model, the network will learn and represent the model. The advantages of this method comparing to use the model directly as the detector are:

- the physical model needs iterations in the case of partially wet regime and is time-consumer. It can not be used as an on-line process,
- the trained ANN is very time-effective and is really simple to use compared to the physical model,
- the resulting tool can also be used on-line. Only the training period will be different, on real data if the user accepts to invest time to do it properly, or on simulated data if no time is available for this task.

dimensionless physical model

The required model need to have the same inputs and outputs variables than the ANN:

- inlet and outlet air relative humidity (ε_{ai} ε_{ao} $\in [0;1]$) and temperature (T_{ai} T_{ao} in °C),
- inlet and outlet water temperature (T_{wi} T_{wo} in °C),
- fan signal control (C_a in %),
- chilled water valve signal control (C_w in %).

The fault detection process is then the following:

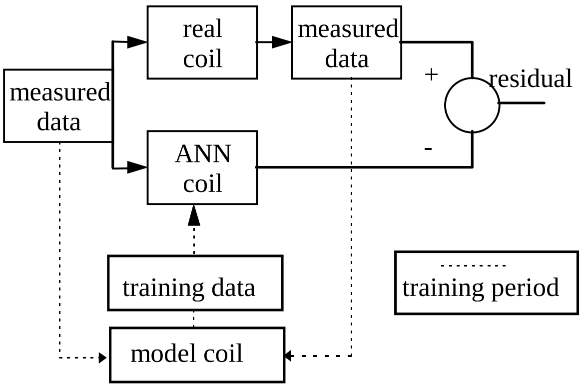

fig 4- fault detection process with training on simulated data

A cooling coil model requiring only signal control [0-1] for air and water flow rates is built. No error is introduced if we consider a simplified cooling coil model as the one presented in [MORISOT, 1998] and being a enhancement of CCSIM model of HVAC2 Toolkit [BRANDEMUEHL, 1993] by introducing the impact of air and water flow rate variations on heat transfer coefficients:

	"dimensionwith"	"dimensionless"
INPUTS	T_{ai} , ε_{ai}, T_{wi} M_a , M_w	T_{ai} , ε_{ai}, T_{wi} M_a/M_{aRat} , M_w/M_{aRat}
PARAMETERS	UA_{extRat} , M_{aRat} UA_{intRat} , M_{wRat}	UA_{extRat}/M_{aRat}, M_{aRat}/M_{aRat} UA_{intRat}/M_{aRat}, M_{wRat}/M_{aRat}
OUTPUTS	T_{ao}, ε_{ao}, T_{wo}	T_{ao}, ε_{ao}, T_{wo}

fig 5- comparison between classical model and dimensionless model

The principle of the dimensionless cooling coil model consists in dividing all flow rate variables or assimilated (heat transfert coefficients) by the nominal specific airflow rate. All **potential** variables (temperature, humidity) are unchanged:

$$M_{aRat}^{adim} = \frac{M_a}{M_{aRat}} \qquad M_{wRat}^{adim} = \frac{M_w}{M_{aRat}}$$

$$UA_{extRat}^{adim} = \frac{UA_{extRat}}{M_{aRat}} \qquad UA_{intRat}^{adim} = \frac{UA_{intRat}}{M_{aRat}}$$

The parameters values are obtained using a nominal rating point chosen on the data-base working point. Typically, an operation point with air and water signal control equals to 100% and when condensation occurs. The method used to determined from this "rating" operation point the heat transfer coefficient is similar to the method used by the CCSIM model in [BRANDEMUEHL, 1993].

"nominal" operation measured
$C_a = 1$, C_w, T_{ai}, ε_{ai}, T_{wi} T_{ao}, ε_{ao}, T_{wo}

Identification process of cooling coil characteristics
UA_{extRat}^{adim} UA_{intRat}^{adim}

others parameters needed for dimensionless simulator
M_{aRat}^{adim} M_{wRat}^{adim}

fig 6- cooling coil characterization

So, It remains necessary to determine M_{aRat}^{adim} and M_{wRat}^{adim} from the fan and valve signal control C_a and $C_{w.}$

fan characteristic

Considering a linear fan characteristic between signal control [0-1] and fan motor frequency [20-50 Hz], and assuming that the volume flow rate is directly proportional to the motor frequency for a centrifugal fan, the input of the model can be the signal control C_a [0-1] with the following typical relationship:

$$\frac{M_a}{M_{aRat}} = \frac{3}{5} C_a + \frac{2}{5}$$

The real fan characteristic has been experimentally determined by using the equal area centroïde method using 4 measured air velocities on the diameter of the duct. The measured characteristic is presented hereafter. Of course, the rating air flow rate depends on network characteristic, which means mixing box damper position and extracted fan air flow rate, as seen on the figure with different characteristics for different amount of fresh air (different positions of mixing box damper).

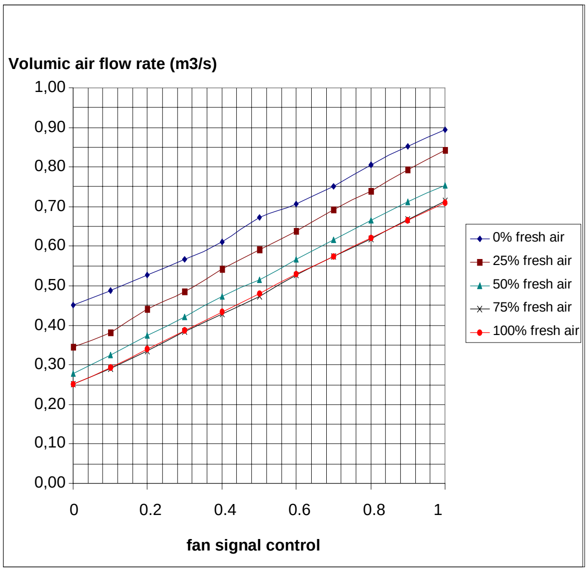

fig 7- absolute fan characteristic

The dimensionless characteristics are extracted from the previous values of measurements and are summarized in the following graph assuming a constant value for air volume mass:

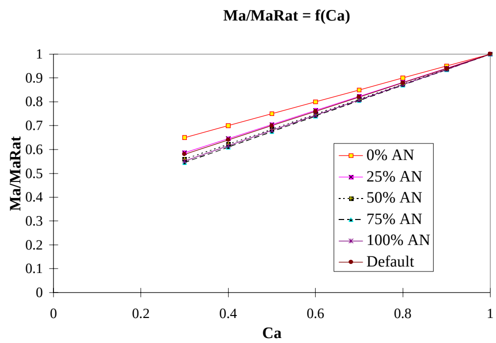

fig 8- dimensionless fan characteristics

The range of variation of signal control taken into account is from 0.3 to 1. Under the value of 0.3 for C_a too much error is introduced.

In order to generalize the experimentation to non-instrumented plants, we prefer to use a default characteristic instead of the real one.

The proposed default equation leads to a maximal relative error of 11% on M_a/M_{aRat} for a configuration with 0% fresh air. Anyway, this configuration (0% fresh air) will not be taken into account according to the necessity of introducing a minimal ratio of fresh air. For the other configurations, the mean relative error induced by the default characteristic is less than 2%. The maximal relative error in the worst case is around 6% for 75% fresh air.

valve characteristic

The valve characteristic is assumed to have the following typical shape (with a valve authority of 1):

$$\frac{M_w}{M_{wRat}} = e^{3.5(C_w - 1)}$$

The measurements of water flowrate lead to a mean relative error of 25%. Considering that the flowmeter used is not accurate, and that the water flow rate is a second order term in the modeling (used to determine UA_{int}^{adim}) , the default characteristic is used.

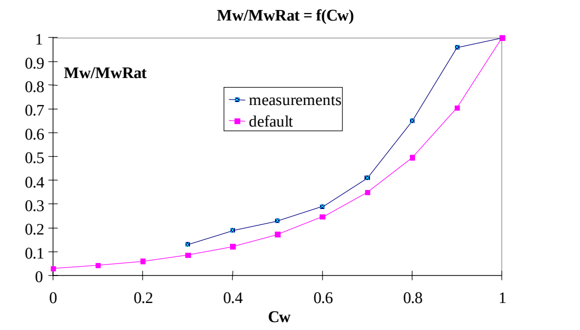

fig 9- real and default valve characteristic

The ratio M_w/M_{aRat} is calculated from M_w/M_{wRat} using a multiplicative factor determinated at the nominal rating point considering the thermal balance between air and water:

$$\frac{M_w}{M_{aRat}} = \frac{M_w}{M_{wRat}} \cdot \frac{\Delta h_{aRat}}{c_{pw}\, \Delta T_{wRat}}$$

The water thermal capacity c_{pw} is not measured but calculated from the composition of chilled water. For water without antifreeze as ethylene glycol, the water thermal capacity value is 4180 J/kg.

The determination of the model inputs from the available measurements or control signal are summarized above:

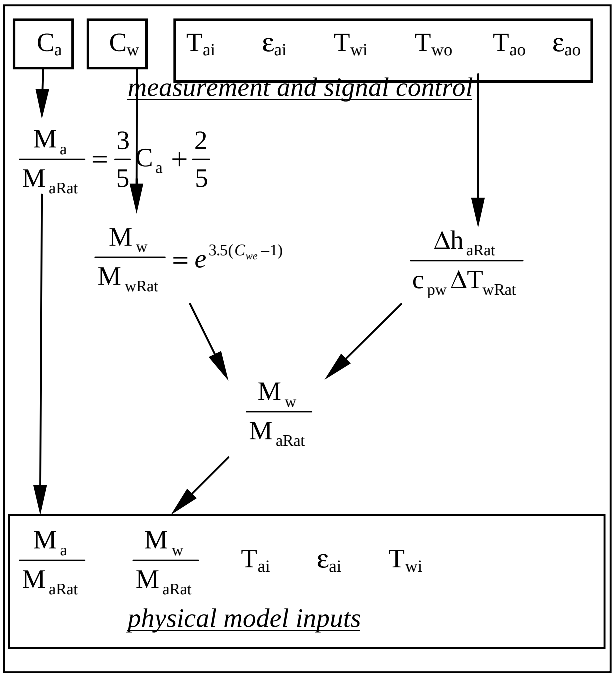

fig 10- from measurements to inputs model

producing simulated training data

A database of simulated values is produced. 490 values are used and all combinations of values are realized on their range of variation. The ranges of variation are presented hereafter:

	C_a	C_e	T_{ai}	ε_{ai} (+)	T_{wi}
unit	-	-	°C	-	°C
from	0	0	18	0.4	7
to	1	1	32	0.7	11

fig 11- inputs range of variation for training data

(+) additional condition: $w_{ai} < 0.015$.

The resulting inlet and outlet air conditions are presented in the following psychometric chart:

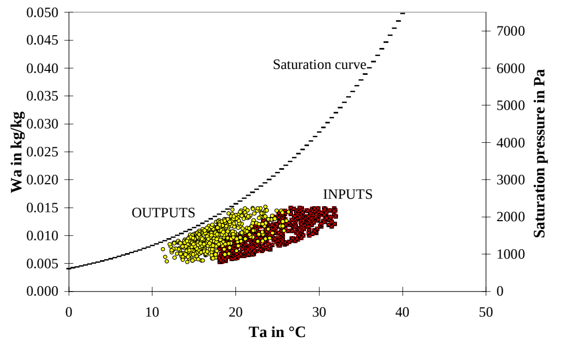

fig 12- inlet and outlet of cooling coil air conditions

The ANN is trained using this database, including all operative conditions of the cooling coil: air and water variable flow rate, condensation with partially and completely wet coil, no condensation.

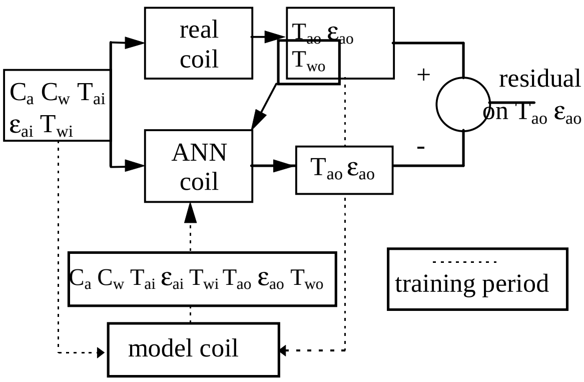

fig 13- fault detection pro with training on simulated data

In a first training shown by the following figure, 100 points are used to train the network and the other 390 points are used as a test data set. The left part of the graph shows the performance of the ANN on the training data set (100 points). The right part contains the performance on a test data set, different from the training data (390 points). A condition for a good training is that the residual should have the same range of value for the training and the test data set. It appears in this case some phenomena of extrapolation because the range of inputs variations taken into account is too low.

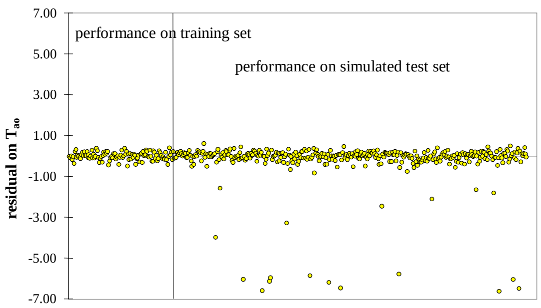

fig 14- performance of ANN on simulated training and test data: obtained error goal = 0.016

The training period measured points are used to identify the parameters of the ANN. The error goal is one of the convergence criteria during this phase. The following figure shows how the parameters converge with an error goal equal to 0.016. The convergence is reached in less than 50 iterations. No increasing of the accuracy is reached by using more iteration.

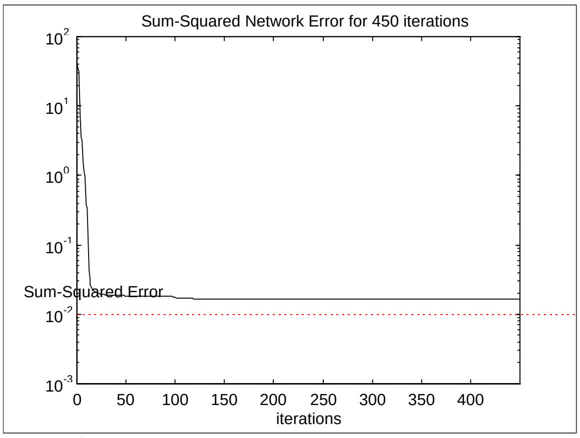

fig 15- Error goal versus iterations during training

Using the same simulated data set, the training is made on 245 points and 245 points are used as data test. The behavior of the network is better with these training conditions (see the right part of the below figure). But, the number of iterations is larger (around 200) than in the previous case, as shown on the following figure. Assuming that parameterization is not time critical, we use from now the ANN obtained with that conditions (with an obtained error goal of 0.03).

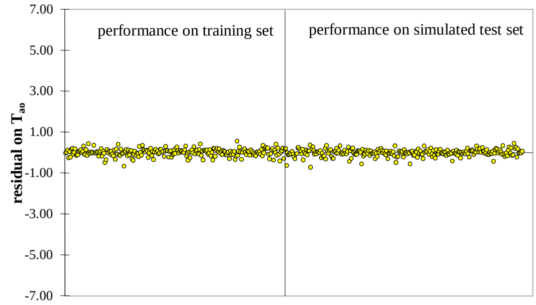

fig 16- performance of ANN on simulated training and test data: error goal = 0.03

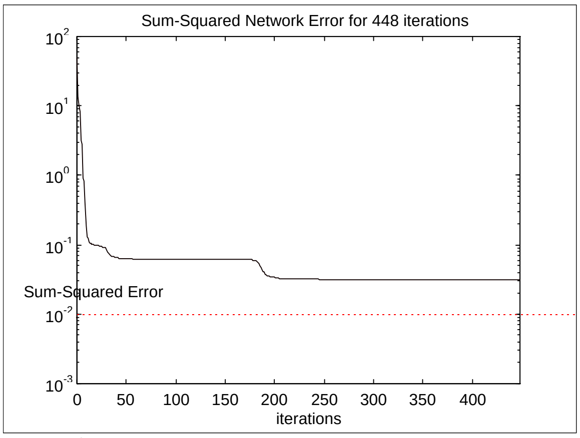

fig 17- Error goal versus iterations during training

The resulting ANN is tested on the plant with normal behavior and faulty operation.

test of performance of the ANN with normal behavior

Normal behavior of the plant is used to test the ANN. The test data set 1 contains fully condensation, for a air signal control varying from 0 to 1 and the water signal control constant at the maximal value. The test data set 2 occurring one week later contains partially wet cooling coil processing for the conditions of air and water signal control. The data set 3, 4 month later, contains a dry operation with C_a and C_e equal 0.3.

The both following graphs present the residual on temperature and relative humidity using ANN trained on simulated data. Considering threshold of 1°C for temperature, the ANN detects no fault. As the humidity point of view, some points are faulty with a threshold of 0.05. These points are when the coil is partially wet and partially dry. Indeed, the method used in this case is the [BRAUN, 1988] method. This method prevents from using iteration but introduces a non-negligible error. It is certainly better to use an iteration method to determinate the percentage of the coil area that is dry or wet.

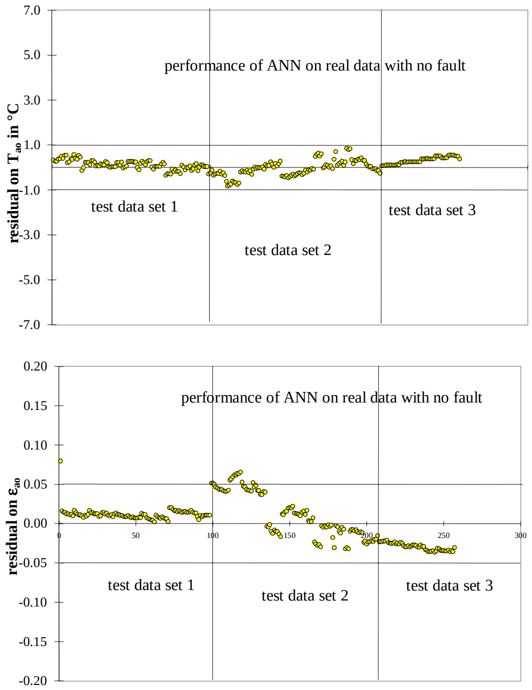

fig 18- performance of ANN for normal behavior

performance of ANN for faulty operation: fouling on air side

Fouling on airside is obtained by inserting before the cooling coil a metallic plate with large holes. Their size can be reduced: two metallic plates with holes can slide one over the other. Fouling is characterized by an area ratio expressing the part of filled air section. The experimental device is presented below:

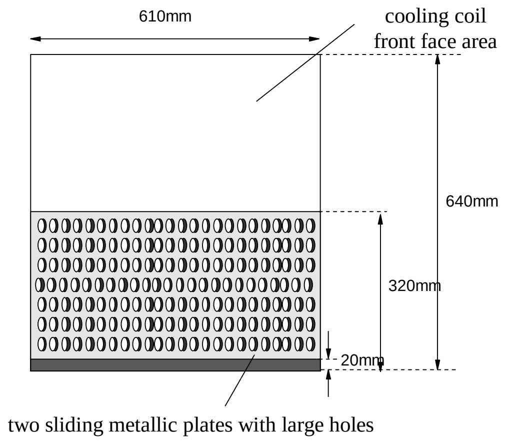

fig 19- front view of the cooling coil with the fouling device

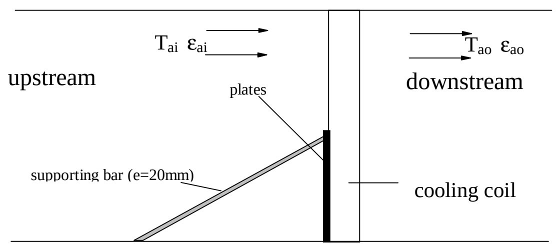

fig 20 side view of the cooling coil with the fouling device

Notice that due to the artificial fouling device, the progressive real fault is changed artificially in a abrupt one.

Due to experimental conditions, only 8 points are available for testing the ANN with this air fouling. The results are presented below. The test data set 4 contains measurements with 50% of filled air section and signal controls of 1for C_a and 0.3 for C_w. The set 5 has 32% of filled air section and C_a is 0.3 for point 7 and 1 for point 8. C_w is 0.3. No condensation occurs in the both sets. From temperature point of view, the ANN detects a faulty operation.

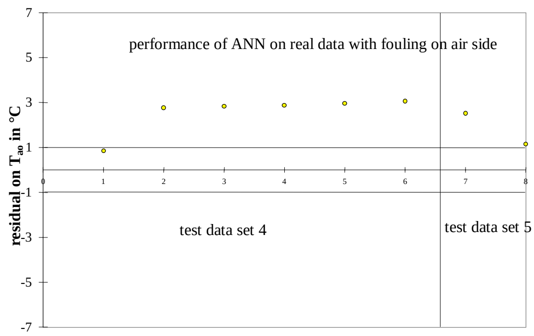

fig 21- performance of ANN for faulty operation: fouling on airside

performance of ANN for faulty operation: faulty inlet air sensor

In case of switching on of the electrical heating coil located just before the cooling coil, the temperature sensor is influenced by the radiative heat transfer of the cooling coil. Normally the two coils are never switched on simultaneously. So this is a default control sequence that creates a sensor deviation. The default on temperature sensor occurs from 500 seconds. This faulty measure is observable on the following figure where we can see that humidity ratio increases crossing the cooling coil. The coil operates in this case without condensation, and the real inlet humidity is quite constant as shown by the outlet humidity ratio. Let us recall that the measured quantity is relative humidity and that humidity ratio is obtained by calculation from ε and T. Due to low values of relative humidity a small error on ε generates a substantive error on w. This fault appears as a progressive one. The fault is detectable on the graph from 1000 s.

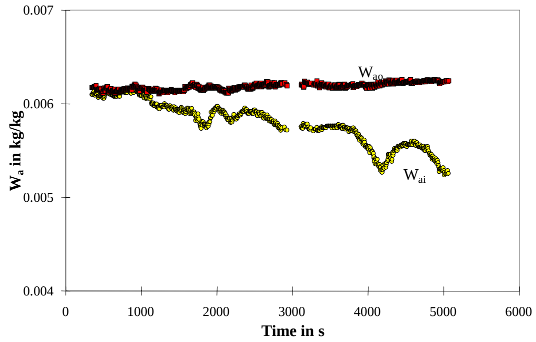

fig 22- inlet and outlet humidity ratio with faulty inlet sensor

As shown in the following figures, the ANN detects the faults. The progressive increasing in the fault appears on the residual variation on temperature and relative humidity. The 1°C threshold for temperature and 0.05 for relative humidity seem to be optimal in this case.

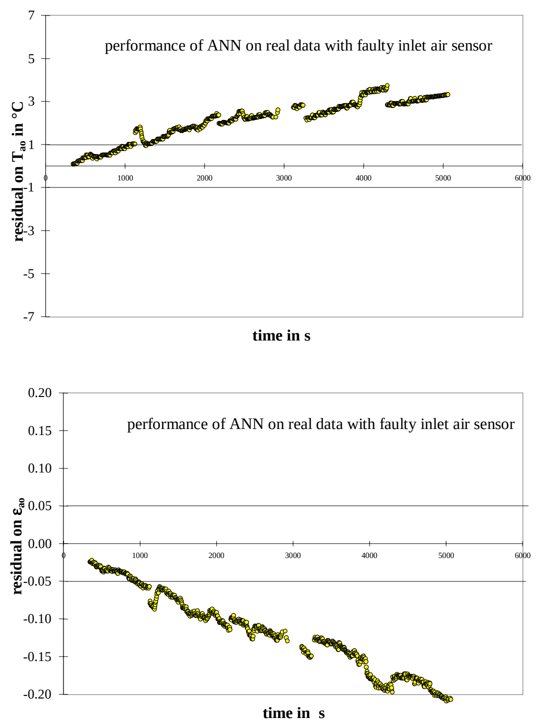

fig 23- performance of ANN for faulty operation: faulty air inlet sensor

CONCLUSIONS

The ANN are really adapted for fault detection application. The theoretical best way to train the network is to use real data from a no-faulty plant and containing all of the possible values for the input variables. Considering that these conditions can be too restricting for a user, an additional solution has been proposed and studied. This solution consists on producing supplementary training data with a dimensionless physical model. This solution does not need any additional sensor that training on real data. The resulting detector is tested on normal behavior and on faulty operation (fouling and sensor deviation). No false alarm appears and the faults are detected. The database for fouling detection is too poor. The experiments have to be completed to really conclude on this side.

ACKNOWLEDGEMENTS

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NOMENCLATURE

b_1 b_2	biases of the ANN	-
C_a	fan signal control	% [0-1]
C_w	chilled water valve signal control	% [0-1]
c_{pw}	water thermal capacity	J/kg°C
h	air specific enthalpy	J/kg dry air
M_a	specific mass air flow rate	kg da/s
M_e	mass water flow rate	kg/s
r	residual	
UA_{int}	water-side heat transfer coefficient	W/K
UA_{ext}	air-side heat transfer coefficient	W/K
w_a	air humidity ratio	kg w/kg da
w_1 w_2	weights of the ANN	-

subscripts:

a	relative to air
w	relative to water
Rat	relative to the rating point
i, o	inlet, outlet
adim	dimensionless variable, variable divided by mass air flow rate.