Journal of Applied Logic 17 (2016) 36–47

Contents lists available at ScienceDirect

Journal of Applied Logic

www.elsevier.com/locate/jal

An intelligent fault detection system for a heat pump installation based on a geothermal heat exchanger

José Luis Casteleiro-Roca [a,*], Héctor Quintián [b], José Luis Calvo-Rolle [a], Emilio Corchado [b], María del Carmen Meizoso-López [a], Andrés Piñón-Pazos [a]

[a] *University of A Coruña, Departamento de Ingeniería Industrial, Avda. 19 de febrero s/n, 15.495, Ferrol, A Coruña, Spain*
[b] *University of Salamanca, Departamento de Informática y Automática, Plaza de la Merced s/n, 37.008, Salamanca, Salamanca, Spain*

A R T I C L E   I N F O

Article history:
Available online 28 September 2015

Keywords:
MLP
J48
FLDA
Heat exchanger
Heat pump
Geothermal exchanger

A B S T R A C T

The heat pump with geothermal exchanger is one of the best methods to heat up a building. The heat exchanger is an element with high probability of failure due to the fact that it is an outside construction and also due to its size. In the present study, a novel intelligent system was designed to detect faults on this type of heating equipment. The novel approach has been successfully empirically tested under a real dataset obtained during measurements of one year. It was based on classification techniques with the aim of detecting failures in real time. Then, the model was validated and verified over the building; it obtained good results in all the operating conditions ranges.

1. Introduction

The increasing price of the energy or the environmental laws, for instance, is what makes people try to use renewable energies when it is possible [41]. The most typical renewable sources are solar and wind energy; but nowadays, others like ocean energy, are increasing their use [32]. Some research works are oriented to optimize or develop new methods on the renewable energy field, with the aim of increasing the installations' performance [30]. Despite people trying to preserve the environment, the installations based on renewable energies must usually have, at least, the same cost as non-renewable solutions to ensure their installation [30]. The above reason concerns to installations based on heat pump with geothermal heat exchangers [30]. These installations carry out large investments with relatively uncertain profitability and, their payback

* Corresponding author.
E-mail addresses: jose.luis.casteleiro@udc.es (J.L. Casteleiro-Roca), hector.quintian@udc.es (H. Quintián), jlcalvo@udc.es (J.L. Calvo-Rolle), escorchado@usal.es (E. Corchado), carmen.meizoso@udc.es (M. del Carmen Meizoso-López), andres.pinon@udc.es (A. Piñón-Pazos).

http://dx.doi.org/10.1016/j.jal.2015.09.007
1570-8683/

periods are usually very long [40]. The payback is variable, depending on the main source, and even can be a net loss [55].

1.1. Heat pump systems

A heat pump provides energy by taking it out from a source, and then transferring it into a house [37]. This energy can be obtained from any source, whether it is cold or hot. But, if this source is warm, then it is possible to achieve higher efficiency [50]. The ground can be a source for the heat pump and, the heat exchangers topology can be vertical or horizontal [37,31]. Horizontal configuration is usually more economical than the vertical type [31]; however this configuration has less efficiency than the other one. With the aim of increasing the performance of the horizontal exchanger, frequently, installers place the exchanger deeper in the ground [45]. Also, a new type of exchanger was developed, by combining the two described topologies; the exchanger is placed in helicoidal form that goes deeper in the ground [20].

Both configurations, vertical and horizontal have their own operation problems, but the horizontal has more disadvantages than the other, among others because the exchanger is closer to the ground surface [38,49]. Due to the proximity to the surface, the weather has influence over the exchanger and the efficiency could be lower [51,39,14]; even that, there are some studies like [16] that show the effect of the exchanger over the ground temperature. For the same reason, the installation may be damaged due to different reasons like crushing, perforations, and so on [4]. Typically, the performance is the same throughout the year, but if any problem appears, then, the efficiency could drop significantly or even disappear [38].

1.2. Fault detection

Fault detection involves the monitoring of a system and the detection when a fault has occurred [28]. The monitoring task differs a lot depending on the system. For example, a use of QCM [15] to control the oil degradation is explained in [9]. Other papers like [8] and [23] use the vibration analysis to monitor a self-levitating bearing. The monitoring task of solar thermal fluid transfer systems is carried out using Neural Network based models and rule based techniques in [24].

The system must be modeled or a knowledge based system must be created with the aim of detecting deviations of the correct performance [29]. There are many systems where fault detection has been implemented with satisfactory results. For instance, [27] proposes a two-stage recognition system for continuous analysis of ElectroEncephaloGram (EEG) signals. [1] proposes a model-based Robust Fault Detection and Isolation (RFDI) method with hybrid structure. A fault detection strategy for wireless sensor networks is presented in [34]. A hybrid two stage one-against-all Support Vector Machine (SVM) approach is proposed for the automated diagnosis of defective rolling element bearings in [26]; [52] shows the robust fault detection problem for non-linear systems considering both bounded parametric modeling errors and measurement noises. As can be seen on the mentioned examples (of fault detection), different soft computing techniques have been used to solve the problem.

1.3. Intelligent systems

Intelligent Systems are being used to solve or optimize several problems on engineering fields nowadays [7,6]. Some researches have been made with the aim of improving a system performance, because classical methods, like the applications based on PID controller [2], are not capable of solving this task. In other investigations, new intelligent techniques are developed to ensure a right system operation [17,33]. Some studies are focused on the development of a hybrid controller combining classical and intelligent techniques; a Neuro-PID controller is designed in [10]. Other papers design a new type of controller like the one explained in [12], an adaptive inverse controller using an online learning algorithm for neural networks.

Fig. 1. Left: Geographic location of the bioclimatic house. Right: External view of the bioclimatic house.

The fields of application for these intelligent systems are very different; for example, [11] explains the use of a hybrid controller to improve the performance of a steel rolling control process. Intelligent algorithms are used to implement a tracking of objects function for a robot in [42]. [13] solves a complex electrical problem using intelligent methods.

But the intelligent techniques are not only restricted to the control field; it is possible to use these algorithms to predict the solar energy production, like in [44]. The field of solar energy has a lot of studies, for example, [19] focuses the study on the relation between solar radiation and atmospheric conditions; [25] shows new climatic indicators base on the urban sprawl.

In other fields, intelligent algorithms are used to detect locally relevant variables [18], or to assist in the verification of some system [53].

1.4. Synthesis of the above

On the last research line, this work describes a new intelligent method to make fault detection on buildings for heat pump systems using geothermal exchanger. The way to detect wrong work-points of operation is creating a model based on classification. This model has been trained with a big dataset of a year of operation, and consequently all weather seasons have been taken into account. The model was tested with a real dataset of failures samples, obtained for this purpose.

This paper is organized as follows. It begins with a brief description of the case of study followed by an explanation of the model approach and the dataset conditioning to perform fault detection through classification techniques. In the next section results are presented, and finally the conclusions and future work are exposed.

2. Case of study

The novel model has been applied to fault detection in a geothermal heat pump. It is a part of the systems installed within a real bioclimatic house. The physical system is described in detail as follows.

2.1. Sotavento bioclimatic house

Sotavento bioclimatic house is a project of a *demonstrative* bioclimatic house of Sotavento Galicia Foundation. The house is located within the *Sotavento Experimental Wind Farm*, which is a center of dissemination of renewable energy and energy saving. The farm is located between the councils of Xermade (Lugo) and Monfero (A Coruña), in the autonomous community of Galicia (Spain). It is at coordinates 43°21′ North, 7°52′ West, at an elevation of 640 m above sea level and at a distance of 30 km from the sea. Fig. 1 shows the geographic location in the Spanish territory (left), and an external view of the bioclimatic house (right).

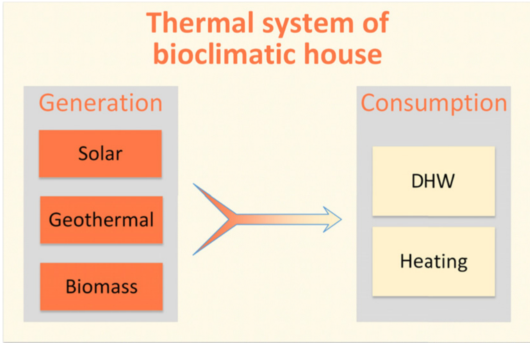

Fig. 2. Thermal installations in the house.

2.2. Installations of the bioclimatic house

Thermal and electrical installations of the bioclimatic house have various renewable energy systems to complement these installations. Fig. 2 describes through a schema the main systems and component of the thermal section of the installation. The thermal installation consists of 3 renewable energy systems (solar, biomass and geothermal) that serve the DHW (Domestic Hot Water) system and the heating system. The electrical installation consists of two renewable energy systems (wind and photovoltaic) and one connection to the grid power, getting supply to the lighting and power systems of the house.

2.3. Description of the thermal installation

Fig. 3 shows through a block diagram, the different components of the thermal section and their interconnections. Overall, the thermal installation can be divided into 3 functional groups:

- Generation group: Solar thermal (1), biomass boiler (2) and geothermal (3).
- Energy accumulation group: Inertial accumulator (5), solar accumulator (4) and preheating (8).
- Consumption group: Underfloor heating (6) and DHW (7).

Following, each functional group is described in more detail.

Generation. The generation group has three collection systems of renewable energy:

- Solar thermal system: It consists of eight solar panels that capture energy from the solar radiation and use it to heat a fluid (ethylene glycol) that flows inside the panels. The heated fluid is taken to the accumulation zone, where through the heat exchanger of the solar accumulator (4) gives up its heat to water stored inside the accumulator, increasing the water temperature for later use.
- Biomass boiler system: It has a biomass boiler type Ökofen, model Pallematic 20, with adjustable power from 7 kW to 20 kW, with a yield of pellets of 90%. It gives the hot water directly to the inertial accumulator (5) at 63 °C.
- Geothermal system: The system consists of a horizontal collector with 5 loops of 100 meters each one, buried at a depth of 2 meters (3.1), and a Heat Pump MAMY Genius – 10.3 kW with a nominal heating power of 8.4 kW and a nominal electrical power consumption of 1.9 kW (3.2). It is possible to extract energy from the ground, which is used to heat up a fluid (water with glycol) that heats the water by a geothermal pump and it is driven directly to the inertial accumulator.

The heat pumps operation is based on the thermal cycle of a gas [22]. The thermal fluid is forced to change its physical state through 4 different operations: Compression, Condensation, Expansion and Vaporization.

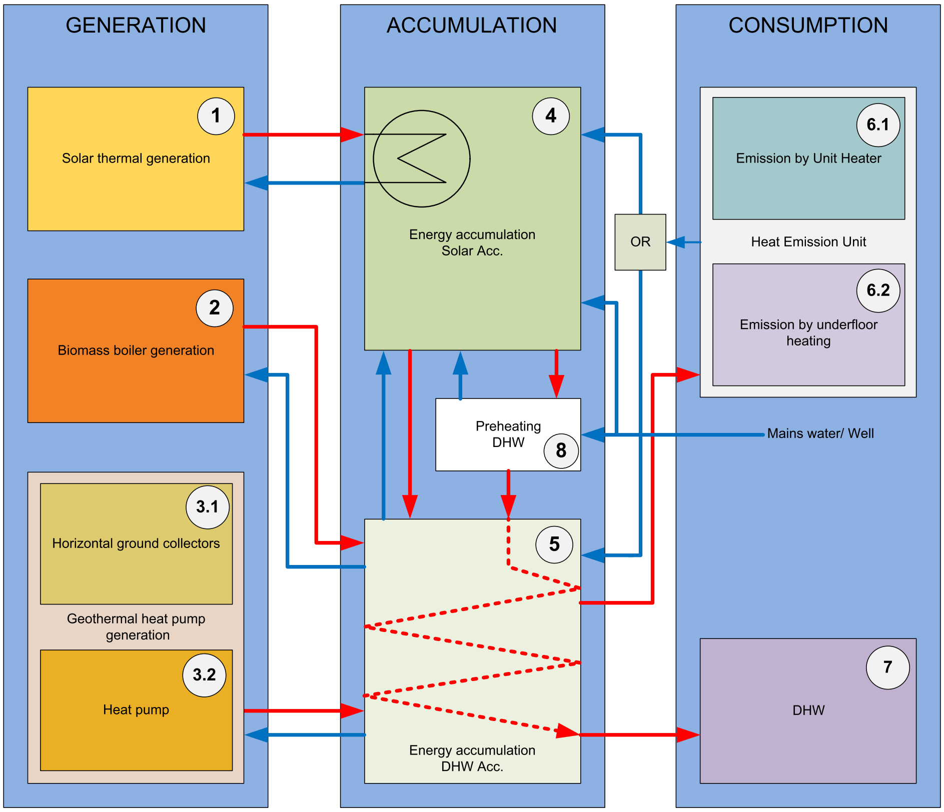

Fig. 3. Block diagram of the thermal systems installed in the bioclimatic house.

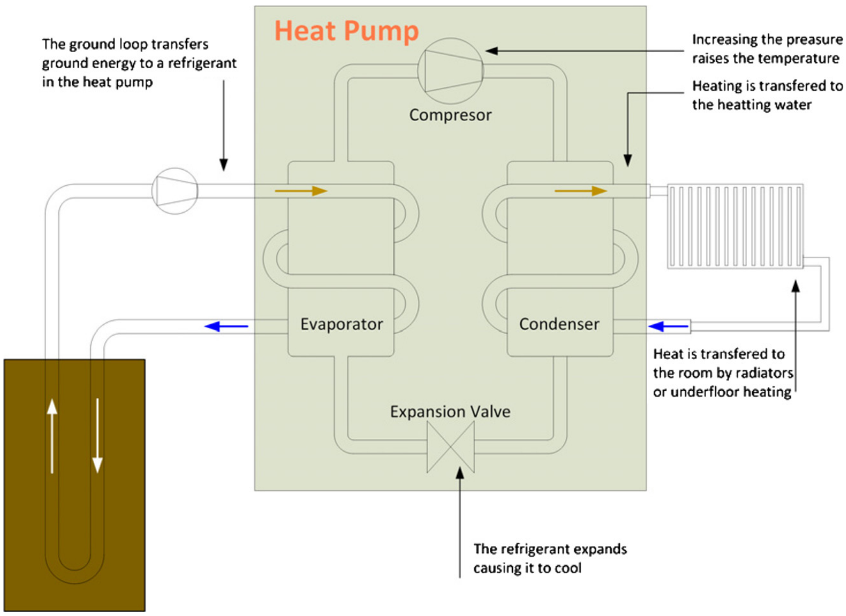

Fig. 4. A geothermal heat pump basic cycle.

The working cycle is shown in Fig. 4, which corresponds to a heat pump when it is used to warm a building. On the other hand, to cold a house, the working cycle is the opposite. In this case, the evaporator would work as a condenser, and vice versa.

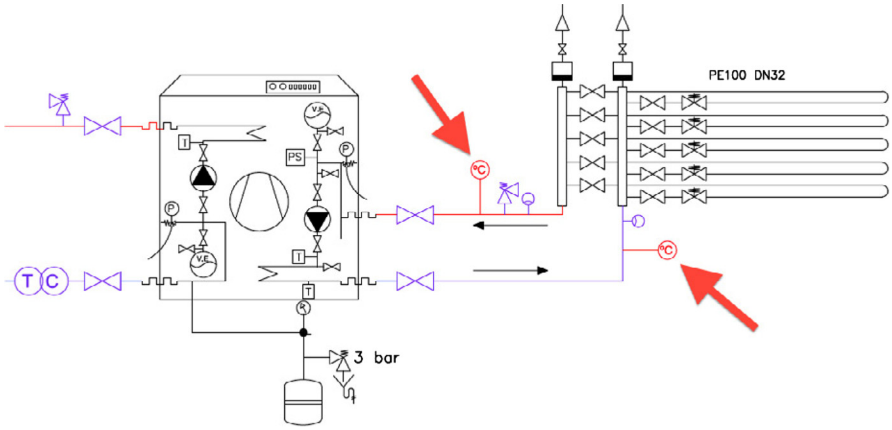

Fig. 5. Heat pump and horizontal exchanger layout.

Accumulation. The system has a solar accumulator with a storage capacity of 1000 liters, which receives energy contribution of solar thermal system. This accumulator is connected in series with the inertial accumulator that has a storage capacity of 800 liters, also it receives energy from the biomass boiler and geothermal system. The use of inertial accumulators is generally recommended in all types of heating systems and its function is to work as thermal energy storage to minimize the start-stop cycles of the units.

Consumption. The house is equipped with DHW and underfloor heating systems, both supplied through the inertial accumulator. The DHW system has been sized based on the Spanish Technical Building Code [43], taking into account that the house only has a bathroom and a kitchen for demonstration purposes. Thus, the DHW system obtained was sized for 240 liters per day. The underfloor heating system consists of a network of cross-linked polyethylene with barrier ethylene vinyl alcohol (EVAL) pipes at a distance of 5 cm below the floor of the rooms of the house. It has 4 distribution collectors above the floor to enable the purging. This system is able to maintain the temperature inside the house between 18 °C and 22 °C; for which, the water circuit should be between 35 °C and 40 °C.

2.4. Geothermal system under study

This section gives a detailed description of the operation of the real geothermal system and its components.

System description. The heat pump with a horizontal heat exchanger is shown in Fig. 5. This study is only focused on two sensors shown in Fig. 5 (thick arrows), in the primary circuit of the heat pump. The heat pump has two different circuits; the primary one provides the heat from the ground (the exchanger) to the heat pump unit, and the other one is connected between the unit and the inertial accumulator.

Geothermal exchanger. The horizontal exchanger has five different circuits, with the aim of isolating parts in case of discovering a failure in one circuit. The installation has several temperature sensors installed along the heat exchanger, to study the ground temperature while the system is running, distributed in four different loops (Fig. 6 shows the exchanger, and its connection to the building). The five circuits are connected all together outside the house and only one pipe goes to the heat pump (one as the output and other as the input of the exchanger).

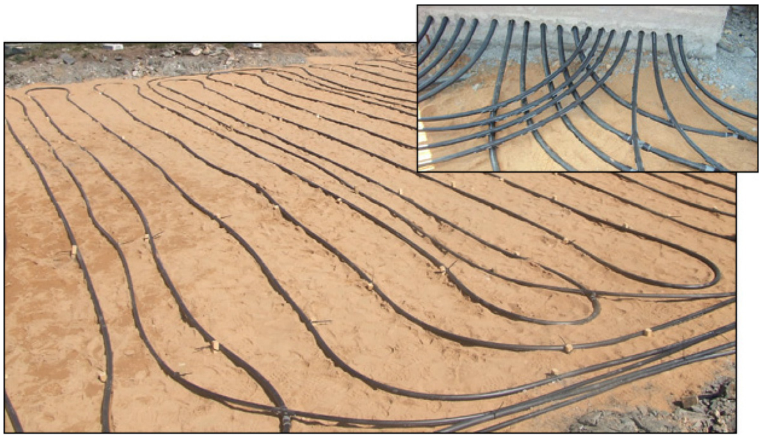

Fig. 6. Installation of the horizontal exchanger.

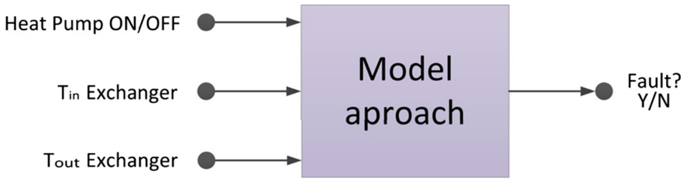

Fig. 7. Model approach.

3. Model approach

The fault detection model is based on the temperature difference at the output of the heat exchanger. These temperatures are measured near the heat pump inside the house. This is an improvement of the method, because it is not necessary to install sensors outside the building.

The model has three inputs. The first one is to indicate the state of the heat pump (*on* or *off*). And the other two inputs are the temperatures of the heat exchanger (Fig. 7).

3.1. Obtaining and conditioning the dataset

The real dataset has been obtained by taking measurements along one year. Each measurement has been taken with a sample time of 10 minutes.

Fig. 8 shows the temperature of the fluid inside the horizontal exchanger. The red-dash line is the temperature of the fluid after heating the ground, and the blue-continuous line is the temperature after the fluid is used by the heat pump. The figure represents a day, 144 measurements (one every 10 minutes). In this figure, Frame A shows a *complete* running cycle. Frame B is the part of the cycle when the heat pump is *on*, and Frame C is the restoration of the temperatures after the system turns *off*. Frame D shows a cycle when the heat pump is *off* for a long time, and it is possible to see that the difference of the temperatures achieved is more or less the same value that for other frames (the restore time does not affect the system).

As the temperature sensors are placed inside the house, the temperatures measured by them is not the real temperature of the fluid in the horizontal exchanger. In Fig. 8, it is possible to appreciate this when the heat pump is *off*, and the fluid is not pumped through the exchanger. In this situation, the temperatures read by the sensors achieved values that are higher than the ground temperature (as is explained in Frame D). However, when the heat pump is working, the sensors measure correct values, and their location does not affect the developed system.

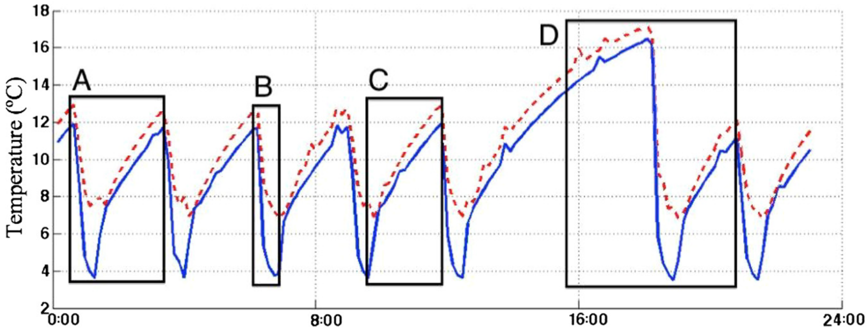

Fig. 8. One day of running cycles. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

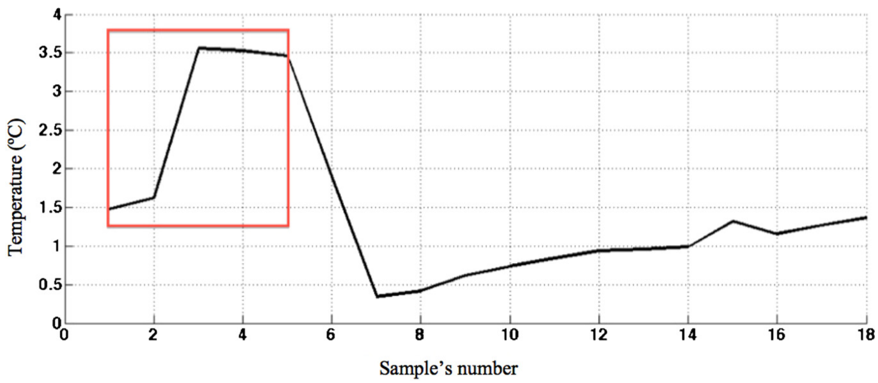

Fig. 9. Ratio between input and output of the heat pump.

The model studies the variation of the temperature ratio from the input to the output of the heat pump (equation (1)). If the heat pump is running or not, the model responds in a different way, then:

- If the heat pump is *on*, the difference between temperatures is going to increase at first (see Fig. 9, into the frame).
- When the heat pump turns *off* (Fig. 9 between the 5th and the 7th samples, out of the frame), the difference between temperatures decreases.

$$\Delta\ T = T_{output} - T_{input} \tag{1}$$

When the heat pump is *off* for a long time, the corresponding data are not taken into account. The dataset is obtained when the heat pump is in operation, and when it turns *off*, only while temperatures do not achieve the steady state.

The initial dataset contains 52 705 samples, and after discarding the non-representative data for modeling, with the rules explained before, the dataset was reduced to 13 612 samples.

3.2. Classification techniques considered to create the model

This section describes the classification techniques used to create the model.

3.2.1. Fisher's Linear Discriminant Analysis (FLDA)

Among the different criteria employed for Discriminant Analysis, the Fisher's Discriminant Criterion [5], tested on this work, has better results than others. When linear classification is possible, it is important to emphasize that good results are obtained with this technique [36,11]. When FLDA technique is employed, the training data is used to obtain hyper planes with the aim of separating the classes. With the algorithms based on this classification technique, the projection that maximizes the class separation for the classes is obtained.

The classification of a dataset with FLDA provides each sample with its projection into a weight with its class label vector. The projection is a scalar value that gives a measurement of the distance of the projection between the sample and the hyper plane. The distinctness between samples is interpreted by the measured distance between them. The FLDA achieves the best separation of the classes by maximizing the quotient of the class mean distance and the class variance. A large distance between the means is desirable to achieve a good separation.

3.2.2. J48 learning algorithm

A decision tree is approached with this method, and they are the most common approaches in machine learning [47,21,35]. The decision trees are used to classify the data into different groups, depending on the variables used in training [47]. The decision trees were obtained by using the J48 algorithm [47,56,46]. J48 algorithm has better performance in most circumstances than other algorithms [46].

This algorithm is based on an entropy calculation to develop the decision tree. Entropy is the probable information based on the partitioning into subcategories according to an attribute. The greatest advantage is the clarity on the subcategory partitions achieved. The feature with the greatest entropy reduction is chosen as the test attribute for the present node. This algorithm has some disadvantages too, like the running-time, which depends on the complexity of the algorithm matches to the tree depth.

3.2.3. A MultiLayer Perceptron (MLP)

The MLP is one of the most used Artificial Neural Network topology (ANN) [47,3]. It is a feedforward ANN, whose internal topology is simple; however, it is very robust [54,57]. The MLP could be divided in 3 different types of layers, the input layer, one (or more) hidden layer, and the output layer.

Each layer has neurons, with a specific activation function. The number of neurons in the input layer must be the same number of system inputs; for the output layer, there must be the same number of system outputs. At the hidden layers, the number of neurons could vary to achieve a good performance. The activation function type could be: Step, Linear, Log-sigmoid or Tan-sigmoid. The connection between neurons is pondered [48].

The architecture of the ANN must be carefully selected to achieve good results. On this work, the MLP only has one hidden layer. Several tests were made with different numbers of neurons at this layer (from 2 to 10), obtaining the best results with 4 neurons. The activation function of the hidden layer neurons was always a Tan-sigmoid, and for the neuron in the output layer was Step (the function used for classification purpose).

4. Results

The results of the classification are shown in Table 1. The performance of the classification techniques was obtained using the following parameters: Sensitivity (SE), Specificity (SP), Positive Prediction Value (PPV), Negative Prediction Value (NPV) and Accuracy (ACC). The equations to calculate these parameters are shown in equations (2) to (6) respectively. Where, TP (True Positives) are the samples where there are no failures, TN (True Negatives) are the samples where there are failures, and the model classifies the samples in a good way. And, FP (False Positives) are the samples where there are failures, FN (False Negatives) are the samples where there are no failures, but the model classifies them in a wrong way.

$$SE = \frac{TP}{TP + FN} \tag{2}$$

Table 1
Confusion matrix.

	FLDA		J48		MLP	
	No Failure (actual)	Failure (actual)	No Failure (actual)	Failure (actual)	No Failure (actual)	Failure (actual)
No Failure (predicted)	2431 47.19%	467 9.07%	3572 69.35%	163 3.16%	3815 74.06%	82 1.59%
Failure (predicted)	1621 31.47%	632 12.27%	480 9.31%	936 18.11%	237 4.60%	1017 19.74%
SE	0.600		0.881		0.941	
SPC	0.575		0.851		0.925	
PPV	0.839		0.956		0.978	
NPV	0.280		0.661		0.811	
ACC	0.594		0.875		0.938	

$$SP = \frac{TN}{TN + FP} \tag{3}$$

$$PPV = \frac{TP}{TP + FP} \tag{4}$$

$$NPV = \frac{TN}{TN + FN} \tag{5}$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

The dataset has been increased by including one hour of *real time* measurements, 3558 samples. When the system takes measurements in *real time*, it saves the parameters every second. During this time of fast acquisition, some typical anomalies in this type of systems has been generated. A fluid leak in the system, an obstruction in a pipe, or a partial failure in the exchanger as a consequence of a pipe manipulation were simulated.

The dataset has been divided in two groups; one for training (70%, 12 019 samples), another to test the classification algorithm (30%, 5151 samples). Table 1 shows the confusion matrix, and the performance parameters that were explained before (equations (2) to (6)). The actual data are the real classification of the data, and the predicted data are the classification given by the algorithms.

5. Conclusions

With the novel model approach, it is possible to know when the geothermal exchanger of an installation based on a heat pump is failing. Very good results have been obtained in general terms. With this approach based on intelligent techniques working as a classification system, it is possible to detect malfunction states.

As can be seen in the results section, the best classification is achieved with MLP, where the percentage of classification Accuracy is near 94%. The models created with other classification techniques also achieve good results as J48 algorithm, with an Accuracy of 87.5%; however FLDA algorithm do not allow to achieve good result. The best detection failures Accuracy is 59.4%.

The model obtained in this research achieves good performance for the Sensitivity and for the Specificity in all cases. If the performance differs between the algorithms, for the application described it was more important to increase the Specificity. The aim is to avoid that the system works with a non-detection failure condition.

Future works will be based on the application of on-line anomaly detection, with the aim of adapting the model to the progressive changes of the system. These changes can occur due to several reasons like weather or dirt.

Acknowledgements

This research is partially supported by the Spanish Ministry of Economy and Competitiveness under project TIN2010-21272-C02-01 (funded by the European Regional Development Fund), SA405A12-2 from Junta de Castilla y León. This work was also supported by the European Regional Development Fund in the IT4Innovations Centre of Excellence project (CZ.1.05/1.1.00/02.0070).

We would like to thank the 'Instituto Enerxético de Galicia' (INEGA) and 'Parque Eólico Experimental de Sotavento' (Sotavento Foundation) for their technical support on this work.

References

[1] H. Abbasi Nozari, M. Aliyari Shoorehdeli, S. Simani, H. Dehghan Banadaki, Model-based robust fault detection and isolation of an industrial gas turbine prototype using soft computing techniques, Neurocomputing 91 (2012) 29–47, http://dx.doi.org/10.1016/j.neucom.2012.02.014.
[2] H. Alaiz Moretón, J.L. Calvo-Rolle, I. García, A. Alonso Alvarez, Formalization and practical implementation of a conceptual model for PID controller tuning, Asian J. Control 13 (6) (2011) 773–784, http://dx.doi.org/10.1002/asjc.264.
[3] E. Alpaydin, Introduction to Machine Learning, 2nd edition, The MIT Press, 2010.
[4] D. Banks, An Introduction to Thermogeology: Ground Source Heating and Cooling, Wiley, 2009.
[5] P.N. Belhumeur, J.P. Hespanha, D.J. Kriegman, Eigenfaces vs. fisherfaces: recognition using class specific linear projection, IEEE Trans. Pattern Anal. Mach. Intell. 19 (1997) 711–720.
[6] J.L. Calvo-Rolle, E. Corchado, A bio-inspired robust controller for a refinery plant process, Log. J. IGPL 20 (3) (2012) 598–616, http://dx.doi.org/10.1093/jigpal/jzr010.
[7] J.L. Calvo-Rolle, E. Corchado, A bio-inspired knowledge system for improving combined cycle plant control tuning, Neurocomputing 126 (2014) 95–105, http://dx.doi.org/10.1016/j.neucom.2013.01.055.
[8] J.L. Calvo-Rolle, R. Ferreiro-Garcia, A. Alonso-Alvarez, Knowledge-based system for vibration analysis in predictive maintenance, DYNA 83 (8) (2008) 484–492.
[9] J. Calvo-Rolle, M. Meizoso-López, M. González-Rodríguez, J. López-Vilariño, M. Cela-Pérez, Oil degradation monitoring with chemical sensors and molecular imprinted polymer, DYNA 85 (9) (2010) 738–745, http://dx.doi.org/10.6036/3843.
[10] J.L. Calvo-Rolle, I. Machón-González, H. López-García, Neuro-robust controller for non-linear systems, DYNA 86 (3) (2011) 308–317, http://dx.doi.org/10.6036/3949.
[11] J.L. Calvo-Rolle, J.L. Casteleiro-Roca, H. Quintián-Pardo, M.d.C. Meizoso-Lopez, A hybrid intelligent system for PID controller using in a steel rolling process, Expert Syst. Appl. 40 (13) (2013) 5188–5196.
[12] J.L. Calvo-Rolle, O. Fontenla-Romero, B. Pérez-Sánchez, B. Guijarro-Berdiñas, Adaptive inverse control using an online learning algorithm for neural networks, Informatica 25 (3) (2014) 401–414, http://dx.doi.org/10.15388/Informatica.2014.20.
[13] J.L. Calvo-Rolle, H. Quintian-Pardo, E. Corchado, M. del Carmen Meizoso-López, R.F. García, Simplified method based on an intelligent model to obtain the extinction angle of the current for a single-phase half wave controlled rectifier with resistive and inductive load, J. Appl. Log. 13 (1) (2015) 37–47, http://dx.doi.org/10.1016/j.jal.2014.11.010.
[14] J. Casteleiro-Roca, L. Fernandez-Serantes, J. Calvo-Rolle, I. Machon-Gonzalez, M. Crespo-Ramos, H. Lopez-Garcia, Study of the effect of a geothermal heat exchanger over the ground, in: 2013 International Conference on New Concepts in Smart Cities: Fostering Public and Private Alliances (SmartMILE), 2013, pp. 1–6.
[15] J. Casteleiro-Roca, J. Calvo-Rolle, M. Meizoso-López, A. Piñón-Pazos, B. Rodríguez-Gómez, New approach for the QCM sensors characterization, Sens. Actuators A, Phys. 207 (2014) 1–9, http://dx.doi.org/10.1016/j.sna.2013.12.002.
[16] J. Casteleiro-Roca, J. Calvo-Rolle, M. Meizoso-López, A. Piñón-Pazos, B. Rodríguez-Gómez, Bio-inspired model of ground temperature behavior on the horizontal geothermal exchanger of an installation based on a heat pump, Neurocomputing 150 (Part A) (2015) 90–98, http://dx.doi.org/10.1016/j.neucom.2014.02.075.
[17] E. Corchado, A. Abraham, V. Snasel, New trends on soft computing models in industrial and environmental applications, Neurocomputing 109 (2013) 1–2, http://dx.doi.org/10.1016/j.neucom.2012.08.032.
[18] M.J. Crespo-Ramos, I. Machón-González, H. López-García, J.L. Calvo-Rolle, Detection of locally relevant variables using SOM–NG algorithm, Eng. Appl. Artif. Intell. 26 (8) (2013) 1992–2000, http://dx.doi.org/10.1016/j.engappai.2013.04.012.
[19] C. Crespo-Turrado, M. del Carmen Meizoso-López, F. Sánchez-Lasheras, B.A. Rodríguez-G'ømez, J.L. Calvo-Rolle, F.J. de Cos-Juez, Missing data imputation of solar radiation data under different atmospheric conditions, Sensor 14 (11) (2014) 20382–20399, http://dx.doi.org/10.3390/s141120382.
[20] P. Cui, X. Li, Y. Man, Z. Fang, Heat transfer analysis of pile geothermal heat exchangers with spiral coils, Appl. Energy 88 (11) (2011) 4113–4119, http://dx.doi.org/10.1016/j.apenergy.2011.03.045.
[21] R. Duda, P. Hart, D. Stork, Pattern Classification, Wiley, 2001.
[22] H. Esen, M. Inalli, A. Sengur, M. Esen, Performance prediction of a ground-coupled heat pump system using artificial neural networks, Expert Syst. Appl. 35 (4) (2008) 1940–1948, http://dx.doi.org/10.1016/j.eswa.2007.08.081.
[23] R.F. Garcia, J.L. Calvo-Rolle, M.R. Gomez, A.D. Catoira, Expert condition monitoring on hydrostatic self-levitating bearings, Expert Syst. Appl. 40 (8) (2013) 2975–2984, http://dx.doi.org/10.1016/j.eswa.2012.12.013.
[24] R.F. Garcia, J.L. Calvo-Rolle, J.P. Castelo, M.R. Gomez, On the monitoring task of solar thermal fluid transfer systems using {NN} based models and rule based techniques, Eng. Appl. Artif. Intell. 27 (2014) 129–136, http://dx.doi.org/10.1016/j.engappai.2013.06.011.

[25] A. Ghanghermeh, G. Roshan, J.A. Orosa, J.L. Calvo-Rolle, Á.M. Costa, New climatic indicators for improving urban sprawl: a case study of Tehran city, Entropy 15 (3) (2013) 999–1013, http://dx.doi.org/10.3390/e15030999.
[26] K.C. Gryllias, I.A. Antoniadis, A support vector machine approach based on physical model training for rolling element bearing fault detection in industrial environments, Eng. Appl. Artif. Intell. 25 (2) (2012) 326–344.
[27] W.-Y. Hsu, Continuous EEG signal analysis for asynchronous BCI application, Int. J. Neural Syst. 21 (4) (2011) 335–350.
[28] R. Isermann, Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance, Springer, 2006.
[29] R. Isermann, Fault-Diagnosis Applications: Model-Based Condition Monitoring: Actuators, Drives, Machinery, Plants, Sensors, and Fault-Tolerant Systems, Springer, 2011.
[30] T. Jenssen, Glances at Renewable and Sustainable Energy, Springer, London, 2013.
[31] S. Kakaç, H. Liu, A. Pramuanjaroenkij, Heat Exchangers: Selection, Rating, and Thermal Design, second edition, Taylor & Francis, 2002.
[32] M. Kaltschmitt, W. Streicher, A. Wiese, Renewable Energy, Springer, Berlin, Heidelberg, 2007.
[33] J. Kang, W. Meng, A. Abraham, H. Liu, An adaptive PID neural network for complex nonlinear system control, Neurocomputing 135 (2014) 79–85, http://dx.doi.org/10.1016/j.neucom.2013.03.065.
[34] S.A. Khan, B. Daachi, K. Djouani, Application of fuzzy inference systems to detection of faults in wireless sensor networks, Neurocomputing 94 (2012) 111–120.
[35] R. Khan, A. Hanbury, J. Stöttinger, A. Bais, Color based skin classification, Pattern Recognit. Lett. 33 (2) (2012) 157–163, http://dx.doi.org/10.1016/j.patrec.2011.09.032.
[36] M. Koç, A. Barkana, A new solution to one sample problem in face recognition using FLDA, Appl. Math. Comput. 217 (24) (2011) 10368–10376.
[37] B.C. Langley, Heat Pump Technology, Prentice Hall PTR, 2002.
[38] C. Lee, Effects of multiple ground layers on thermal response test analysis and ground-source heat pump simulation, Appl. Energy 88 (12) (2011) 4405–4410, http://dx.doi.org/10.1016/j.apenergy.2011.05.023.
[39] A. Omer, Ground-source heat pumps systems and applications, Renew. Sustain. Energy Rev. 12 (2) (2008) 344–371, http://dx.doi.org/10.1016/j.rser.2006.10.003.
[40] L. Ozgener, A review on the experimental and analytical analysis of earth to air heat exchanger (EAHE) systems in Turkey, Renew. Sustain. Energy Rev. 15 (9) (2011) 4483–4490, http://dx.doi.org/10.1016/j.rser.2011.07.103.
[41] D. Porter, Comprehensive Renewable Energy, Elsevier, 2012.
[42] H. Quintián-Pardo, J.L. Calvo-Rolle, O. Fontenla-Romero, Application of a low cost commercial robot in tasks of tracking of objects, DYNA 175 (2012) 24–33.
[43] R.D. 314/2006, 17 march, which approves the 'Código Técnico de la Edificación' (BOE 74, 2006).
[44] H. Quintián-Pardo, J.L. Calvo-Rolle, E. Corchado, A hybrid regression system based on local models for solar energy prediction, Informatica 25 (2) (2014) 265–282.
[45] A. Rezaei, E. Kolahdouz, G. Dargush, A. Weber, Ground source heat pump pipe performance with tire derived aggregate, Int. J. Heat Mass Transf. 55 (11–12) (2012) 2844–2853, http://dx.doi.org/10.1016/j.ijheatmasstransfer.2012.02.004.
[46] L. Rokach, Data Mining with Decision Trees: Theory and Applications, Series in Machine Perception and Artificial Intelligence, World Scientific Publishing Company, Incorporated, 2008.
[47] O. Rud, Data Mining Cookbook: Modeling Data for Marketing, Risk, and Customer Relationship Management, Data Warehousing/Data Mining, John Wiley & Sons, 2000.
[48] J. Rynkiewicz, General bound of overfitting for MLP regression models, Neurocomputing 90 (2012) 106–110, http://dx.doi.org/10.1016/j.neucom.2011.11.028.
[49] B. Sanner, C. Karytsas, D. Mendrinos, L. Rybach, Current status of ground source heat pumps and underground thermal energy storage in Europe, Geothermics 32 (4–6) (2003) 579–588, http://dx.doi.org/10.1016/S0375-6505(03)00060-9.
[50] H. Sauer, R. Howell, Heat Pump Systems, Krieger Publishing Company, 1991.
[51] V. Tarnawski, W. Leong, T. Momose, Y. Hamada, Analysis of ground source heat pumps with horizontal ground heat exchangers for Northern Japan, Renew. Energy 34 (1) (2009) 127–134, http://dx.doi.org/10.1016/j.renene.2008.03.026.
[52] S. Tornil-Sin, C. Ocampo-Martinez, V. Puig, T. Escobet, Robust fault detection of non-linear systems using set-membership state estimation based on constraint satisfaction, Eng. Appl. Artif. Intell. 25 (1) (2012) 1–10, http://dx.doi.org/10.1016/j.engappai.2011.07.007.
[53] X.M. Vilar-Martínez, J.A. Montero-Sousa, J.L. Calvo-Rolle, J.L. Casteleiro-Roca, Expert system development to assist on the verification of TACAN system performance, DYNA 89 (1) (2014) 112–121, http://dx.doi.org/10.6036/5756.
[54] P.D. Wasserman, Advanced Methods in Neural Computing, 1st edition, John Wiley & Sons, Inc., New York, NY, USA, 1993.
[55] Wikipedia, Geothermal heat pump, http://en.wikipedia.org/wiki/Geothermal_heat_pump#cite_note-economics-38, 2013.
[56] I.H. Witten, E. Frank, Data Mining: Practical Machine Learning Tools and Techniques, second edition, Morgan Kaufmann Series in Data Management Systems, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 2005.
[57] Z. Zeng, J. Wang, Advances in Neural Network Research and Applications, 1st edition, Springer Publishing Company, Incorporated, 2010.